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Identification of Little Tuna Species Using Convolutional Neural Networks (CNN) Method and ResNet-50 Architecture

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ABSTRACT
Indonesia is home to a vast array of biodiversity, including various species of little tuna. However, the process of identifying little tuna species is still challenging due to their diversity. The Indonesian Society and Fisheries Foundation (MDPI), which has the task of collecting fisheries data manually, is prone to significant identification errors. Therefore, the author proposes the utilization of Deep Learning, a Machine Learning method due to its ability to model various complex data such as images or pictures and sounds. This approach can facilitate the identification process of little tuna. In this research, the Resnet-50 architecture is utilised in the modelling process with the original dataset of 500 images. In this study, several test scenarios were also applied. The best results obtained are global accuracy of 91% and matrix accuracy value of 95%. These results were obtained using an augmented dataset with some parameter adjustments to the model built. With these good accurate identification, the MDPI Foundation is expected to better manage fisheries data and use it to support sustainable fisheries management.
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1. INTRODUCTION

Fish are a marine biota with physiological mechanisms that are not owned by animals on land. The species diversity of fish plays an important role in an ecosystem, where the number of marine biota can affect the organisms in it [1]. One of the fish that has a diverse level of species diversity is little tuna. There are four types of little tuna that can be found in Indonesian waters, namely: Frigate Tuna (Auxis thazard), Bullet Tuna (Auxis rochei), Mackerel Tuna (Euthynnus affinis), and Longtail Tuna (Thunnus tonggol) [2].

The identification of little tuna species is hindered by the existence of diverse varieties, making direct visual identification challenging. Traditional methods, such as manual observation and reference-based identification, are prone to human error, leading to inaccurate species classification. To address this limitation, this research aims to develop a robust and accurate automated system for identifying little tuna species using machine learning techniques. By leveraging the power of machine learning, specifically convolutional neural networks (CNNs), we seek to create a reliable tool that can assist in precise species identification, thereby improving fisheries management and conservation efforts.

In this research, Deep Learning programming algorithm technology is utilised [3]. Currently, the most effective Deep Learning method for image recognition is Convolutional Neural Network (CNN) [4]. The CNN algorithm is one of deep learning algorithms developed with the Multilayer Perceptron (MLP) method. Its purpose is to enable the processing of two-dimensional data, such as images and audio. CNN is a deep learning method with the most significant results because it has an image recognition system in human vision that functions to imitate, enabling the algorithm to process image information[4]. Furthermore, the selection of CNN architecture in this study is Resnet-50. This is due to the fact that the Resnet-50 architecture has achieved successful ImageNet challenge results [5] and a high accuracy rate compared to ResNet with other layers [6]. This is the rationale behind utilizing the Resnet-50 CNN method in this study, as it is capable of performing digital image processing and achieving a high level of accuracy in identifying objects or image classification.

There are several studies used as literature reviews that are relevant to this research. These include research conducted by Ariawan, Isaac et al, 2022 with the title "Classification of Three Reef Fish Genus Using Convolution Neural Network". This research uses CNN in the process of identifying patterns, body structure and distribution of reef fish species diversity. The results obtained in this study are an accuracy rate of 85.31%. In addition, the results obtained precision of 89.92% and sensitivity of 86.49% with the difference from the average value is not too large, so it can be said that the model built in the study is quite good. Based on these things, it can be concluded that the CNN classification method can be used well to classify reef fish according to their genus [7]. The next study was conducted by Elvin & Chairisni, 2022 entitled "Classification of Fish Images Using Convolutional Neural Network". This research also applies the CNN method to more than 10 species with each species consisting of 1000 images or more. At this stage, the results are obtained in the form of a training loss value of 0.189203, a validation loss value of 0.033459, and an accuracy value of 0.991029. The next step is the evaluation process. In this process, the prediction accuracy result is 99.1% precision and 0.98 recall. Based on the results obtained, it can be concluded that the accuracy in this research is very good, so this research can be declared capable of accurately predicting the image inputted by the user [8].

