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Detection of the Types of Consumable Saltwater Fish in the Coastal Area of Likupang Uses the Convolutional Neural Network Method

Pendeteksian Jenis Ikan Air Asin yang Dapat Dikonsumsi di Perairan Likupang Menggunakan Metode Convolutional Neural Network

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Abstract – In the coastal area of Likupang, many types of saltwater fish can be consumed, such as tuna and skipjack. Yet, there are also types of saltwater fish that cannot be consumed or protected by the government, such as Napoleon fish and sea kingfish. Thus, this research aimed to build a desktop application that can automatically classify consumable and non-consumable saltwater fish species more accurately and promptly using a suitable image recognition method like the Convolutional Neural Network (CNN). CNN has abilities to distinguish images by recognizing several pixels in a two-dimensional image and RGB (Red, Green, Blue) colors which are then converted into a matrix with various values, making it easier for the system to recognize the two-dimensional image. By using 40% test data (143 images) and 60% training data (213 images), this study obtained test accuracy in identifying and classifying images of consumable fish, non-consumable fish, and non-fish images with each percentage of 94%, 98%, and 95% respectively.

Keywords: Convolutional Neural Network, Detection, Fish, Likupang, CNN

Abstrak – Di perairan Likupang terdapat banyak jenis ikan air asin yang bisa dikonsumsi, seperti ikan Tuna dan Cakalang. Namun, ada juga jenis ikan air asin yang tidak bisa dikonsumsi atau dilindungi oleh pemerintah, seperti ikan Napoleon dan ikan Raja Laut. Oleh karena itu, penelitian ini bertujuan untuk membangun aplikasi *desktop* yang dapat secara otomatis mengklasifikasikan spesies ikan laut yang dapat dikonsumsi dan tidak dapat dikonsumsi dengan lebih akurat dan cepat menggunakan metode pengenalan citra yang sesuai *seperti Convolutional Neural Network* (CNN). CNN memiliki kemampuan untuk membedakan gambar dengan mengenali beberapa piksel pada gambar dua dimensi dan warna RGB (*Red, Green, Blue*) yang kemudian diubah menjadi matriks dengan berbagai nilai, sehingga memudahkan sistem untuk mengenali gambar dua dimensi tersebut. Dengan menggunakan 40% data uji (143 citra) dan 60% data latih (213 citra), penelitian ini mendapatkan akurasi uji dalam mengidentifikasi dan mengklasifikasikan citra ikan konsumsi, ikan tidak konsumsi, dan citra non-ikan dengan persentase masing-masing 94% , 98%, dan 95%.

Kata Kunci: Jaringan Saraf Konvolusional, deteksi, ikan, Likupang, CNN

INTRODUCTION

Indonesia, as the largest archipelagic country in the world, has economic potential derived from marine resources (Massijaya, 2016). Fish is not only a source of food, but fish also has economic value so fish must be protected, maintained, preserved, and utilized for the welfare of the community (Hassan, 2020). Therefore, all activities related to the processing and utilization of fish resources and their environment from pre-production, production, and processing to marketing carried out in a fishery business system are regulated in Law Number 31 of 2004 (Kementerian Kelautan dan Perikanan, 2017).

Almost all types of saltwater fish can be consumed by humans, ranging from tuna, skipjack, and other types of saltwater fish that are often sold in the market.

doi:

However, there are several types of saltwater fish that cannot be consumed because they are protected, such as napoleon fish and king sea fish. The criteria for protected saltwater fish species are saltwater fish that are endangered, rare, and in a limited (endemic) distribution area (Hassan, 2020). The threat of fish extinction is often caused by overfishing, pollution of fish habitats due to fishing using explosives and toxic materials, as well as a decline in fish populations caused by decreased reproduction rates of several types of saltwater fish (Kementerian Kelautan dan Perikanan, 2017). The coastal area of East Likupang District, North Minahasa Regency, especially the coastal area of Likupang is known as a producer of fish, especially tuna and skipjack, even famous for their types of coral demersal fish and there are also types of saltwater fish that cannot be consumed or protected.

