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The Optimization of CNN Algorithm Using Transfer Learning for Marine Fauna Classification

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Abstract: Marine ecosystems have an important role in the survival of all living things. One of the marine ecosystems that must be preserved is marine fauna. Marine fauna are all types of organisms that live in the marine environment. Marine fauna has a huge biodiversity that includes different species in various shapes and sizes. Therefore, efforts are needed to monitor and protect marine fauna so that the marine ecosystem can remain stable. One way to monitor marine fauna is by using classification technology. One of the technologies that can be used in marine fauna classification technology is Convolutional Neural Network (CNN). CNN is one of the classification methods that can be used to classify objects in images with a high level of accuracy. The CNN architecture models used are MobileNet, Xception, and VGG19. Furthermore, the method used to improve the performance of the CNN algorithm is the Transfer Learning method. The test results show that the MobileNet architecture model produces the highest accuracy value of 91.94% compared to Xception and VGG19 which only get an accuracy value of 87.64% and 88.76%. This shows that the MobileNet model has a more optimal performance in classifying marine fauna.

Keywords: CNN; Transfer Learning; Deep Learning; Classification; Marine Fauna

INTRODUCTION

Marine fauna is an important part of the marine ecosystem that has an important role in maintaining environmental balance. Marine fauna is also an important source of protein for coastal communities and has high economic value as a natural resource. However, the survival of marine fauna is threatened due to activities carried out by humans such as pollution, industrial waste disposal into marine waters, overfishing, mangrove deforestation, plastic pollution and so on. In addition, other factors such as climate change and habitat change also affect the condition of marine fauna. Therefore, efforts are needed to monitor and protect marine fauna so that marine ecosystems can remain stable and can provide optimal benefits for society and the environment.

One way to monitor marine fauna is by using classification technology (Thomas et al., 2020). The technology can classify the types of marine fauna and this is very important because it can be used to determine the number of existing species, determine endangered species, determine species that can be used as indicators of marine environmental conditions and marine protection policy development. One of the technologies that can be used in marine fauna classification technology is Convolutional Neural Network (CNN). CNN is a classification method that can be used to classify objects in images with a high level of accuracy (Anjani et al., 2021). CNN has been proven to be able to perform image classification well (Sun et al., 2020). Furthermore, the method used to improve the performance of the

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CNN algorithm is the transfer learning method (Alya et al., 2023). This method is used to take the concept of a predefined model and apply it to a new problem (Murugaiyan et al., 2021). Transfer learning is very effective in overcoming the problem of marine fauna classification because it can increase the accuracy of the model without having to do data training from scratch (Verfuss et al., 2019).

Many studies have been conducted related to classification. Previous research conducted by (Lan et al., 2020) which conducted classification with CNN using 20 types of fish with a total of 1,179 data. The study shows that the transfer method with the Inception-V3 model can be used to predict fish species and produce an accuracy of 89%. Another study was also conducted by (Shaha & Pawar, 2018) using transfer learning for image classification with VGG19, AlexNet, and VGG16 models. Tests were also conducted by comparing hybrid learning approaches and SVM. The performance analysis results obtained showed that the VGG19 architecture performed better than the others in classifying images. On the other hand, (Adhikary, 2022) with his research using the VGG-16 model with a dataset of 9,460 data to predict low-resolution fish images resulted in an accuracy of 96.5%.

In addition, another study was also conducted by (Desai et al., 2022) who used a Deep Learning approach to classify fish species. The results showed that the Xception model was able to predict fish datasets in Turkish supermarkets totaling 9000 data and produced an accuracy of 99.18%. Although these three models have been studied to predict fish species, research related to these three methods still requires further research.

