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Fish Diseases Classification Based on Color Feature Using Convolutional Neural Network and Transfer Learning

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ABSTRACT

Fish disease is one of the threats that can inhibit fish production. It is important for fish cultivators to be able to recognize the types of diseases that can attack fish. In reality, many do not understand the knowledge of this disease, especially for novice cultivators. Handling of diseased fish using an automatic recognition system is expected to prevent significant post-harvest losses. The success of deep learning as an introduction based on digital images is its advantage in being able to recognize diseases in fish. Convolutional Neural Networks are a type of neural network in deep learning, usually used to process data in the form of images. The research process involved is: image collection, image processing, system design, and testing and accuracy results. The image dataset used is 1950 consisting of 1610 training data, 190 validation data and 150 testing data which will be tested on the model. Each dataset has 3 classes namely: normal, redpsot and whitespot. A classification system for diseases in fish uses two models, namely CNN and VGG-16 with transfer learning. Based on the results of system testing, the CNN model produces an accuracy of 77%, while the VGG-16 model with transfer learning produces an accuracy of 80%. So that the implementation of the VGG-16 model with transfer learning is relatively good in classifying fish disease types. Regardless, the detection performance could be improved by conducting a subsequent study with a larger number of datasets.

1. INTRODUCTION

Indonesia is a country that is nicknamed a maritime country because almost 70% is water and 30% is land. Therefore, currently fish farming is developing as a business opportunity or raising it to meet the protein nutritional needs of the community. In aquaculture as well as in the natural environment, disease poses a threat to fish. Worldwide, disease is recognized as one of the most significant threats to the economic success of aquaculture. A wide variety of infectious organisms, including bacteria, viruses, protozoa, and metazoan parasites, cause fish disease [1]. Due to its capacity to rapidly spread through water to neighboring aqua-farms, fish disease is a serious issue. To control these diseases, prompt and accurate diagnosis is necessary [2]. Modern aquaculture relies heavily on the identification of fish diseases, and prompt, real-time diagnosis is essential for the prompt and precise treatment of diseases [3].

As a method for identifying visual images, Computer Vision plays an important role in the field of digital information technology [4]. Intelligent systems in the view of Computer Vision must be an important part for breeders as a container or means of building efficiency [5]. One example of the use of computer vision is to be able to recognize the type of disease in fish. Along with increasing innovation, Using artificial neural networks that mimic the functions of the human brain, many studies are improving the operation of these intelligent systems. Classification of fish diseases can increase fish production.

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Forward chaining is used as a reasoning method to get the result of disease identification [6]. Forward Chaining and CBR are machine learning methods with high accuracy but still depend on experts, that's why they are also called expert system methods. SVM is a fairly good machine learning method for image classification, but SVM has low accuracy if the number of features is greater than the number of samples. CNN is a deep learning method that can solve problems in Forward Chaining and CBR. CNN also has better performance than other machine learning and deep learning methods in image classification. However, to obtain high accuracy, a large dataset is required [7].

Obtaining large datasets can be assisted by the data augmentation method, which is a method for transforming datasets so as to increase the sample variants of the dataset. The use of data augmentation is expected to increase the accuracy of the CNN as well as avoid over-fitting. Not only does 3 use data augmentation, the dropout method can also reduce over-fitting by stopping feature detectors randomly with a certain probability at each training epoch [8].

CNN performance can be improved by using a different architecture, namely VGG-16 which has the highest accuracy compared to several other CNN architectures such as AlexNet, InceptionV3 and VGG-19 [9]. Another method to improve the accuracy of CNN is to use transfer learning. Transfer learning is a method in which a deep learning model that has been trained by a previous dataset is reused in another dataset.

This research is based on several previous studies, which are one of the basic references for researchers in making research. From previous studies did not get a similar title, and of course there are differences from previous studies. In reference to research on how to detect fish disease using CNN. A total of 90 images of healthy fish and two types of fish infectious diseases were tested, namely Whitespot and Redspot. The application of CNN to various test datasets resulted in a good detection accuracy of 94.44%. It can be concluded that CNN is relatively good at detecting and classifying the type of disease in infected fish [10].