Classification of consumable and non-consumable saltwater fish species in Likupang waters not only requires deep knowledge but is also time-consuming. With the development of computer vision, it is possible to automate the classification of consumable and non-consumable saltwater fish species more efficiently and accurately. Knowing the many types of saltwater fish that cannot be quickly distinguished between consumable and non-consumable fish, it is necessary to have a powerful method for image "acknowledgment and computer vision structure" like deep learning (Gaba, et al., 2022, p.144).

Convolutional neural network (CNN) is a derivative of the deep learning methods that can accept input in the form of images to recognize any aspect or object in an image as well as distinguish one image from another (Haar, Elvira, & Ochoa, 2022; Gaba, et al., 2022; Coulibaly, et al., 2022; Wijaya, Soelaiman, & Suartika, 2016). This CNN method is suitable for image processing to detect and recognize objects in a two-dimensional image (Pratiwi, Cahyanti, & Lamsani, 2021; Kusrini, Luthfi, & Rahim, 2020; Kosasih & Fadila, 2019). Huang et al. (2022) dan Haar et al. (2002) also pointed out that CNN has high accuracy in *image recognition* amongst many domains by identifying pixels in a two-dimensional image and RGB (Red, Green, Blue) colors which are then converted into a matrix with various values, making it easier for the system to recognize the two-dimensional image (Seo & Kwon, 2017).

There are studies related to fish recognition and classification using various methods such as SURF, SVM (Support Vector Machine), and CNN. For instance, Fuoad, et al. (2013) used SIFT (Scale Invariant Feature Transform) and SURF followed by SVM while Qin, et al. (2016) only employed the SVM method. Yet, both studies have successfully detected and categorized the underwater fishes and their variants and managed to achieve "94.4% detection accuracy" and "98.64% classification accuracy against a real-world fish recognition dataset respectively" (Prasenan & Suriyakala, 2022, p.3). On the other hand, Salman, et al., (2019) used CNN and SVM to classify fine-grained fish species captured off the Western Australia coast and managed to achieve 94.3% accuracy. Furthermore, research conducted by Villon, et al. (2018) also employed CNN for fish species identification using underwater fish images. Their test dataset consisted of "1,197 images representing 9 fish species and was trained over 900,000 fish images. Evaluation shows that different performance is observed for individual fish species" (Prasenan & Suriyakala, 2022, p.3). The differences between the previous studies and this study in fish image detection and classification lay in the types of fish, the number of datasets used, fish habitat, and parameters used to implement the CNN method. Those parameters were the number of channels, and the different lengths, and height sizes of each image. The reason for choosing and utilizing the CNN method rather than the SVM method was that CNN tends to outperform SVM when given as much training and computational powers as possible because "CNN was determined to have a static-significant advantage over SVM when the pixel-based reflectance samples used without the segmentation size" (Hassan, et al., 2019, p. 1861).

This study aimed to create a desktop application that can detect which saltwater fish species in the coastal area of Likupang are consumable and non-consumable using the CNN method. This application was built to facilitate the process of classifying saltwater fish species that can be consumed and cannot be consumed or protected in Likupang waters with a faster time and higher level of accuracy. The dataset used in this application is 356 image data in various formats, such as JPG, JPEG, and IMG which are divided into test data and training data. The data is 40% of test data images (143 images) and 60% of training data images (213 images).

This paper is divided into four parts that are the introduction, research method, results and discussion, and conclusions and recommendations. First, the introduction will outline the research background to provide the context in which this study was conducted. Next, it will address the research methodology, including the software development life cycle. Then, the results and discussion are provided before the conclusion and future works.

RESEARCH METHOD

There were four stages of the research framework, namely data collection, pre-processing, processing, and validation. This part will address each stage in detail for a better understanding of how this research was conducted.

Stage I: Data Collection

This part would contain the details of data required for the research, including the data source, data type and format, and the data split for the training data and test data.

Stage II: Pre-processing

In this stage, the collected images were sorted out to ensure that the quality of the images had good resolution as it has effects on image detection. Furthermore, all the images were to be resized without comprising the image quality.

Stage III: Processing

This stage is regarded as crucial as it would implement the CNN method to detect which fishes in the coastal area of Likupang are consumable and non-consumable.