LITERATURE REVIEW

Before conducting research, researchers have conducted studies related to literature related to previous research that has been done before. Research by (Muhandisin & Azhar, 2022) conducted research using Transfer Learning techniques to diagnose malaria. This study used an image dataset of 27,660 images of malaria blood cell images. The results obtained with the VGG16 model produced an accuracy of 96% and the ResNet 50 model produced an accuracy of 98%. Another research was conducted by (Arrofiqoh & Harintaka, 2018) who conducted plant classification using CNN. This research uses 5 types of plant classes, namely rice, shallots, chili banana, and coconut. The accuracy result obtained for training data is 100%, for validation data it produces 93% accuracy and 82% accuracy on test data. The test results show that the CNN method can distinguish plant types well. Likewise, research conducted by (Michele et al., 2019) conducted research using SVM and CNN with the MobileNet model for palmprint recognition. The results showed that the SVM classifier with the MobileNet V2 model successfully tested with an accuracy rate of 100%. In addition (Rismiyati & Luthfiarta, 2021) have also successfully conducted research using transfer learning and Artificial Neural Network models to classify food/non-food images. The results show a high accuracy of 95.83%. Likewise, research conducted by (IBRAHIM et al., 2022) classifies the maturity level of tea leaf shoots using two CNN architectures, namely VGGNET 19 and ResNet50. The test results using the VGGNET19 architecture get the best accuracy value of 97.5%.

METHOD

The type of research used includes experimental research. This experimental research is a systematic scientific approach to understanding cause and effect relationships between variables in a particular context.

Convolutional Neural Network (CNN)

CNN (Convolutional Neural Network) is one type of architecture in artificial deep learning specifically designed for processing structured data such as images and videos (Michele et al., 2019). CNN has become one of the most widely used techniques in the field of pattern recognition and computer vision.

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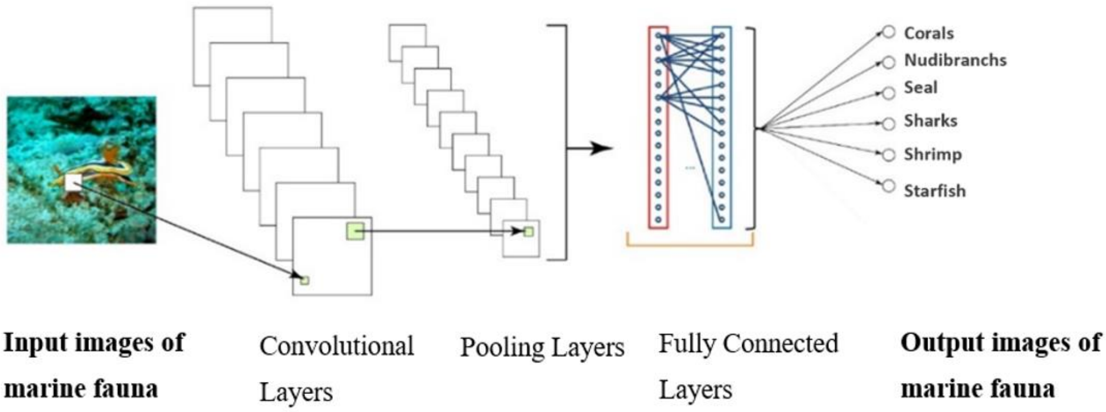

Fig 1. Illustration of the flow of marine fauna classification process with Convolutional Neural Network

As illustrated in the figure above, the classification stages using the Convolutional Neural Network algorithm include:

1. Input in the form of images of marine fauna in JPG format
2. The convolutional layers stage breaks the image into small pieces
3. The pooling layers stage simplifies the image with a set filter
4. Fully connected layers calculate the probability weights for each class or type of marine fauna.
5. Output in the form of predicted marine fauna types

Transfer Learning

Transfer Learning is a technique in artificial intelligence where the knowledge learned by a pre-trained model is redirected to train a new model. This approach can save time and resources, as the model does not have to be trained from scratch on the second task (Meena et al., 2022). The weights and biases learned in the first task can be used as a starting point, and adjusted in the second task.