This study raises the problem of classifying fish disease types based on color features using CNN and VGG-16 architectures with a transfer learning approach. From the classification using these two models, it can be seen which architecture gives the best performance results. In previous studies, a comparison of the CNN and VGG-16 architectures had not been carried out, so this research was conducted to determine the comparison of VGG-16 architectures. Differences in the number and quality of datasets used in this study from previous studies will affect the architectural design of the model by adjusting image problems that can produce different values.

2. METHOD

The research method is defined as the stages that are passed in conducting a research. In Figure 1 are the steps taken for the classification of Fish Disease Systems using CNN and Transfer Learning.

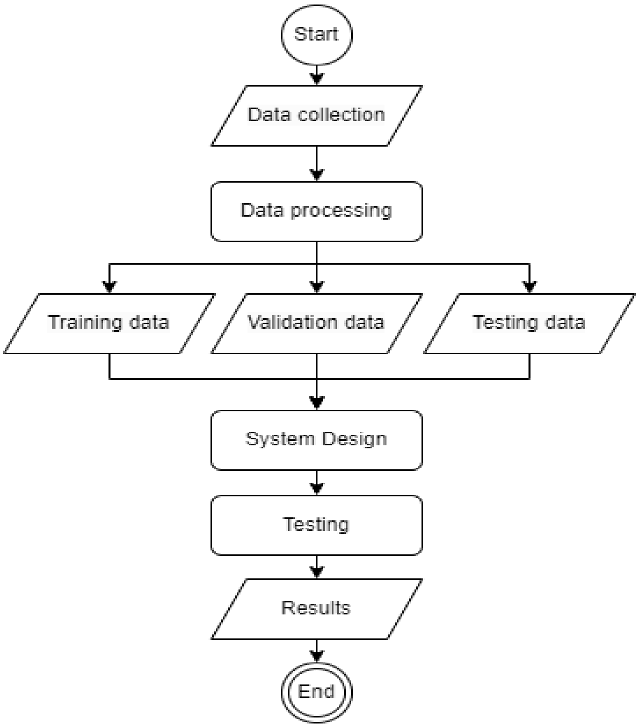

Figure 1. Flowchart of Research Stages

The point of research is to have stages but to obtain research results that are in accordance with what has been discussed and examined in the problem in the introduction.

2.1 Data Collection

The main stage is to collect image data as an object material studied in research. The researcher collected data which was used as a dataset in the form of images of fish infected with the disease. The data collected comes from observations by taking self-portraits using an Android camera, internet searching with the Google Image and Kaggle sites entitled "Fresh Water Fish Disease Dataset" [11]. The image data being sought is in the form of normal fish with good or smooth fish skin characteristics, redspot fish which have red spots and whitespot fish which have white spots on the skin of the body, fins, tail, even the head. As in the picture below 2 below.

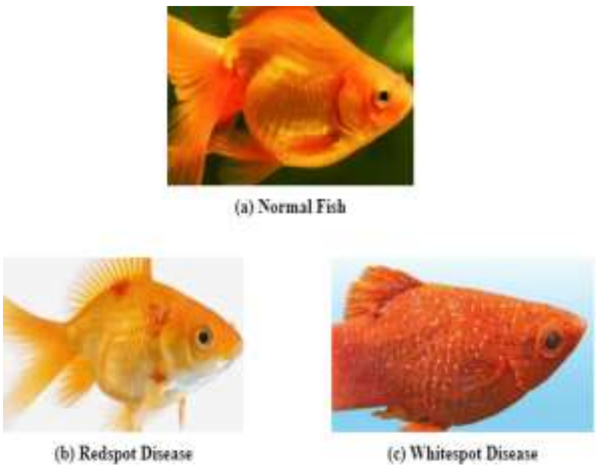

Figure 2. Fish image dataset

2.2 Data Processing

After getting the image data, the next stage is the need to do data processing, where the image will be processed with augmentation techniques, namely cropping and changing the dimensions of the image (Resize). This cropping & resizing step is very effective when used by dividing an image into approximately 4 new images, with the aim that the fish image will be more focused on the affected part of the skin. Like figure 3 below.

