Classifying Types of Koi Fish Using Convolutional Neural Network (CNN)

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ABSTRACT

Koi fish is a popular ornamental fish with many enthusiasts due to its diverse patterns and beautiful colors. Some types of koi fish even look very similar, making it difficult for many people to distinguish or recognize them. Convolutional Neural Network is an algorithm in the field of Deep Learning that can be used to process data in a grid format, including two-dimensional images like pictures. The research was conducted by collecting data through capturing images of koi fish, which were used as a dataset with ten classes: Asagi, Bekko, Goromo, Kohaku, Sanke, Showa, Shusui, Tancho, Utsuri, and Yamato Nishiki. Based on the research results using 1000 image data, the data was divided into 640 training data, 160 validation data, and 200 testing data. The outcome of this training process yielded a high-performance MobileNet V2 model with an accuracy rate of 92% and a loss of 0.4365. In comparison, the VGG16 model achieved an accuracy rate of only 82%, and the ResNet 50 model reached an accuracy rate of 49%. This indicates that the CNN architecture model can be effectively used for the classification or identification of koi fish.

KEYWORDS
Koi Fish
Deep Learning
Convolutional Neural Network
MobileNet V2

1. Introduction

Indonesia is a country rich in abundant fish resources. This is due to its location surrounding the equator and its tropical climate, which creates a different environment from cold or subtropical regions. It is estimated that there are around 40,000 fish species in the world [1]. According to data from Wikipedia (https://id.wikipedia.org/wiki/Ikan) up to August 20, 2023, more than 27,000 fish species have been identified worldwide. In Indonesia itself, there are approximately 4857 identified fish species, with about 1225 species inhabiting freshwater and 3632 species found in the marine environment of Indonesia. All of this signifies the wealth and biodiversity in Indonesia that need to be conserved and maintained for sustainability.

Indonesia can be considered as one of the countries with abundant global fisheries wealth. Within its waters, including both seas and freshwater bodies such as lakes, rivers, and swamps, there are no less than 2,000 diverse fish species [2]. However, only about 25% of this total number can be cultivated. The vast expanse of Indonesia's aquatic areas stands as a significant factor driving the fishing industry, including the ornamental fish market. Among the various types of ornamental fish popular in Indonesia, koi fish, also scientifically known as Cyprinus rubrofuscus, holds a special place. The allure of its patterns and colors makes koi fish highly sought after by a broad spectrum of people. The variations within koi fish types are quite extensive, hinging on their patterns and colors. Additionally, many among them exhibit similar pattern colors, making it challenging to discern one type from another [3]. This intricacy poses difficulties for those unfamiliar with koi fish, as they encounter obstacles in distinguishing between each type.This lack of knowledge often leads to many people purchasing koi fish solely based on visual judgment, without understanding the true koi fish type. The repercussions of this include incorrect care and upkeep of the koi fish they possess. As a result, aspects such as color contrast, health, and the growth of koi fish can be impacted, sometimes even diminishing. Therefore, it is important for koi fish enthusiasts

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to delve deeper into knowledge about various koi fish variations and proper care techniques in order to maintain the quality and health of the koi fish they are nurturing.

Digital image processing has made it possible to efficiently identify freshwater fish. Technological advancements, especially in the field of digital cameras, have facilitated humans in capturing images of freshwater. With the aid of computational progress, recognizing various types of freshwater fish through digital images has become increasingly accurate. Convolutional Neural Network (CNN) is an algorithm in the field of Deep Learning that extends the capabilities of the Multi-Layer Perceptron (MLP) and is specifically designed to process data in a grid format, including two-dimensional images like pictures [4]. CNN requires less preprocessing compared to other image classification algorithms. The Convolutional Neural Network method is employed to recognize labeled data using a supervised learning approach, which means the model is trained with labeled data and can then categorize new data into existing categories. The structure of the Convolutional Neural Network involves several layers, including convolutional layers, activation layers, pooling layers, and fully connected layers.

The Convolutional Neural Network method is one suitable approach for classification, as it is inspired by the way visual processing occurs in the human brain, particularly in the visual cortex. This research also employs transfer learning to expedite the training process. Transfer learning utilizes knowledge or models from a source domain that have been formed and trained by a specific dataset. Several researchers who have utilized the CNN method for image processing have achieved favorable results with high levels of accuracy.