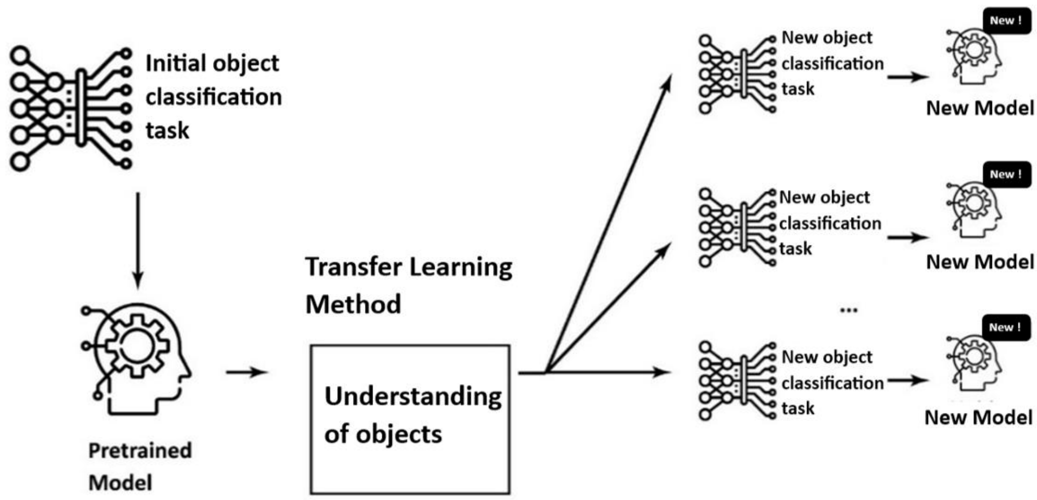

Fig 2. Illustration of Transfer Learning

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Work Procedures

The research flow carried out in this study is divided into several stages, namely input image datasets, then preprocessing datasets, training and validation sets, loading the base model, testing and evaluating the model. The flowchart of the research method can be seen in Figure 3.

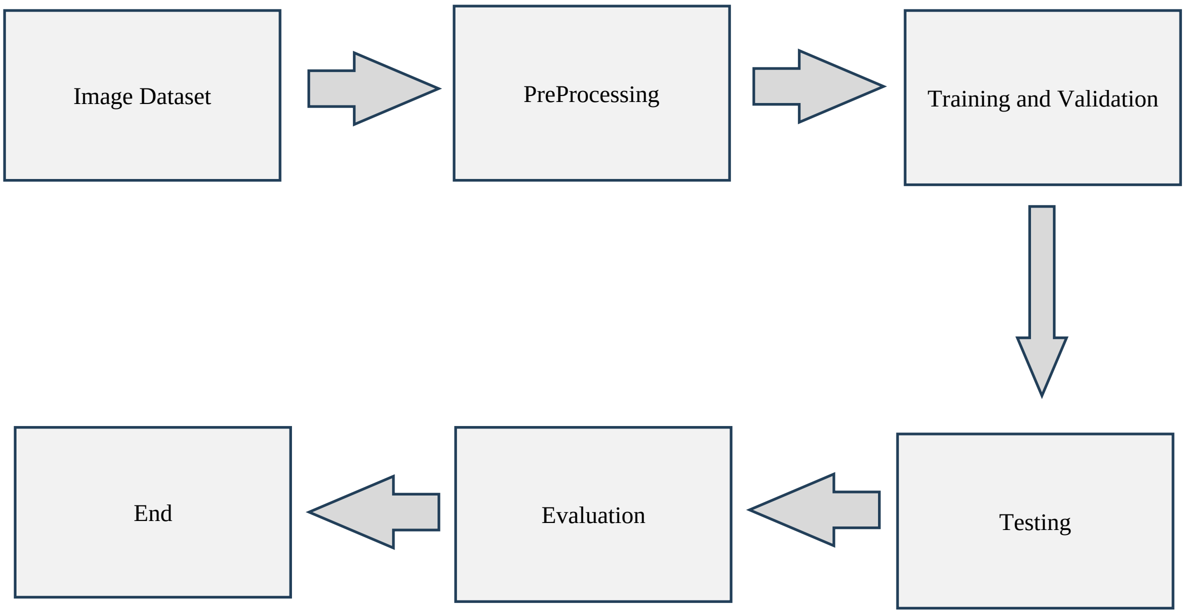

Fig 3. The Research workflow

1. **Image Dataset**

Collecting marine fauna image data that will be used in this research. Then the image dataset is divided into several parts according to the type of fauna, such as coral, Nudibranch, Seal, Shark, Shrimp, and Starfish.

2. **Preprocessing**

In this stage, preparation and improvement of data quality are carried out in order to produce more accurate results, including resizing to 224 x 224 pixels, data augmentation, and dividing the data set into three parts, which are 80% for training data, 10% for validation data, and 10% for testing data.

3. **Training and Validation**

At this stage the data that has been preprocessed is carried out model training. The models used in this research are MobileNet, Xception, and VGG19. Furthermore, it is also model validation to measure performance and optimize previous training.

4. **Testing**

After training, the next step is testing the trained model. Testing is carried out to determine whether the image prediction performed on the trained model is accurate or not.