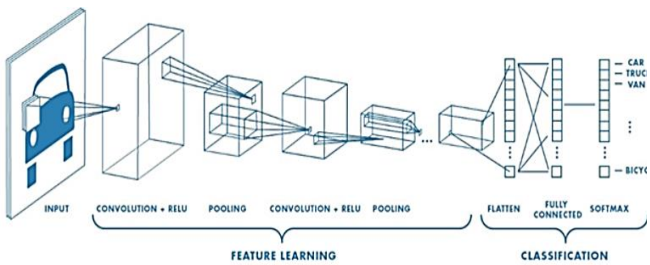

Figure 1 How CNN Method Works (Sari, 2021)

Three layers of CNN methods used in this research are the convolutional layer, subsampling layer, and fully connected layer.

1. Convolutional Layer

The purpose of using convolution for an image is to be able to extract features from the input image, then convolution will produce a linear transformation of input data that matches the spatial information on the existing data (Pratiwi, Cahyanti, & Lamsani, 2021; Gaba, et al., 2022). The workings of the convolutional layer are to apply a filter matrix to an input matrix by calculating the dot product of the two matrices (Sari, 2021).

According to Rahim et al. (2020), there are several properties in a convolutional neural network, namely length, width, depth, stride, and zero padding, that would be discussed in the later part.

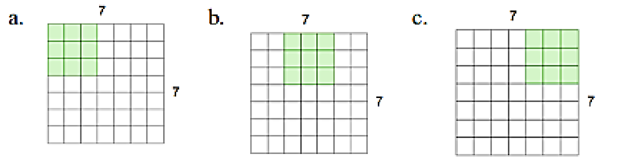

Figure 2 Operation of Convolution (Karlam, 2019)

In Figure 2, the input matrix size is 7x7x1 and the filter size is 3x3x1 with a stride value of two it will produce a 3x3 matrix.

2. Subsampling Layer

Subsampling or pooling layer is a process of reducing the size of an image data, subsampling has the aim of increasing the position invariance of features and reducing the dimension value of the feature map (down-sampling) so that it can speed up the computational work process because the parameters that must be updated will be increasingly a little so that it can overcome the problem of overfitting (Pratiwi, Cahyanti, & Lamsani, 2021). Pooling commonly used is Max Pooling and Average Pooling. Max Pooling to determine the maximum value of each filter shift, while Average Pooling will determine the average value (Walter , 2022).

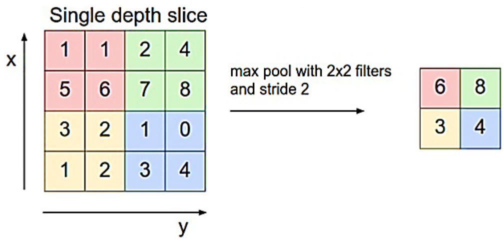

Figure 3 An Example of Pooling Layer (Pratiwi, Cahyanti, & Lamsani, 2021)

The red, green, yellow, and blue columns are the columns whose maximum values were chosen so that the results of the process can be seen in the set of tables on the right.

3. Fully Connected Layer

According to Wijaya et al. (2016), the fully connected layer (hidden layer) is a layer where all the neurons on the CNN are activated after all the neurons in the layer are connected like a normal neural network. The fully connected layer aims to transform the dimensions so that the data obtained in the classification process can be first transformed into one-dimensional data so that they can be entered into the fully connected layer (Liu, Kang, Zhang, & Hou, 2018).

The formula for the next layer is as follows (Wijaya, Soelaiman, & Suartika, 2016):

$$O_k = \left(\sum_{i=0}^{m} x_{k,i}\, w_{k,i} \right) + b_k \quad k = 0, 1, 2, \ldots t \tag{1}$$

Where t is the total neurons in the target layer, m is the total neurons in the previous layer, and O for symbolized the output value. While x is the input value and w is the weight or bias.