Previously, a study titled "Fish Image Classification Using Convolutional Neural Network" was conducted by Elvin and Chairisni Lubis. This research involved 20 fish species, with each species having more than 1000 image data. Based on the testing results of fish image classification with Convolutional Neural Network, the conclusion was drawn that this program achieved a very high accuracy and recall rate of 0.991395798 and 0.991109061, respectively. This high accuracy rate indicates that the fish image classification program can accurately identify fish species within the input images [5].

The next study was conducted by R. Mehindra Prasmatio, Basuki Rahmat, and Intan Yuniar titled "Fish Detection and Recognition Using Convolutional Neural Network Algorithm." In this research, the system employed image processing as the recognition process for 9 types of freshwater fish: Arowana, Comet Fish, Guppy, Goldfish, Turtle, Molly Fish, Manfish, Platys, and Redfin Fish. Consequently, there were a total of 9 possible classifications in this study. Each fish type was categorized into a directory based on its species. Each directory contained 100 images sourced from Google as the dataset, resulting in a total dataset of 900 images. The results of this study indicated an accuracy rate of 85.14%, wherein 23 out of 27 images were correctly predicted, while 4 images were not accurately predicted. Additionally, the precision value reached 77.8%, and the recall value reached 85.2% [1].

The subsequent study was conducted by Septian Fauzi, Puspa Eosina, and Gibtha Fitri Laxmi with the title "Implementation of Convolutional Neural Network for Freshwater Fish Identification." The dataset of freshwater fish images used in this research consisted of 300 images, divided into 10 species of freshwater fish. Each class contained 30 images in .JPG format. The dataset was divided with an 80% (240 images) ratio for training data and a 20% (60 images) ratio for testing data. In the architecture structure developed by the researchers, there were 3 convolutional layers. These 3 layers aimed to extract more detailed and deep features. Additionally, in the fully connected layer, the researchers applied 256 neurons to a hidden layer with ReLU activation and produced an output of 10, corresponding to the number of classes under investigation. The results from the CNN classification model demonstrated its capability in identifying freshwater fish image data with a good accuracy level of 88.33% [5].

2. Method

This study discusses the classification of koi fish types using the Convolutional Neural Network method. In this research, a dataset of koi fish images was obtained from the Kaggle website (https://www.kaggle.com/datasets/dangtantai/trainkoi). The acquired dataset comprises 1000 image datasets. This dataset consists of 10 classes of koi fish types: Asagi, Bekko, Goromo, Kohaku, Sanke, Showa, Shusui, Tancho, Utsuri, and Yamato Nishiki. Additionally, this research also encompasses several stages as follows:

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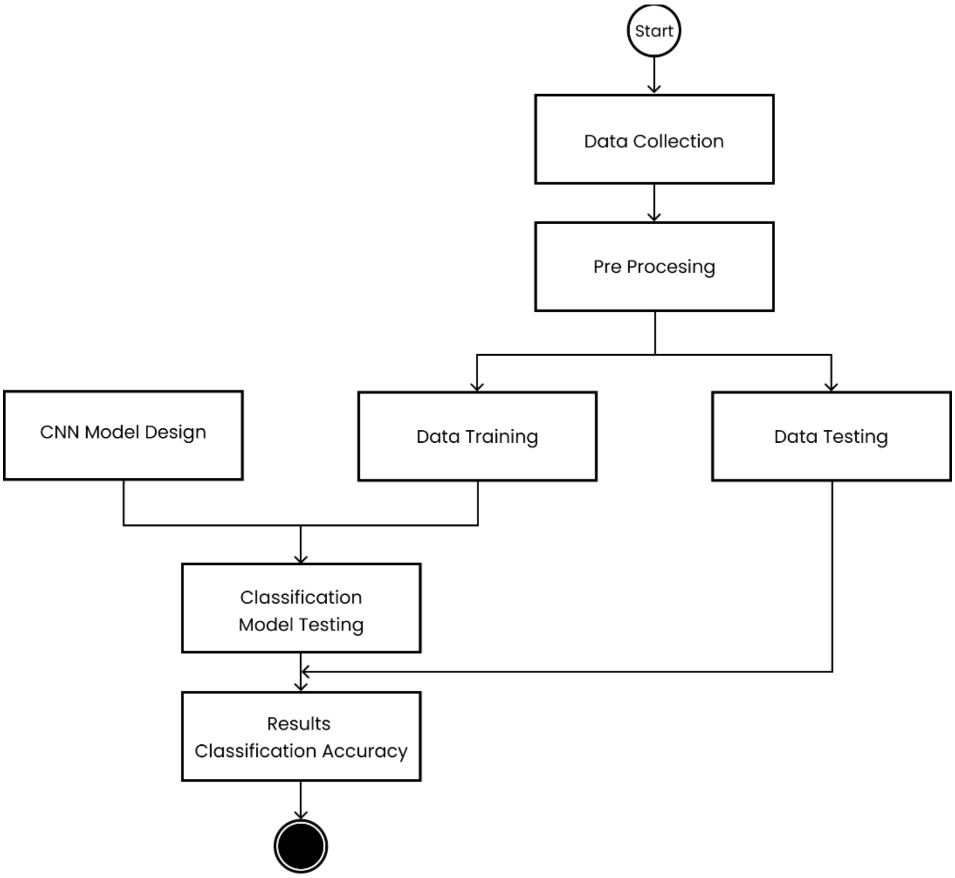
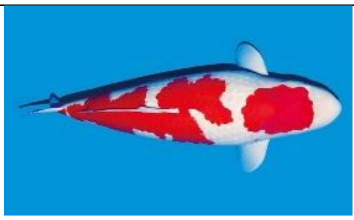
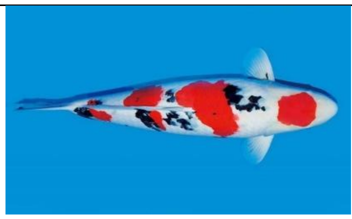


Figure 1. Stages of Research

2.1. Dataset

The dataset used in this study is a koi fish dataset obtained from the Kaggle website (https://www.kaggle.com/datasets/dangtantai/trainkoi). The dataset consists of 10 classes, and each class is labeled with its respective type, all with the same size of 224 x 224. Sample datasets can be seen in the table below.

Table 1. Sample Koi Fish

Asagi	Bekko	Goromo
		
Kohaku	Sanke	Showa
		
Sushui	Tancho	Utsuri

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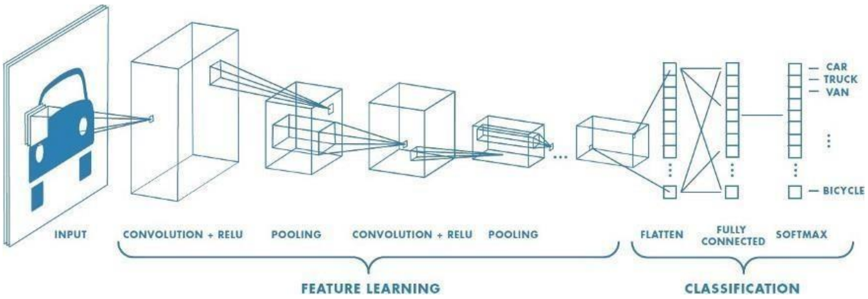
Yamato Nishiki		
		

2.2. Purpose Method

Building a classification model that will be used for data processing requires several stages such as determining the number of layers, kernel size, filter size, activation function, and pooling layer size. Here is the architecture of the Convolutional Neural Network.



Figurearsi 2. Architecture Convolutional Neural Network

This classification of koi fish types implements several architectural models, namely ResNet 50, VGG16, and MobileNet V2. Each model uses a dataset that has been divided into 640 training data, 160 validation data, and 200 testing data. In the testing process, various parameters are utilized, such as accuracy, precision, recall, and F1-score.

2.2.1. ResNet 50

ResNet 50 is one of the architectures of Convolutional Neural Networks that can overcome training challenges in deeper networks, such as performance degradation as the network becomes deeper (vanishing gradient) and the tendency for overfitting. The number 50 in ResNet 50 represents the total number of layers used in its architecture, including convolutional, normalization, activation, and fully connected layers[6].

2.2.2. VGG 16

VGG 16 is one of the architectural models of Convolutional Neural Networks where the number 16 refers to the quantity of layers employed in that architecture. VGG 16 also stands as a significant architecture in the advancement of convolutional neural networks and has been utilized in numerous tasks such as image recognition, object detection, semantic segmentation, and various other computer vision tasks[7].