5. **Evaluation**

The final stage is evaluation. The evaluation aims to measure and calculate the performance of the architecture model used.

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RESULT

Dataset

The dataset used in this research is sourced from from https://www.kaggle.com/datasets/vencerlanz09/sea-animals-image-dataste. This research uses 6 species of marine fauna image with a total of 2970 data. The following is a sample of the marine fauna species dataset used.

Fig 4. Dataset Sample

Preprocessing Data

Before training the data with the CNN model, the first step is to preprocess the data. In this process, the image size that previously consisted of various image sizes was converted into one size, measuring 224 x 224 pixels. In addition, the data will also be divided into 3 parts, which are 80% for training data, 10% for validation data, and 10% for testing data with a total of 2970 images.

Training Process

At this stage, the data that has been preprocessed previously will be trained. This training uses three Convolutional Neural Network architecture models namely MobileNet, Xception and VGG19. Each model is given an iteration parameter in the training process of 40 epochs with a learning rate of 0.00001. All models in this study were trained with Adam's optimizer.

1. MobileNet Architecture

MobileNet is a Convolutional Neural Network (CNN) architecture that utilizes several techniques to achieve high efficiency and speed. MobileNet can provide good performance in image recognition, while also reducing computational requirements and model size (Michele et al., 2019). The training process with MobileNet Architecture can be seen in the graph below.

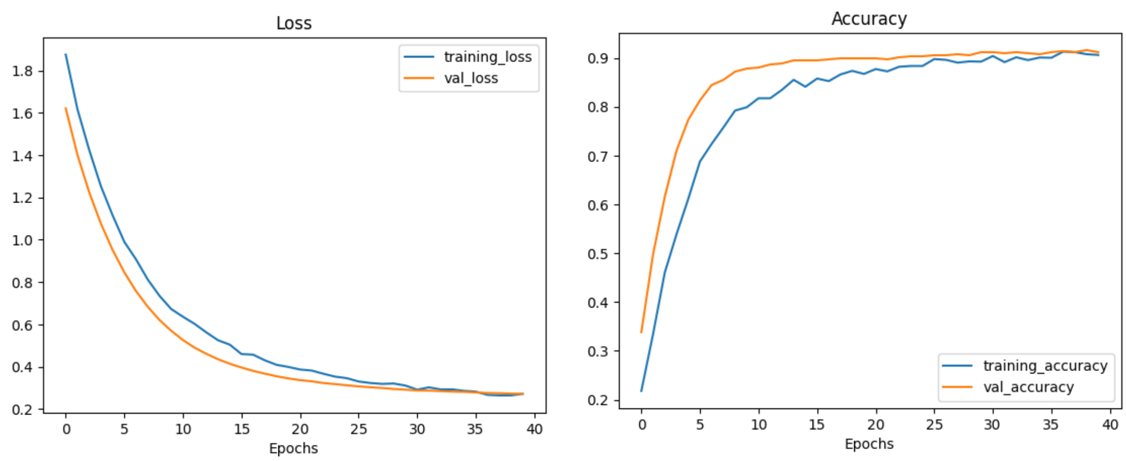

Fig 5. Training and Validation on MobileNet Architecture

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Based on model training with 40 epochs, the training accuracy value is 0.9060 and the loss value is 0.2713. As for the validation value, the accuracy obtained is 0.9216 and the validation loss value is 0.2857. The value is obtained based on the last value at epoch 40.

2. Xception Architecture

Xception is a pretrained model similar to Inception-v3, but is based on a different architecture called "separable convolution". This allows the Xception model to achieve high accuracy with fewer parameters and fewer calculations, which makes it faster and more efficient to use (Gülmez, 2022). The training process with Xception Architecture can be seen in the graph below.