The next study was conducted by Septian, et al. (2019) with the title "Implementation of Convolutional Neural Network for Freshwater Fish Identification". In this study, there are 300 freshwater fish datasets, which are then divided into a ratio of 80% training data (240 images) and 20% test data (60 images). The result of the accuracy rate obtained in this study is 88.3%. Thus, it can be said that the implementation of CNN method in this study works well because this method is able to recognize digital images of freshwater fish [9]. The next research is the research of Eko Prasetyo, et al, 2021 with the title "Comparison of Convolutional Neural Network for Freshness Classification of Milkfish in Eye Image". In this study, the freshness classification of milkfish (very fresh and not fresh) was carried out with the parameter of fish eyes. In this research, the CNN method is implemented with 4 architectures, namely Xception, MobileNet-V1, Resnet-50 and VGG 16. The results obtained show that Resnet-50 is in second place with a classification accuracy of 87% [10].

This research makes a significant contribution to the field of fish species identification, especially tuna, with some fundamental differences compared to previous studies. The highly specific focus on tuna species, as well as the use of ResNet-50's advanced deep learning neural network architecture, enables the development of a more accurate and efficient classification model. In addition, this research makes use of a larger and more diverse database and applies data augmentation techniques to improve model generalization. Thus, this research not only resulted in an improved classification model, but also opened up opportunities for the development of broader artificial intelligence-based applications that can help the fisheries sector. Consequently, the research will present an explanation of the scheme and results of identifying the type of little tuna using the CNN method with the Resnet-50 architecture.

2. MATERIAL AND METHOD

The research runs from March 2023 to January 2024. As for the use of the amount of data in this study, it starts by dividing a total of 500 tuna image datasets into 80% for training data (400 images) and as much as 20% for test data (100 images). Each class of tuna has 100 tuna images for training data and 25 images for test data based on the Pareto Principle theory. Then in this study there are also several hyperparameters used such as batch size, epoch, optimizer, and learning rate as parameters that support the success of the model in the training process and data testing.

The following figure is a research flowchart that provides an overall picture of the methodology used in this research. From tuna image data collection, data processing, model training, to performance evaluation, each step in this diagram is interrelated and contributes to the success of the research, which can be seen in Figure 1. Research Methodology.

2.1 Construction of Little Tuna Image Dataset

The dataset in this research is the image data of little tuna taken based on the reference from [2]. The fish image samples were taken from several regions and have been validated by the staff of the Indonesian Society and Fisheries Foundation (MDPI). Sampling of various types of little tuna is done in several locations, so that the images of tuna obtained are more varied and not only sourced from one area. Exploration of the availability of tuna was carried out at Bias Lantang Beach, East Seraya Village (Karangasem Regency), Pengalon Beach, Antiga Klod Village (Karangasem Regency), Segara Kusamba Beach, Kusamba Village (Klungkung Regency), Kedonganan Beach, Kedonganan Village (Badung Regency) and the sea of Belitung area. The data collection process was carried out by going directly to several areas where the availability of little tuna. The following is the results of the acquisition of little tuna images can be seen in Figure 2 Image of Little Tuna.