2.2.3. MobileNet V2

MobileNetV2 is one of the architectural models of Mobile-Based Convolutional Neural Networks used to prevent excessive utilization of computing resources. Within the MobileNetV2 model, there are two blocks: one with a stride of one and another with a stride of two for downsampling. MobileNetV2 also includes three layers for each of these blocks, where the first layer is a 1x1 convolution with ReLU6, the second layer is a depthwise convolution, and the third layer is another 1x1 convolution without nonlinearity. This implies that if ReLU is used again, the network will possess linear classification power in the non-zero volume part of the output domain[8].

3. Results and Discussion

The CNN model mentioned above, according to its architecture, will be implemented in Google Colab using Python 3.8. This training will be conducted in two stages: training and testing. The following are the results of the tested architectural model.

Table 2. Accuracy Comparison

Architecture	**Comparison**		
	Epoch	***Accuracy***	***Loss***
ResNet 50	100	49,50%	1,4323
VGG 16	50	82,50%	0,6227
MobileNet V2	50	92%	0,4365

3.1. Training Model Results

The training and validation process involves several architectural models, namely ResNet 50, VGG16, and MobileNet V2. The results of the training and validation graphs are as follows.

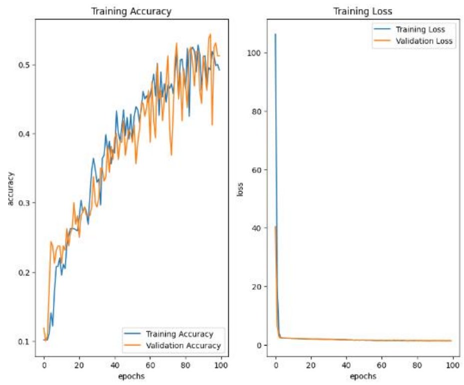


Figure 3. Training Model ResNet 50

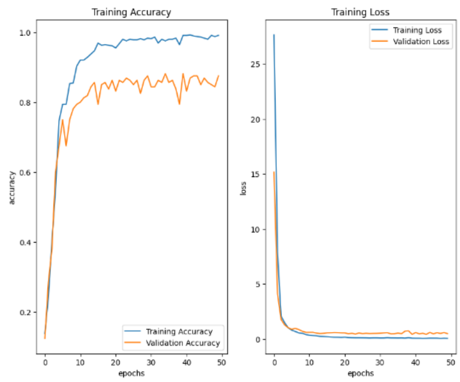


Figure 4. Training Model VGG 16

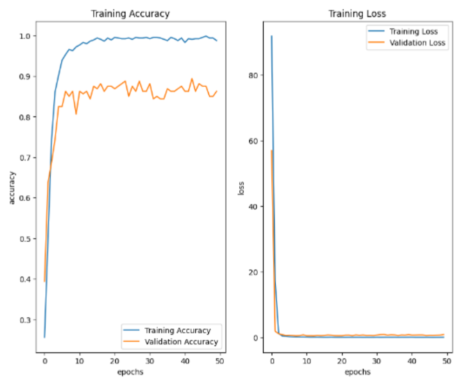


Figure 5. Trainig Model MobileNet V2

Based on the above, the accuracy results from several training models' architectures are as follows. The ResNet 50 architecture model achieved an accuracy rate of 49.50% with a loss value of 1.4323, while the VGG 16 architecture model achieved an accuracy rate of 82.50% with a loss value of 0.6227, and the MobileNet V2 architecture model reached 92% accuracy with a loss value of 0.4365. The training process used images of the same size, which is 128 x 128 pixels.

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3.2. Data Testing Result

The testing process utilizes a total of 200 test data divided into 10 classes for each type of koi fish, with each class consisting of 20 test data.