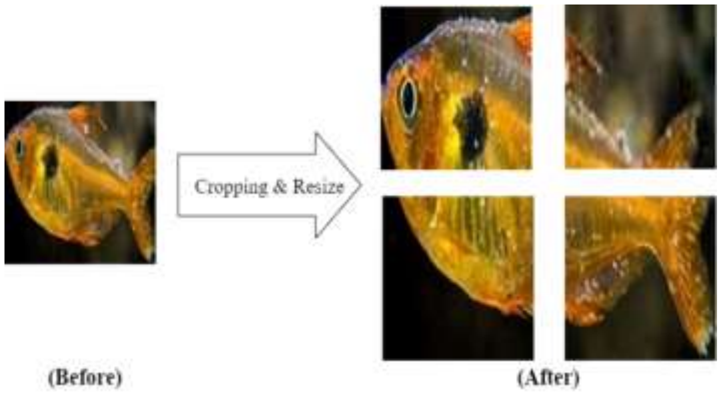

Figure 3. Cropping & Resize

The division of data obtained manually will be divided into training data and validation data as model training material and data testing as a test of the model made.

2.3 Convlutional Neural Network and Transfer Learning

At this stage it is necessary to design a system for conducting research, namely the use of the CNN method and transfer learning to classify fish diseases based on image color features. Starting from input data, data preprocessing using augmentation techniques with extracted features is then classified using two models, namely CNN and transfer learning with VGG16 as the architecture used. In Figure 4 you can see the system design scheme. In simple terms, the system design that is made consists of five parts, namely; Input data as the initial process of entering previously processed data, preprocessing data with augmentation techniques, models design makes two CNN and VGG-16 transfer learning models, Models Training with dataset training and dataset validation, Evaluation is a model test with dataset testing.

Convolutional Neural Network (CNN): Convolutional Neural Network is one of the deep learning methods used to classify. This classification uses a convolutional layer which aims to calculate the convolution between the input and the filter. The CNN method can fetch and extract features in an unattended way. This is what makes the CNN method different from machine learning methods which require predefined features. The class of artificial neural networks known as convolutional neural networks (CNN), which has emerged as the standard for a number of computer vision tasks, is generating interest in a number of fields, including radiology.