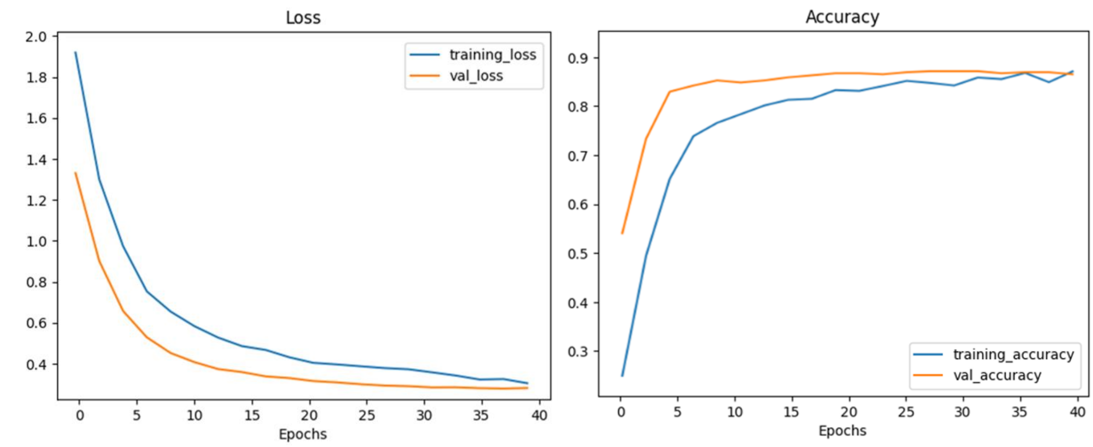

Fig 6. Training and Validation on Xception Architecture

Based on model training with 40 epochs, the training accuracy value is 0.8865 and the loss value is 0.3639. As for the validation value, the accuracy obtained is 0.8708 and the validation loss value is 0.3103. The value is obtained based on the last value at epoch 40.

3. VGG19 Architecture

The VGG19 architecture is one of the well-known convolutional neural network (CNN) architectures due to its simple structure yet highly effective in image recognition. The VGG19 architecture is commonly used as the basis for many object recognition and image classification applications. (Meena et al., 2022). The training process with VGG19 Architecture can be seen in the graph below.

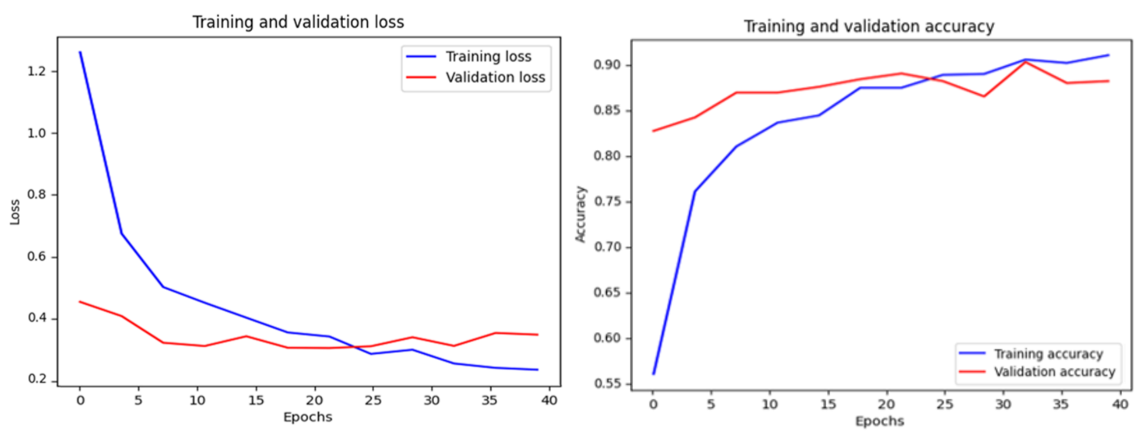

Fig 7. Training and Validation on VGG19 Architecture

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Based on model training with 40 epochs, the training accuracy value obtained is 0.9108 and the loss value is 0.2361. As for the validation value, the accuracy obtained is 0.8824 and the validation loss value is 0.3941.

Figures 5, 6 and 7 show the accuracy and loss values of the training data and validation data. The MobileNet and Xception models are quite stable compared to the VGG19 model. All three models produce quite good values. This indicates an optimal result.The comparison of the three models can be seen in the following table.

Table 1. Comparison Result

Architecture Model	Training Data		Validation Data	
	Loss	**Accuracy**	**Loss**	**Accuracy**
MobileNet	0.2713	0.9060	0.2857	0.9216
Xception	0.3639	0.8865	0.3103	0.8708
VGG19	0.2361	0.9108	0.3941	0.8824

From the above results, it can be seen that the MobileNet model obtained a loss value in the training data of 0.2713, lower than the loss value in the validation data of 0.2857. The accuracy value on the validation data obtained is higher at 0.9216 compared to the accuracy value on the training data of 0.9060. This shows that the model has good capabilities. In the Xception model, the loss value obtained in the training data of 0.3639 is higher than the loss value in the validation data of 0.3103. For the accuracy value in the validation data, a low value of 0.8708 is obtained compared to the accuracy value in the training data of 0.8865. In the VGG19 model, the loss value obtained in the training data of 0.2361 is lower than the loss value in the validation data of 0.3941. As for the accuracy value in the validation data, a lower value is obtained, which is 0.8824 compared to the accuracy value in the training data of 0.9108.