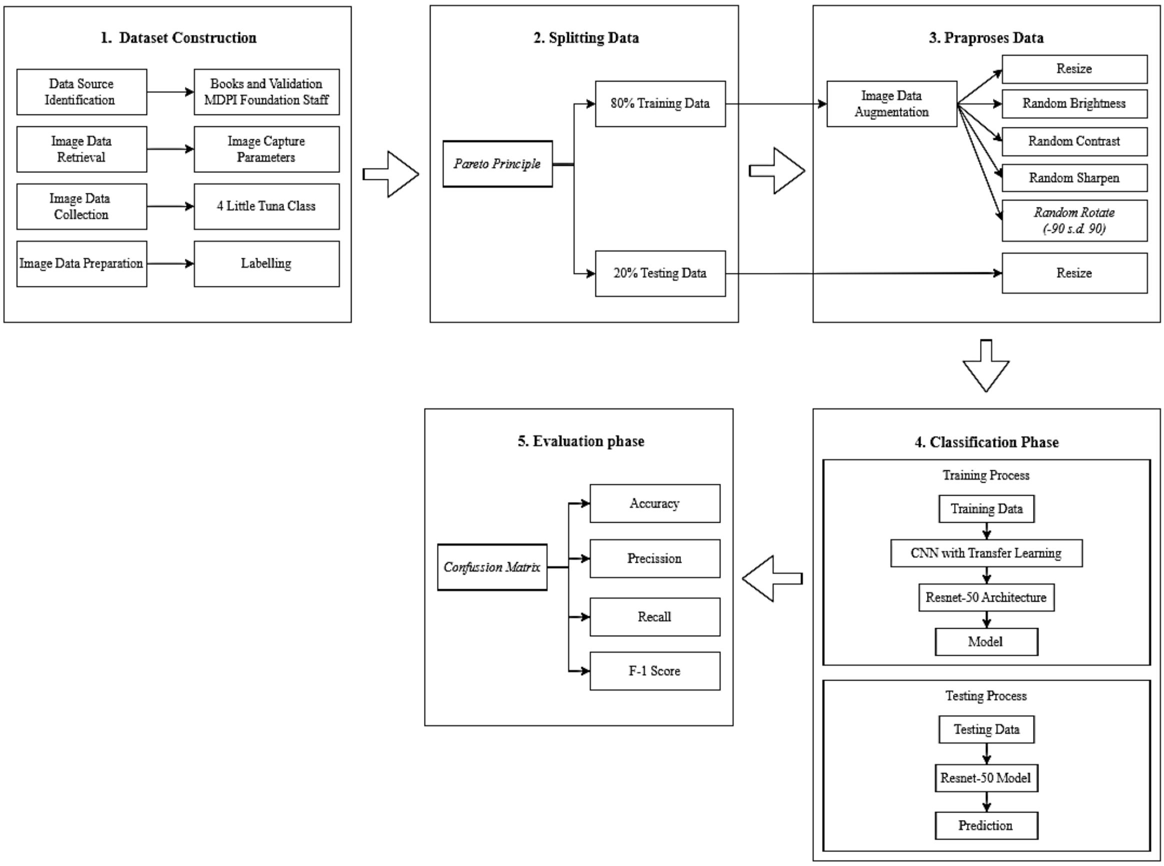
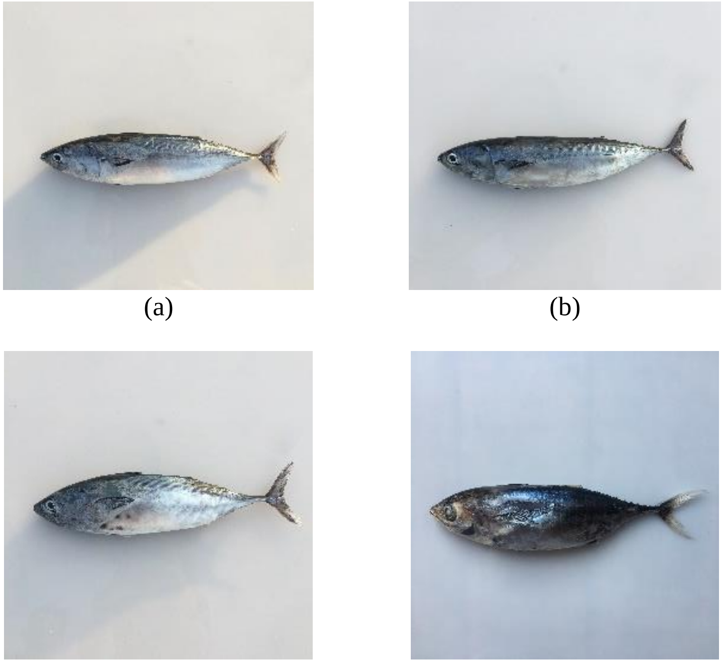