Activation Function

The activation function is a nonlinear function that allows an artificial neural network to be able to perform transformations on the input data so that the dimensions can be higher and then a simple hyperplane cut will be carried out which can allow for the classification process (Wijaya, Soelaiman, & Suartika, 2016). The advantage of performing the activation function is that it can speed up the configuration process carried out by Stochastic Gradient Descent (SGD), but this function also has a weakness that it can become fragile in the training process until the process can make a unit die (Awangga & Putro, 2020).

There is an activation function on CNN, namely the Rectification Linear Unit (ReLU) function. ReLU function is an output value that can be expressed as 0 if the input is negative and if the input value is positive then the output on the neuron is the activation value itself. The formula for ReLU is as follows (Karlam, 2019):

$$\boldsymbol{R(z) = \max(0, z)} \tag{2}$$

Karlam (2019) also explained that if $z < 0$ then the result of R(z) is 0. Whilst, when $z = 0$ or $z > 0$ then the result of R(z) is z itself.

Input Layer

The input layer is a layer that can accept input or input consisting of various X variables. The input layer consists of various neurons that can be connected to several outer layers of the artificial neural network (Awangga & Putro, 2020). The input layer serves to accommodate the pixel values of the input image. For an image with a size of 64x64 with 3 RGB color channels (Red, Green, Blue), then the input will be a pixel array measuring 64x64x3.

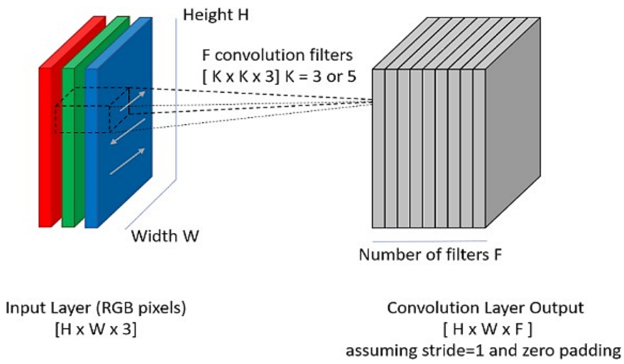

Figure 4 A RGB Input Layer (Pratiwi, Cahyanti, & Lamsani, 2021)

Stride

Stride is a parameter or constraint that can determine the amount of filter shift. If the value of a stride is 1, then the convolutional filter will shift by 1 pixel moving horizontally and vertically (Yepez & Ko, 2020). The smaller the value of a stride, the more detailed the value of the information we will get on input, but this stride process has a large computation time (Awangga & Putro, 2020). However, by using a stride of small value we will not always get good performance. The number of stride values used in this research is 1 stride.

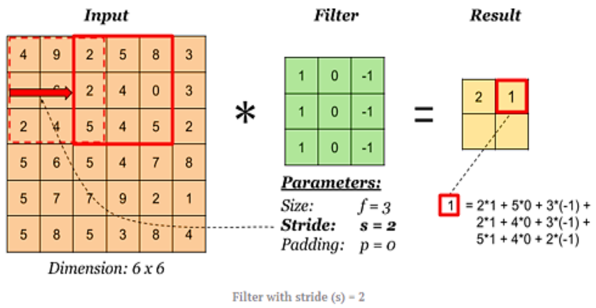

Figure 5 An Example of Stride Used

Padding

Padding or also often called zero padding is a parameter used to determine the number of pixels (containing a value of 0) to be added to each side of the input. It aims to be able to manipulate the output dimensions of the convolution layer (feature map) (Awangga & Putro, 2020). Padding aims to enable us to measure the output dimensions so that they remain the same as the input dimensions or at least minimize them so that they are not drastically reduced so that we can use deeper convolution layers so that more features can be extracted (Wiranata, Wibowo, Patmasari, Rahmania, & Mayasari, 2018). For example, the dimensions of the actual input are 5x5, if you do convolution with a 3x3 filter and a stride of 2, you will get a feature map with a size of 2x2. However, if you add 1 zero padding, then the resulting feature map is 3x3 in size (more information is generated). To calculate the dimensions of the feature map, one can use the following formula:

$$Output = \frac{W+N+2P}{S} + 1 \quad (3)$$

Notes:
W = Input Length/Height
N = Filter Length/Height
P = Zero Padding
S = Stride

Stage IV: Validation

A confusion Matrix is a performance measurement for machine learning classification problems where the output can be two or more classes (Angdresey, Sitanayah, & Kairupan, 2021; Rahim, Kusrini, & Lutfi, 2020). In this paper, we used a confusion matrix to evaluate the performance of the CNN method in this research.