The highest validation accuracy result is obtained by the MobileNet model of 92.16%, followed by the VGG19 model with a value of 88.24%, and the Xception model with a value of 87.08%.

After training and testing the model, the next step is to evaluate the performance of the model using the confusion matrix. The following are the results of the confusion matrix obtained from the three models.

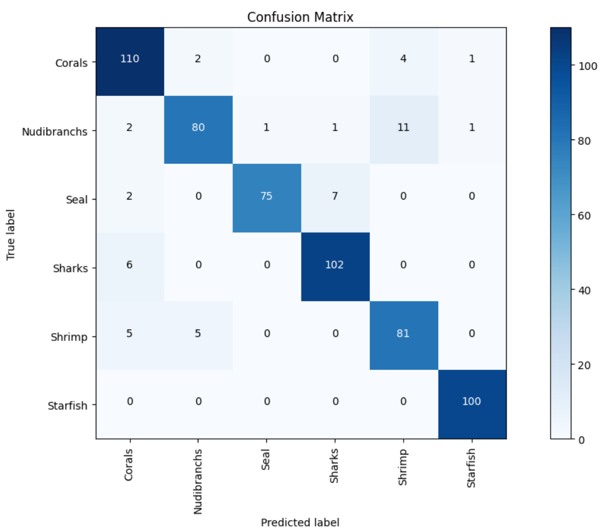

Fig. 8 Confussion Matrix Result on MobileNet

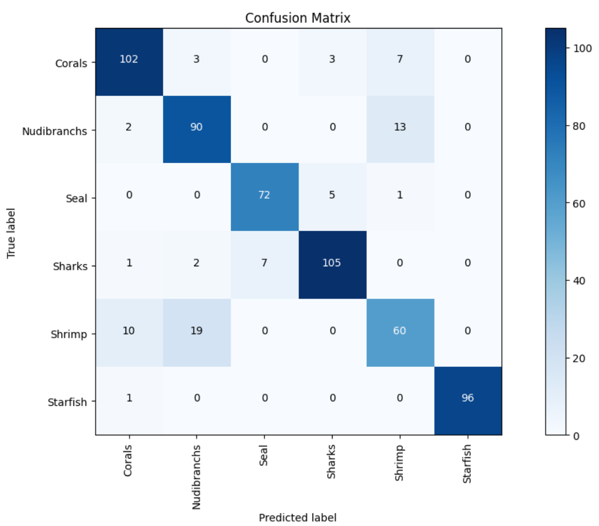

Fig. 9 Confussion Matrix Result on Xception

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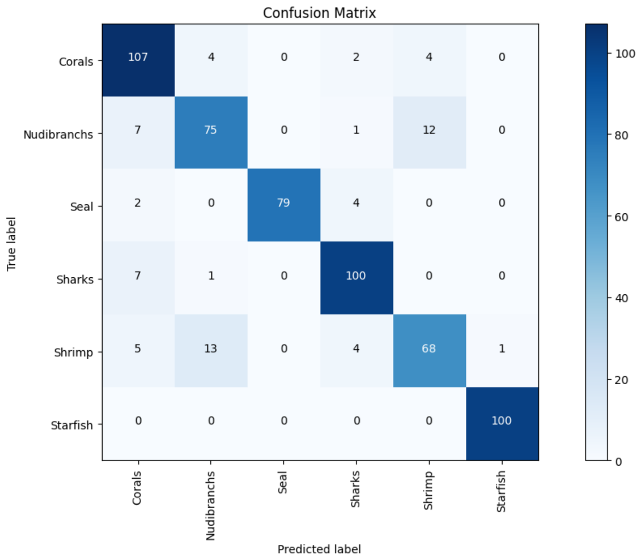