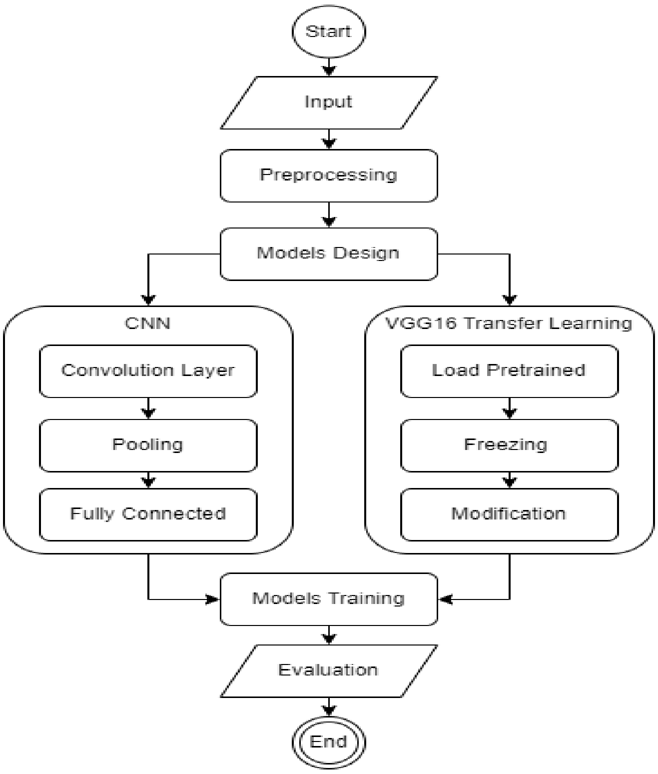

Figure 4. System Design Flowchart

Convolution layers, pooling layers, and fully connected layers are just a few of the building blocks that make up CNN's ability to automatically and adaptively learn feature spatial hierarchies through backpropagation [12]. Figure 5 shows an illustration of architecture Convolutional Neural Network model.

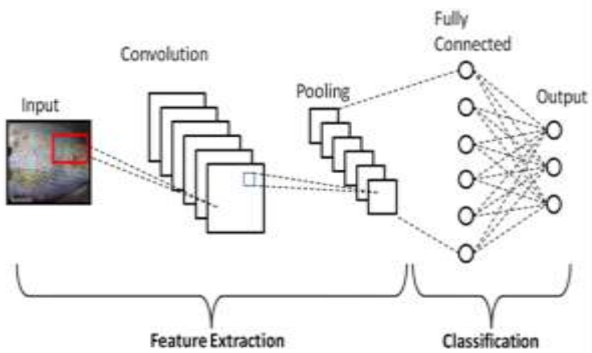

Figure 5. CNN Architecture

At the feature learning stage, the first process that must be completed is the convolution layer. Between the input matrix and the filter matrix kernel, the convolution operation will be performed in the convolution layer. Convolution is an addition operation between two matrices whose results are then summed [13]. The feature map is the output of the CNN algorithm convolution process. The Convolutional Layer is the fundamental interaction that is the CNN computation. The convolution layer performs the convolution procedure on the resulting values from the previous layer or the included layer. The convolution requirement in the image data expects to separate the elements of the image.

The pooling layer stage comes after the convolution layer in the CNN architecture. This pooling layer basically consists of a filter with a certain size that will be used in a certain way to move the feature map from the convolution layer to the next layer. In the pooling layer, various ways can be done such as max pooling, average pooling and sum pooling. The Max pooling process works by determining the value

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spread across windows. Most of CNNs working in image recognition have the lower layers composed to alternate convolutional and max pooling layers, while the upper layers are fully connected traditional MLP NNs [14].

Full Connected Layers is the merging stage starting from the Convolutional Layers and Pooling Layers stages where the resulting data that has been processed remains in the form of a multi-dimensional array, it is necessary to flatten or reshape it in the form of a vector so that it can be used as input from the full connected layer. This process can take a long time depending on the number of features generated. When compared to deeper datasets and vice versa, the shallow CNN requires a greater number of Fully Connected layers and a greater number of neurons in wider datasets [15].

Visual Geometry Group (VGG): Dasar dari rekayasa jaringan VGG adalah dapat menentukan dampak kedalaman jaringan konvolusi pada akurasinya untuk pengenalan citra berskala besar. Terdapat dua kunci utama pada model ini, yaitu rekayasa dan kedalaman lapisan konvolusi. Model ini memberikan pengembangan secara kritis dengan memakai kedalaman 16 hingga 19 lapisan konvolusi. VGG-16 adalah salah satu VGGnet model yang menggunakan 16 layer sebagai model arsitekturnya. Berikut ini adalah contoh gambar ilustrasi arsitektur model VGG-16.