This research used a system development life cycle that consisted of four phases, namely analysis, design, implementation, and testing. Each phase would collaborate with the research framework that addressed the data collection, pre-processing, processing, and validation.

Analysis

The following part would briefly address the four stages of the research framework to provide a better understanding of how this research was conducted.

Data Collection

The dataset for this research consisted of 356 images that were obtained from an open-access repository of images published online at the website Kaggle (https://www.kaggle.com/). This dataset thus was separated into the training data (213 images) and the testing data (143 images). For the training data, 13 images were discarded due to poor image quality. The remaining 200 high-quality images consisted of consumable saltwater fish, 78 images of non-consumable saltwater fish, and 78 other images (not fish). This dataset can be seen in Figure 6.

Figure 6 Dataset

The following table provided information about the original images downloaded from the website Kaggle.

Table 1 Original Images for Data Collection

Type of Fishes	Image Size (kb)	Resolution (pixels)
Consumable fish	128	567 x 240
Non-consumable fish	62	603 x 164
Non-fish images	62	1,000 x 665

Images to upload in the application must have either in the form of jpg, BMP, png, or tiff formats with a maximum image file size of 20 MB.

Pre-processing

Pre-processing techniques used in this research included grayscale, thresholding, segmentation, and resizing. A gray or grayscale image is an image that only has one channel so displayed only the intensity value or gray level, ranging from 0 to 255. The value 0 represents black and the value 255 represents white. The calculation to find the value of grayscale using the following equation (Hibatullah, 2019):

$$\mathbf{y = (0{,}2989 * R) + (0{,}5870 * G) + (0{,}1141 * B)} \quad (4)$$

Thresholding is a process in which the result is a binary image of a grayscale image or color image by setting the pixel value to the value 0 or 1 depending on the threshold value whether the pixel value is below or above the threshold (Hibatullah, 2019). This research also performed segmentation processes by which the data used were images binary results from the thresholding process. Then, cuts were made for each line (vertical) first, and next cut each column (horizontally) on the image resulting from line cutting. In resizing processes an image becomes larger or smaller than the size of the previous image with a size that is predetermined. In this research, the grass code image that has been segmented at this stage segmentation is resized to 64 x 64 pixels.

Table 2 Resized Images

Original Image	**Resized Image**
	
688 x 458 pixels	64 x 64 pixels
	
1,000 x 762 pixels	64 x 64 pixels

Processing

This part would outline how CNN was implemented in this research. The model built using the CNN method consists of the number of layers used, the filter size, the pooling layer, and the activation function. The input image on the CNN model uses an image with a size of 64x64x3 pixels. The number three refers to an image that has three channels, namely Red, Green, and Blue (RGB). The input image will then be processed first through the convolution process and the pooling process at the feature learning stage, the number of convolution processes in this design has two convolution layers where each convolution has a different number of filters and kernel sizes. Then, do the flattening process or the process of changing the feature map resulting from the pooling layer using max pooling. The following is a description of the stages of the development framework.

A. Convolution Layer

A new image is generated from the convolution layer to display the input image. The convolution layer process uses a filter for each image used. The process of filtering each image entered will be resized and inserted into a filter with a matrix size of 6x6. The 6x6 matrix on the input image is used so that the recognition of two-dimensional images based on color performed by CNN obtains maximum accuracy results. After inserting the image, the image will be converted into a matrix containing values according to the colors contained in the image. If the matrix used is larger, the level of color accuracy obtained will also be closer to the image. The following example in the filter stage can be seen in Figure 7.