Fig. 10 Confussion Matrix Result on VGG19

We can see the number of incorrectly predicted data and the number of correctly predicted data. The number of incorrectly predicted data is shown in the light blue box and the number of correctly predicted data is shown in the dark blue box. Based on the confusion matrix results in Figure 8, it shows that the Coral class is correctly predicted as many as 110 images and there are 7 incorrectly predicted images, in the Nudibranchs class there are 80 correctly predicted images and there are 16 incorrectly predicted images, in the Seal class there are 75 correctly predicted images and there are 9 incorrectly predicted images, in the Sharks class there are 102 correctly predicted images and there are 6 incorrectly predicted images, in the Shrimp class there are 81 correctly predicted images and there are 10 incorrect images, while in the Starfish class all 100 images can be predicted correctly.

In Figure 9, it shows that the Coral class predicts 102 images correctly and 13 images are wrongly predicted, in the Nudibranch class there are 90 images that are correctly predicted and there are 15 images that are wrongly predicted, in the Seal class there are 72 images that are correctly predicted and there are 6 images that are wrongly predicted, in the Sharks class there are 105 images that are correctly predicted and there are 10 images that are wrongly predicted, as well as the Shrimp class there are 60 images that are correctly predicted and there are 29 images that are wrongly predicted, while in the Starfish class there are 96 images that are successfully predicted correctly and there is 1 image that is wrongly predicted.

In Figure 10, the Coral class shows 107 correctly predicted images and 10 incorrectly predicted images, the Nudibranch class has 75 correctly predicted images and 20 incorrectly predicted images, the Seal class has 79 correctly predicted images and 6 incorrectly predicted images, the Sharks class has 100 correctly predicted images and 8 incorrectly predicted images, the Shrimp class has 68 correctly predicted images and 23 incorrectly predicted images, while the Starfish class has all 100 correctly predicted images.

The following are the accuracy, precision, recall, and f1-score values obtained as shown in Table 2.

Table 2. CNN Architecture Performance

Architecture Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
MobileNet	91.94 %	92.13 %	91.89 %	91.93 %
Xception	87.64 %	87.62 %	87.64 %	87.58 %
VGG19	88.76 %	88.82 %	88.75 %	88.71 %

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Based on the evaluation results obtained, MobileNet architecture obtained an accuracy value of 91.94%, precision of 92.13%, recall of 91.89 % and F-1 Score of 91.93%, Xception architecture model obtained an accuracy value of 87.64%, precision of 87.62%, recall of 87.64% and F-1 Score of 87.58%. While the VGG19 architecture model gets an accuracy value of 88.76%, precision of 88.82%, recall of 88.75% and F-1 Score of 88.71%. From the test results it can be seen that the MobileNet architecture model gets the highest accuracy rate of 91.94%, after that VGG19 gets an accuracy value of 88.76%, and Xception gets an accuracy value of 87.64%.

DISCUSSIONS

CNN (Convolutional Neural Network) is one type of architecture in artificial deep learning specifically designed for processing structured data such as images and videos. CNN has become one of the most widely used techniques in the field of pattern recognition and computer vision. Applying Transfer Learning techniques is very useful in model development to be more efficient and accurate, especially when training data is limited. This is because transfer learning involves using existing knowledge in pre-trained models to speed up and improve the training of new models. This approach can save time and resources, as the model does not need to be trained from scratch on a second task.

The results obtained in this study show the success of Transfer Learning on the CNN algorithm in classifying marine fauna images. The MobileNet architecture model successfully classifies marine fauna types with accuracy value of 91.94%, precision of 92.13%, recall of 91.89 % and F-1 Score of 91.93%, Xception architecture model obtained an accuracy value of 87.64%, precision of 87.62%, recall of 87.64% and F-1 Score of 87.58%. While the VGG19 architecture model gets an accuracy value of 88.76%, precision of 88.82%, recall of 88.75% and F-1 Score of 88.71%.

CONCLUSION

Based on research that has been conducted using Transfer Learning on CNN models, the best results are obtained in classifying 6 types of marine fauna. The MobileNet architecture model produces the highest accuracy value of 91.94% compared to Xception and VGG19 which only get an accuracy value of 87.64% and 88.76 %. This shows that the MobileNet model has better performance in classification than other models. It can also be concluded that utilizing the Transfer Learning method on CNN models is very useful for improving performance and so that the resulting model is more accurate, besides that the resulting model becomes more optimal.

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