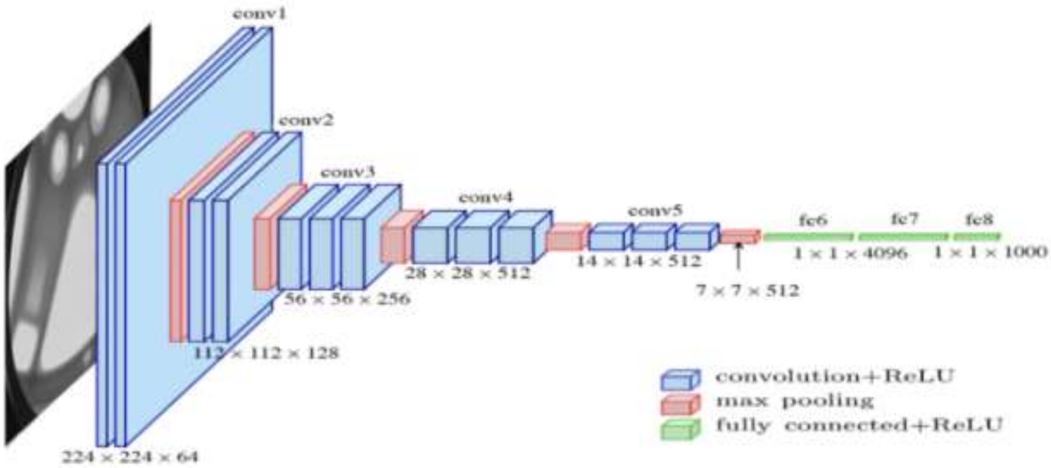


Figure 6. VGG-16 architecture [16]

Figure 6 is a VGG-16 model that was previously made by the Oxford research group. VGG-16 normally uses 5 convolutional blocks which are then connected to 3 MLP classifiers. The output layer uses the sigmoid activation function if there are 2 or less categories, and the softmax activation function if there are 3 or more categories in the dataset. VGG-16 won the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in first and second positions, where 1,000 categories and 1,000 data were used in each category [17]. VGG-16 is one of the CNN architectures by applying a transfer learning approach, aiming to transfer knowledge from a large data set known as the source domain to a smaller data set, which is the target domain [18]. Since the model was trained on a large dataset, it has learned to accurately represent low-level features like spatial, edges, rotation, lighting, and shapes. These features can be shared across problems in computer vision to facilitate knowledge transfer and serve as a feature extractor for new images [19]. When a new dataset is smaller than the one used to train the pre-trained model, Transfer Learning is typically used [20].

At this stage, the system that has been created and trained will test the test data obtained, the results of the classification will be recorded to obtain accuracy, precision, recall and F1-Score at a later stage. The level of accuracy obtained aims to be able to show the level of correctness of the classification of types of diseases in fish. A high level of accuracy means that the model can properly classify the types of fungal diseases in fish.

After testing, the next step is to analyze the test results. The test results are then calculated to get the success rate of the method used. The method used is the Confusion Matrix to calculate the value of precision, recall, F1-Score and accuracy.

3. RESULTS AND DISCUSSION

This research seeks to create a system that can classify fish diseases based on RGB color features. Classification results can be seen in the level of accuracy of the model in the testing process. The collected data is then processed by cropping and resizing it into several parts with the aim of making more data. The results of the data obtained amounted to 1950 data, which were then divided into 3 datasets with descriptions of 1610 of these data as training data, 190 as validation data, and 150 for testing data. Each dataset has 3 classes, namely: normal, redspot and whitespot.