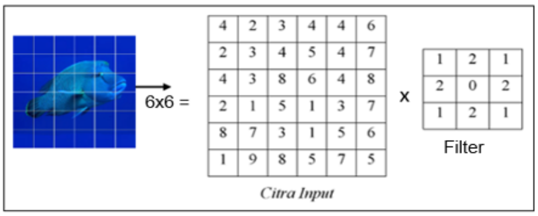

Figure 7 Object Filter

The input image obtained by the CNN method gives values randomly depending on the color sensitivity that can be recognized by the CNN method. The smaller the value entered in the kernel, the more detailed and accurate the results will be. The image has been filtered to get the value of the pixels for that image. The calculation of the pixel value is multiplied by the kernel value and converted to a convolved feature.

Parameters used are filter=3, stride=1, channel=3, and padding = 0.

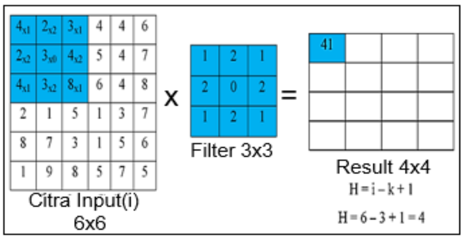

Figure 8 Convolution Operation (1)

The picture above is a way of calculating the convolution operation, the value of the input image is multiplied by the kernel value after which the values obtained will be added up and entered into the output image which will later become the pooling layer.

Calculation 1 = 4x1 + 2x2 + 3x1 + 2x2 + 3x0 + 4x2 + 4x1 + 3x2 + 8x1 = 41

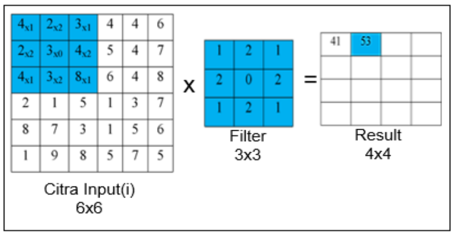

Figure 9 Convolution Operation (2)

The value in the input image will be shifted one column to the right and multiplied by the kernel value and then summed and inserted into the output image.

Calculation 2 = 2x1 + 3x2 + 4x1 + 3x2 + 4x0 + 5x2 + 3x1 + 8x2 + 6x1 =53

This process is repeated to get the next result. The last convolution operation is shown in Figure 10.

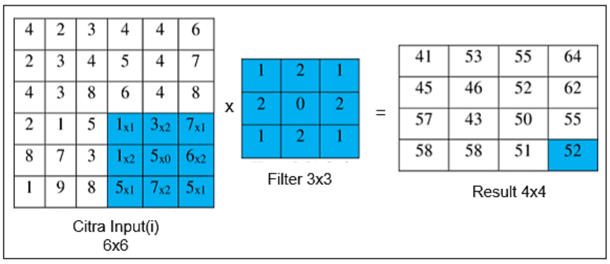

Figure 10 Convolution Operation (16)

Calculation 16 = 1x1 + 3x2 + 7x1 + 1x2 + 5x0 + 6x2 + 5x1 + 7x2 + 5x1 = 52

B. Pooling Layer

Max pooling was performed to downsample by reducing the size of the input image and sending only the important data to the next layers in CNN. This research used max pooling to increase the accuracy of image detection. The properties of the pooling layers are filter=2, stride=2, pooling type=max, and pooling size-2x2. The result of using the max pooling is displayed in Figure 11.

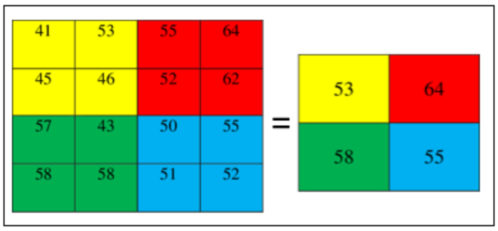

Figure 11 Max Pooling

C. Fully Connected Layer

Fully connected layers form the last few layers in the network which compiles the data extracted from the previous layers to form the final output. Figure 12 would demonstrate the fully connected layer for this research.