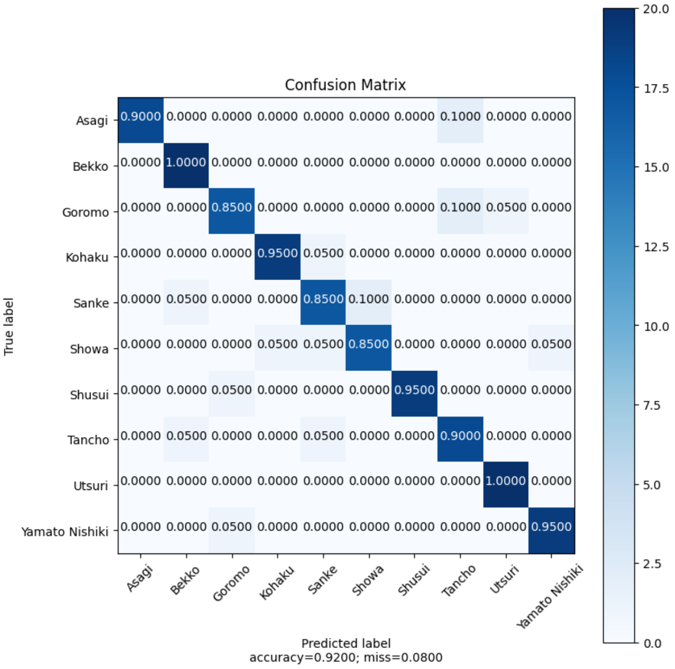

Figure 6. Confusion Matrix MobileNet V2

Based on the data from the above confusion matrix, it can be concluded that the testing process achieved an accuracy of 92% with a 8% miss rate. The Confusion Matrix table for the Asagi type of koi fish was correctly predicted for 18 image data with 2 missing predictions for the Tancho type of koi fish. For the Bekko type of koi fish, 20 image data were correctly predicted with no missing predictions. For the Goromo type of koi fish, 17 image data were correctly predicted, with 2 missing predictions for Tancho and 1 missing prediction for Utsuri. The Kohaku type of koi fish was correctly predicted for 19 image data, with 1 missing prediction for Sanke. The Sanke type of koi fish was correctly predicted for 17 image data, with 2 missing predictions for Showa and 1 missing prediction for Bekko. The Showa type of koi fish was correctly predicted for 17 image data, with 1 missing prediction for Sanke, 1 missing prediction for Kohaku, and 1 missing prediction for Yamato Nishiki. The Shusui type of koi fish was correctly predicted for 19 image data, with 1 missing prediction for Goromo. The Tancho type of koi fish was correctly predicted for 18 image data, with 1 missing prediction for Bekko and 1 missing prediction for Sanke. The Utsuri type of koi fish was correctly predicted for all 20 image data without any missing predictions. The Yamato Nishiki type of koi fish was correctly predicted for 19 image data, with 1 missing prediction for Goromo.

These data were also tested using precision, recall, and f1-score. The results of this testing can be seen as follows.

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Tabel 3. Hasil pengujian

Fish Spesies	**Testing Parameter**		
	Precision	***Reccal***	***F1-Score***
Asagi	1.00	0.90	0.95
Bekko	0.91	1.00	0.95
Goromo	0.89	0.85	0.87
Kohaku	0.95	0.95	0.95
Sanke	0.85	0.85	0.85
Showa	0.89	0.85	0.87
Shusui	1.00	0.95	0.97
Tancho	0.82	0.90	0.86
Utsuri	0.95	1.00	0.98
Yamato Nishiki	0.95	0.95	0.95

From the above test results, we can conclude to calculate the Overall Accuracy for the classification of koi fish species as follows:

$$\text{Overall Acuracyy} = \frac{\textit{Total All Poin}}{\textit{Total Number Of Testing Enties}}$$

$$\text{Overall Acuracyy} = \frac{184}{200} = 0{,}92 = 92\%$$

3.3. New Data Testing Result

The testing process uses a total of 200 test data divided into 10 classes for each type of koi fish, with each class consisting of 20 test data.

Figure 7. Results of Predicted Classification of Koi Fish TypesH

4. Conclusion

Based on the results of the conducted analysis, several conclusions can be drawn. The Convolutional Neural Network model in this training, utilizing a total of 1000 datasets divided into 640 training data, 160 validation data, and 200 testing data, with 10 classes of koi fish types. The architecture that performed the best is the MobileNet V2 model with an accuracy of 92% and a loss of 0.4365. On the other hand, the VGG16 model achieved an accuracy of only 82.50%, and the ResNet 50 model achieved an accuracy of 49.50%. From the training and testing results, it can be concluded that the application of the Convolutional Neural Network method is effective in classifying different types of koi fish.

Declarations

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Conflict of interest. The authors declare no conflict of interest.
Additional information. No additional information is available for this paper.

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