Figure 1. Research Methodology



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

Figure 2. Image of Little Tuna,
(a) Frigate Tuna, (b) Bullet Tuna, (c) Mackerel Tuna, (d) Longtail Tuna

Based on the research conducted by [11] regarding the amount of sample data for model building, it is recommended that the amount of data in each class is balanced, this is because if the data per class has a different amount or is imbalanced, it can decrease the model performance, as well as other effects of imbalanced datasets in the form of decreasing the value of other model evaluation metrics such as recall, precision and F1-score. The final stage of the dataset building process is the labeling stage or providing data labels on each image data to facilitate the training model process to recognize and distinguish objects and features in the image.

2.2 Splitting Data

In this study, the division of training data and test data is done using the split ratio data method based on the Pareto principle, which states that 80% of events are generated from the remaining 20%, and is commonly used in data mining [12]. Thus, the use of the amount of data in this study starts by dividing a total of 500 datasets of little tuna images into 80% for training data (400 images) and up to 20% for test data (100 images). Each class of little tuna has 100 little tuna images for training data and 25 images for test data.

2.3 Preprocessing Data

The data preprocessing stage starts from the collection of the original data set image of 500 images with an initial size of 3024x3024 pixels. The image used as input image is an RGB image. The next stage is resizing, the resize selection is based on a literature study on Resnet-50 architecture, namely 224x224, which gives the best performance on the architecture [6].

After resizing the image, the next step is to reproduce the little tuna image by performing augmentation in the form of random brightness, contrast, sharpening, and rotation between -90 and 90 degrees. All these augmentation techniques were chosen based on the literature on data augmentation by [13], which aims to make the deep learning model able to learn the same image but in different directions and conditions, so that in the end it can help improve the model's performance in predicting images that have never been seen before.

These four augmentation techniques are performed on the training data only, so the amount of initial image data is increased from 100 little tuna images in each class to 1,600 little tuna images. Meanwhile, the test data is only resized without any augmentation. The data augmentation process is performed using the Python 3.10 programming language and displayed on

Figure 3. Preprocessing of Little Tuna Image. Below is an illustration of the preprocessing steps that have been carried out where (a) is the original image measuring 3024x3024, (b) the resized image measuring 224x224, (c) image augmentation after experiencing random brightness, (d) image augmentation after experiencing random contrast, (e) image augmentation after experiencing random sharpen, and (f) image augmentation after experiencing random rotate between -90 to 90 degrees.

Figure 3. Preprocessing of Little Tuna Image

2.4 Clasification

The classification process starts from training. The training process is the stage of learning the given data (training data) so that later it can be used by the model to find hidden features and patterns in the data. In the data training process, the proposed architecture or model, Resnet-50, is used. In the data training process, several hyperparameters are also used such as batch size, epoch, optimizer, and learning rate as parameters that support the success of the model in the training process and data testing. After the training process is completed, the results of the training process are stored in a model to be retrieved during the testing process.

After the training process is completed, the results obtained from the process are stored in a model with a format that is H5 or known as Hierarchical Data Format (HDF). This model will later be used during the testing phase using test data, which will then produce a confusion matrix [14].

The test phase is carried out to evaluate the performance of the system learning model in identifying the type of tuna using Resnet-50. In this phase, the model is given new input data that has never been used before. The classification results of the model are compared with the actual type of tuna to determine its success rate.

2.5 Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of artificial neural network architecture specifically designed for processing image data. CNNs have become one of the most popular tools in the fields of image recognition, natural language processing, and more. CNNs consist of several layers, including a convolutional layer, a pooling layer, and a fully connected layer [15].

2.6 Resnet-50

ResNet-50 is one of the variants of deep CNNs and has achieved excellent performance in various image recognition tasks. ResNet-50 uses residual connections to overcome the vanishing gradient problem often encountered in deep neural networks. Residual connections allow information from previous layers to flow directly into deeper layers, facilitating the training of very deep networks [6].