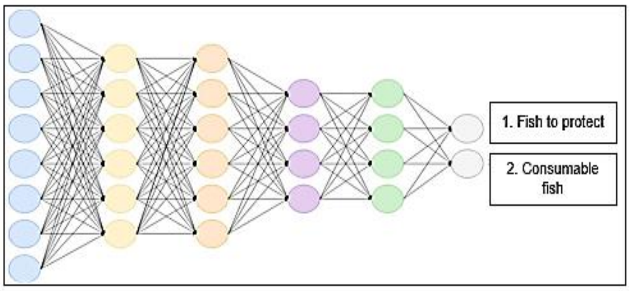

Figure 12 Fully Connected Layer

Validation

A confusion matrix was used to calculate the accuracy of detecting the types of saltwater fish that are consumable and non-consumable in the coastal area of Likupang.

System Design

Figure 13 demonstrated how this research intended to implement the CNN method into the application to generate a reliable classification model. It showed how CNN utilizes the convolution process by moving a convolution kernel (filter) of a certain size to an image, the computer gets new representative information from the result of multiplying the part of the image with the filter used.

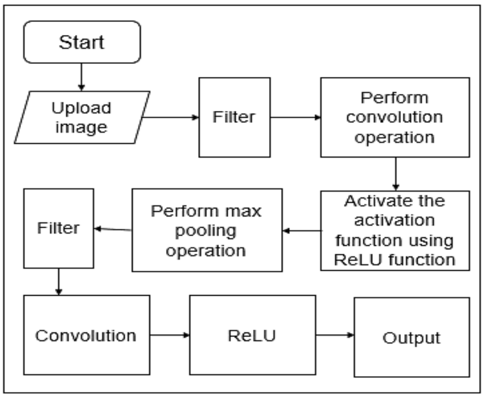

Figure 13 The Convolution Process in CNN

Each small image from the convolution results is then used as input to produce a feature representation. This gives CNN the ability to recognize an object, regardless of where it appears in an image. A large image is changed to a small array (a group of numbers). To reduce the size of the array, down-sampling is used, the use of which is called max pooling or taking the largest pixel value in each pooling kernel. That way, even if you reduce the number of parameters, the most important information from that section is still retrieved.

The activation function is at the stage before doing the pooling layer and after doing the convolution process. At this stage, the convoluted value is subjected to an activation function. reLU function is the output value of the neuron that can be expressed as 0 if the input is negative. If the input value of the activation function is positive, then the output of the neuron is the value of the activation input itself.

Data Collection

Figure 14 showed how the user inputs the image into the application. The input image would be processed using the CNN method.

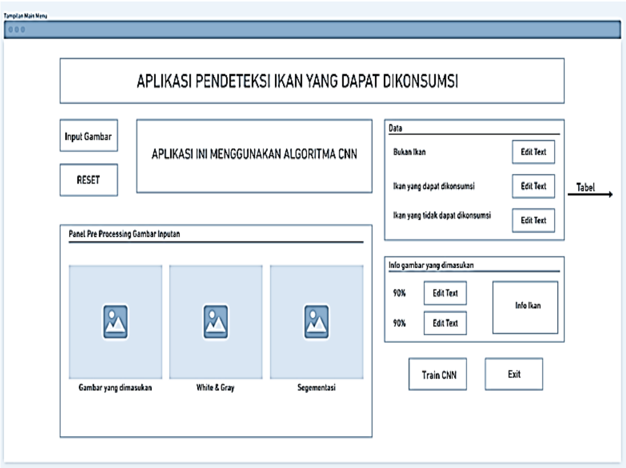

Figure 14 Application Interface

Pre-processing

Grayscale, thresholding, segmentation, and resizing images were a few pre-processing techniques used in this research.

Processing

In Figure 14, the input image is first processed through the convolution process and the pooling process at the feature learning stage. There are two convolution layers by which each convolution has a different number of filters and kernel sizes. Next is the flatten process or the process of changing the feature map resulting from the pooling layer using max pooling. The pooling process uses a size of 2x2 with stride 1 where the number of kernel shifts to the input matrix is one. The max pooling method works where the window will shift according to the size and stride to get the maximum value with 2x2 max pooling results.

Validation

A confusion matrix was used to calculate the accuracy of the algorithm in detecting whether the fish in the input image is consumable or not.

RESULT AND DISCUSSION

This part will address the implementation of the CNN method to detect and classify the types of saltwater fish in the coastal area of Likupang. It also discussed the testing process of the trained model on the new test dataset.