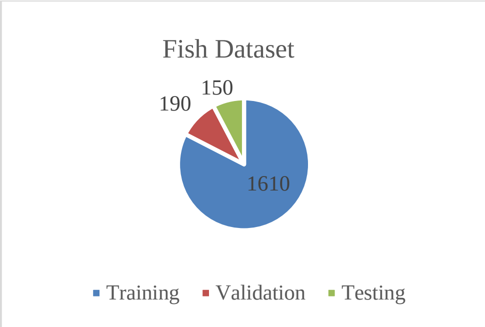
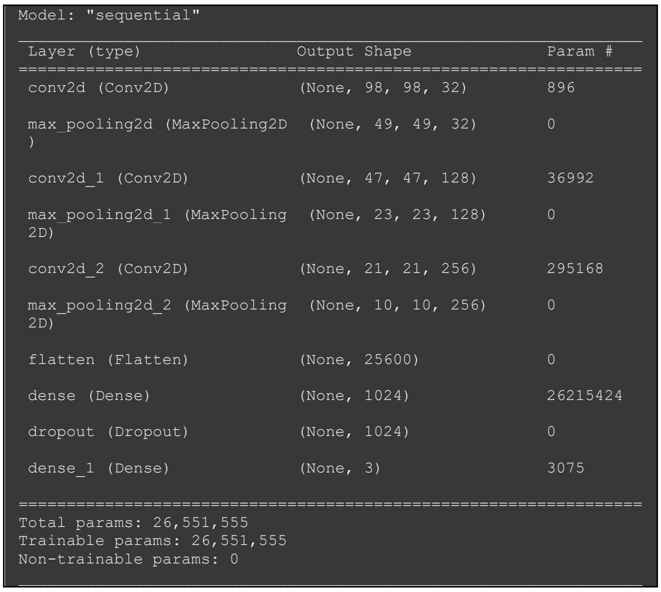


Figure 7. Dataset Spliting Manual Visualization

This step is carried out after pre-processing the next dataset is designing the model to be used, namely CNN and VGG16.

3.1. CNN Model

The first model built is CNN which will later be trained with data training and validation. The design of the CNN model can be seen in figure 8.



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 98, 98, 32)        896

 max_pooling2d (MaxPooling2D  (None, 49, 49, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 47, 47, 128)       36992

 max_pooling2d_1 (MaxPooling  (None, 23, 23, 128)      0
 2D)

 conv2d_2 (Conv2D)           (None, 21, 21, 256)       295168

 max_pooling2d_2 (MaxPooling  (None, 10, 10, 256)      0
 2D)

 flatten (Flatten)           (None, 25600)             0

 dense (Dense)               (None, 1024)              26215424

 dropout (Dropout)           (None, 1024)              0

 dense_1 (Dense)             (None, 3)                 3075

=================================================================
Total params: 26,551,555
Trainable params: 26,551,555
Non-trainable params: 0
_________________________________________________________________
```

Figure 8. CNN Model Summary

The picture above is the CNN architectural design used. It has 3 convolution layers, each of which has max-pooling, 2 fully connected/dense layers, this model also uses flatten and dropout with a probability parameter of 0.2. Each layer has a parameter set.

The next model to be built is VGG16 with a transfer learning approach which will later look for the results of model testing performance to obtain an accuracy value from the testing data. The following is an explanation of the process of making the VGG16 transfer learning model in the system by adjusting to the problems discussed in this study, namely for the classification of fish diseases. The design steps for the VGG-16 model are as follows:

1) Load Pre-trained model VGG-16 as the first task.
2) Freezing feature extraction pre-trained layer.
3) Modify the model for the second task.

After carrying out these steps, the VGG-16 architectural model with a transfer learning approach can be used. The model created can be seen in the figure 9.

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 100, 100, 3)]     0

 block1_conv1 (Conv2D)       (None, 100, 100, 64)      1792

 block1_conv2 (Conv2D)       (None, 100, 100, 64)      36928

 block1_pool (MaxPooling2D)  (None, 50, 50, 64)        0

 block2_conv1 (Conv2D)       (None, 50, 50, 128)       73856

 block2_conv2 (Conv2D)       (None, 50, 50, 128)       147584

 block2_pool (MaxPooling2D)  (None, 25, 25, 128)       0

 block3_conv1 (Conv2D)       (None, 25, 25, 256)       295168

 block3_conv2 (Conv2D)       (None, 25, 25, 256)       590080

 block3_conv3 (Conv2D)       (None, 25, 25, 256)       590080

 block3_pool (MaxPooling2D)  (None, 12, 12, 256)       0

 block4_conv1 (Conv2D)       (None, 12, 12, 512)       1180160

 block4_conv2 (Conv2D)       (None, 12, 12, 512)       2359808

 block4_conv3 (Conv2D)       (None, 12, 12, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 6, 6, 512)         0

 block5_conv1 (Conv2D)       (None, 6, 6, 512)         2359808

 block5_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

 block5_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

 block5_pool (MaxPooling2D)  (None, 3, 3, 512)         0

 global_average_pooling2d (G  (None, 512)              0
 lobalAveragePooling2D)

 flatten_1 (Flatten)         (None, 512)               0

 dense_2 (Dense)             (None, 1024)              525312

 dropout_1 (Dropout)         (None, 1024)              0

 dense_3 (Dense)             (None, 3)                 3075

=================================================================
Total params: 15,243,075
Trainable params: 528,387
Non-trainable params: 14,714,688
_________________________________________________________________
```