The commonality between CNN and ResNet-50 is that both are a type of artificial neural network, CNN and ResNet-50 are designed to process image data using convolutional layers, and both CNN and ResNet-50 can be used for various tasks such as image classification, object detection, and image segmentation.

2.7 Evaluation

The evaluation stage is a stage carried out to determine the performance or accuracy level of success in the proposed Convolutional Neural Network architecture, namely the Resnet-50 architecture in identifying and classifying the type of tuna. The testing process will be carried out by utilizing the confusion matrix method to obtain the accuracy value of the classification process carried out on the dataset.

3. RESULTS AND ANALYSIS

The classification model formed in this research is run on a cloud computing hardware, namely Google Collaboratory, using the Python programming language and several source libraries such as Keras, which are used in the CNN architecture development process. In this research, there are 11 scenarios and system trials that have been planned to measure the effectiveness of the methods used. The following is a detailed explanation in

Table 1. Test Scenarios and Results.

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No.	Parameter Model	Pipeline Augmentation	Image Data Sharing	Results
1	Resizing Data, Epoch : 100, Learning Rate : 1e-4, Batch Size : 16, GlobalAveragePooling2D	-	Train Image : 400, Test Image : 100	Train : 99,50%, Test : 92,71%
2	Resizing Data, Early Stop Patience = 10, Learning Rate : 1e-4, Batch Size : 16, Reduce Learning Rate, GlobalAveragePooling2D	-	Train Image : 400, Test Image : 100	Train : 99,25%, Test : 90,62%
3	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, Reduce Learning Rate, Freeze Backbone, GlobalAveragePooling2D	-	Train Image : 400, Test Image : 100	Train : 98,75%, Test : 91%
4	Epoch : 100, Batch Size : 16, Learning Rate : 1e-4, Reduce Learning Rate, Freeze Backbone, GlobalAveragePooling2D	-	Train Image : 400, Test Image : 100	Train : 99,75%, Test : 91%
5	Resizing Data, Epoch : 100, Learning Rate : 1e-4, Batch Size : 16, GlobalAveragePooling2D	Random Brightness, Random Contrast, Sharpen, Rotate	Train Image : 1600, Test Image : 100	Train : 99,25%, Test : 73,96%
6	Resizing Data, Epoch : 100, Learning Rate : 1e-4, Batch Size : 16, GlobalAveragePooling2D	Random Brightness, Random Contrast, Sharpen, Gaussian Blur	Train Image : 1600, Test Image : 100	Train : 99,69%, Test : 87,50%
7	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, Reduce Learning Rate, Freeze Backbone, GlobalAveragePooling2D	Random Brightness, Random Contrast	Train Image : 638, Test Image : 100	Train : 99,53%, Test : 85%
8	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, GlobalAveragePooling2D	Random Brightness, Random Contrast	Train Image : 638, Test Image : 100	Train : 98,90%, Test : 90%
9	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, GlobalAveragePooling2D	Random Brightness, Random Contrast	Train Image : 638, Test Image : 100	Train : 97,65%, Test : 91%
10	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, GlobalAveragePooling2D	Random Brightness, Random Contrast	Train Image : 638, Test Image : 100	Train : 99,37%, Test : 91%

No.	Parameter Model	Pipeline Augmentation	Image Data Sharing	Results
11	Early Stop Patience = 10, Batch Size : 16, Learning Rate : 1e-4, zoom_range : 0.1, GlobalMaxPooling2D	Random Brightness, Random Contrast	Train Image : 638, Test Image : 100	Train : 99,06%, Test : 91%

The results of the trial, based on the original dataset, indicated that test scenario 1 yielded the highest overall accuracy value (92.71%) and confusion matrix value. In contrast, the augmented dataset yielded the highest overall accuracy value (91%) and confusion matrix value in test scenario 9. The confusion matrix for test scenario 1 and test scenario 9 is presented in the following image and accompanied by an explanation.

The confusion matrix image in figure 4 illustrates that the model with test scenario 1 can correctly recognize image objects in 88% of cases, or 88 out of 100 images. The model with test scenario 1 has demonstrated success in recognizing image objects across a range of classes. It has correctly identified the IkanAbu class in 23 out of 25 images, the IkanKomo class in 15 out of 25 images, and both IkanKrai and IkanLisong classes in 25 out of 25 images.

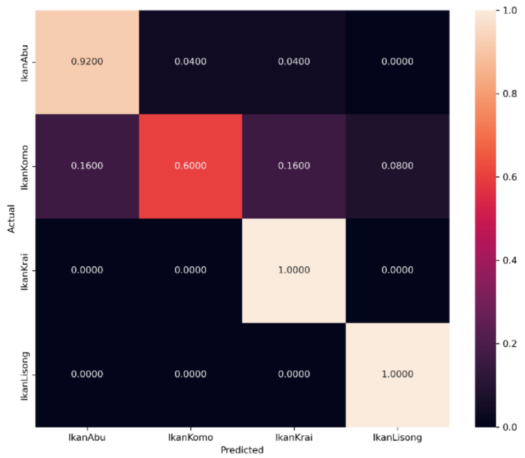

Figure 4. Confusion Matrix Result of Testing Scenario 1

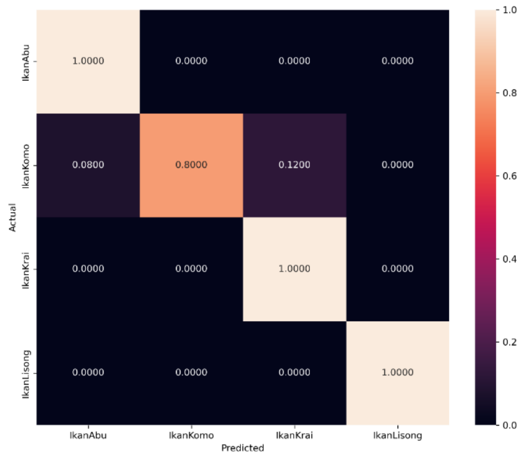

Figure 5. Confusion Matrix Result of Testing Scenario 9

The confusion matrix image above illustrates that the model with test scenario 9 can correctly recognize image objects in approximately 95% of cases, or 95 out of 100 images. While the details for each class, the model with test scenario 9 has succeeded in recognizing the image object correctly starting from the IkanAbu class which managed to increase in recognizing well, namely 25 out of 25 images which shows that in test scenario 9 managed to increase the accuracy value in the IkanAbu class, then there is the IkanKomo class which managed to recognize 20 out of 25 images, and there are classes of IkanKrai and IkanLisong which managed to recognize 25 out of 25 images.

Based on the results of the confusion matrix evaluation in the explanation above, it can be concluded that the results of Test Scenario 9 have the advantage of making improvements in object recognition in each class compared to the results of Test Scenario 1. The results of Test Scenario 1 are very weak in recognizing the IkanAbu and IkanKomo classes, and based on this fact, the best model to be reported is Test Scenario 9. This is because in the results of the confusion matrix of test scenario 9, an increase in accuracy in the IkanAbu class to 100% and the IkanKomo class to 80%. So for the next phase of improving the global/overall accuracy can be done by adding more records to the class that contributes the lowest accuracy.

4. CONCLUSION

This research has successfully developed a highly accurate tuna classification model using the ResNet-50 architecture. With an accuracy rate of 91%, with the following parameters were used: Early Stop Patience = 10, Batch Size: 16, Learning Rate: 0.001, a batch size of 16, and an early stop patience of 10. The model is able to clearly distinguish between different types of Little Tuna. This impressive result opens up opportunities for the application of artificial intelligence technology in various aspects of fisheries. The things that need to be done for further research are more observations in the dataset retrieval process, and increasing the image data in each class so that it can represent each type of tuna more representatively and the system can evolve better. In addition, hyperparameters such as number of layers, batch size, learning rate, and dropout can be optimized in more detail and compared with other methods to achieve a better level of accuracy in similar cases.

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