Figure 9. VGG-16 Model Summary

The image architecture model has been applied with these three steps, load the existing VGG-16 pre-trained model with imagenet weights, then freeze extraction layers on all pre-trained layers, then modify the model by making a classification using global average pooling, flatten, fully connected/dense layer and dropout.

3.2. Train Process Results

The training process is carried out on two models using training data and data validation. The positive outcome of the training process is one of the most important aspects of a successful image-based fish disease classification process. Good results from the training process will greatly affect the results of the next trial process on the two models. Of course, to create the best CNN model architecture, it is necessary to have an experimental process so that the CNN set parameters obtained are not the best instant or direct. This training process uses iteration parameters with batch sizes of 32 and 35 epochs. Therefore, to obtain feature extraction from the required features, a training process will be carried out and repeated

35 times. From the CNN model training process, the training and validation accuracy values are shown in the image in graphic form. The results of the model training process can be seen in Figure 10.

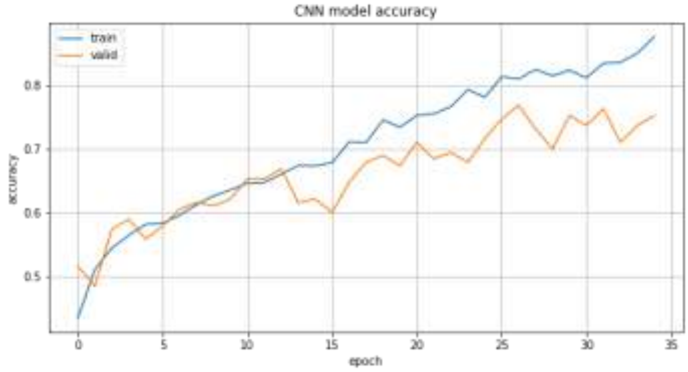


Figure 10. CNN Model Training Performance Graph

The CNN model without the application of other methods produces performance with training and validation accuracy of 88% and 75% while the loss values are 31% and 83%. It can be seen in Figure 4.7 that the training performance graph of this model results in overfitting with a comparison between training and validation accuracy reaching 13%.

Just like the previous CNN model, the training process for the VGG-16 model uses the same training data and validation data but the number of epochs used is 25. The results of the accuracy of the VGG-16 model training can be seen in the following figure. The VGG-16 model only applies transfer learning and does not use fine-tuning. The results are shown in Figure 11.

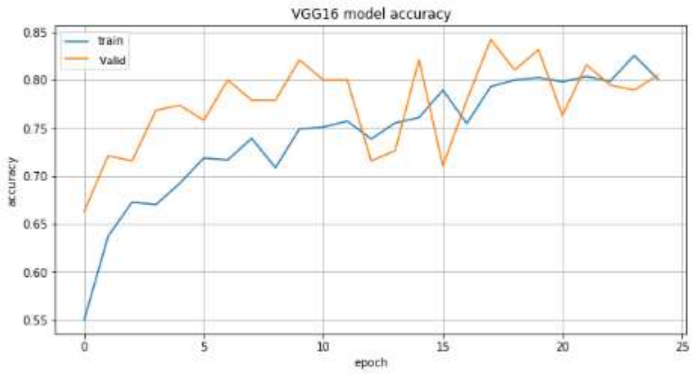


Figure 11. VGG-16 Model Training Performance Graph

The VGG-16 model with the application of transfer learning produces a balanced model with training and validation accuracy values of 80% and 81%. So the use of the VGG-16 model with transfer learning can increase the accuracy value obtained compared to the previous model.

3.3. Test Process Results

Testing was carried out using testing data totaling 150 new images. The implementation of the two models will be tested to obtain the predicted value of the confusion matrix and this value will be calculated to find the level of accuracy.

3.3.1. CNN

After testing with data testing the results of the implementation of the CNN architectural model obtain the predicted value as shown in table 1.

Table 1. CNN Model Testing Data Prediction

Matrix	Normal	Redspot	Whitespot
Normal	37	5	8
Redspot	5	36	9
Whitespot	4	3	43

The prediction results of the CNN model for data testing are quite satisfactory, as shown in the table above. 13 of the 50 data tested in the Normal class have wrong predictions. There are 14 wrong data in 50 Redspot class data. Conversely, the 7 images in the Whitespot class make the wrong prediction. In other words, there are 49 incorrectly predicted images from a total of 150 test data

$$accuracy = \frac{All\ True\ Positive}{Total\ Number\ Testing\ Entries} \times 100\% \tag{1}$$

$$= \frac{37+36+43}{50+50+50} \times 100\% \tag{2}$$

$$= \frac{116}{150} \times 100\% \tag{3}$$

$$= 77\% \tag{4}$$

From these calculations, the accuracy of the classification of fish diseases using the CNN model is 77%. The results obtained from the calculation of accuracy using the confusion matrix.

3.3.2. VGG-16 Transfer Learning

The test results with the same testing data, the implementation of the VGG-16 architectural model with the transfer learning approach obtained the predicted value as shown in table 2.

Table 2. VGG-16 Model Testing Data Prediction

Matrix	Normal	Redspot	Whitespot
Normal	34	10	6
Redspot	3	41	6
Whitespot	4	1	45

Based on the prediction results table above, the prediction results from the VGG-16 model with transfer learning to data testing show quite good results. In the Normal class of the 50 data tested there are 16 data that have wrong predictions. Redspot class of 50 data there are 9 incorrect data. Whereas in the Whitespot class only 5 images have wrong predictions. So a total of 150 test data or tests, there are 30 incorrectly predicted images. Then it will be calculated using the accuracy formula as follows.

$$accuracy = \frac{All\ True\ Positive}{Total\ Number\ Testing\ Entries} \times 100\% \tag{5}$$

$$= \frac{34+41+45}{50+50+50} \times 100\% \tag{6}$$

$$= \frac{121}{150} \times 100\% \tag{7}$$

$$= 80\% \tag{8}$$

From these calculations, the accuracy value using the VGG-16 model and transfer learning is 80%. So it can be concluded with the results of all accuracy in both models into a table 3 below.

Table 3. Accuracy Results of Both Models

Models	Training(Accuracy)	Validation(Accuracy)	Testing(Accuracy)
CNN	88%	75%	77%
VGG-16	80%	81%	80%

4. CONCLUSION

In this study, the researchers succeeded in creating a system using two CNN models and transfer learning for classification of fish diseases which aims to determine the performance of the two models which were relatively good to use in this case. From this study, the results of the CNN model performance were quite good in classifying fish diseases in image datasets. By testing 150 testing data, an accuracy of 77% is obtained. Given the poor quality and insufficient quantity of data obtained, these results are quite satisfactory. And this research has also implemented the VGG-16 model for classification of diseases in fish. Learning the transfer of the VGG-16 model by carrying out the same test obtained an accuracy test of

80%, the implementation of the VGG-16 model can increase the results of the accuracy value in classifying the types of diseases in fish. The use of fine-tuning on the VGG-16 model and the addition of the quality of the amount of data is expected to increase the value of a better accuracy.

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