Implementation

Table 3 displayed the hardware and software required for application development.

Table 3 Development Environment

	Resources
Hardware	CPU Intel Core i58250U, SSD 256 GB, RAM 8GB, Windows 10.
Software	1. C# for coding 2. MySQL for the database 3. phpMyAdmin for DBMS 4. Google Chrome to display the application contents.

Data Collection

Figure 15 is an interface for users to upload an image of a fish to be classified. That image was then processed using the CNN method.

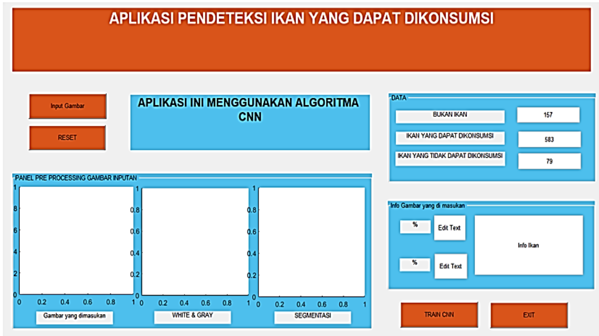

Figure 15 View Page

Figure 16 Upload Image For Detection

Pre-processing

The use of pre-processing techniques to transform the raw data into an understandable format was considered important. It cleaned the data and made it suitable for building and training the models which also increase the accuracy and efficiency of those models. This research used grayscale, thresholding, segmentation, and resize techniques to prepare the input image for further analysis in the processing stage. The result of applying the pre-processing techniques to the input images can be seen in Figure 17.

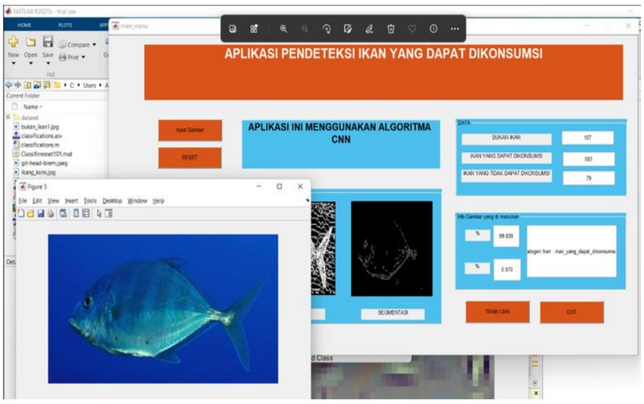

Figure 17 Pre-processing

Processing

In this part, the input image in Figure 17 was split into smaller overlapping images. Then, the algorithm loaded every smaller image into a small neural network. Each small image from the convolution results was then used as input to produce a feature representation. This gave CNN the ability to recognize an object, regardless of where it appears in an image. Next, it was to save the results of each thumbnail into a new array. To reduce the size of the array, this research used max pooling or taking the largest pixel value in each pooling kernel. An array is a group of numbers, so using that small array we can input it into another neural network. The final neural network would decide whether the image matched or not as shown in Figure 18.

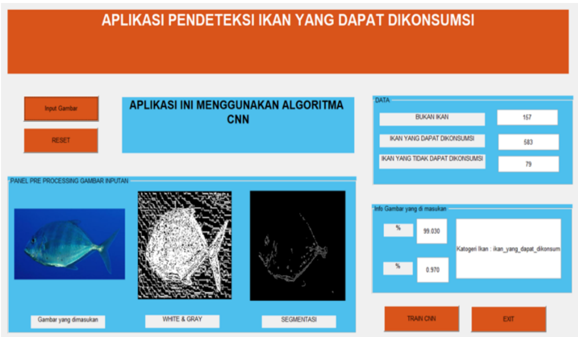

Figure 18 The Classification Result

Testing

The CNN model classifier was tested to see how well this classifier can detect and classify the input images. After the original image was uploaded, this input image was changed into a white and grey image as displayed in Figure 19 below.

Figure 19 The Input Image Changed into a White and Grey Image

The input image was converted into an image segmentation display which will then obtain the classification results from the input image as shown in Figure 20.

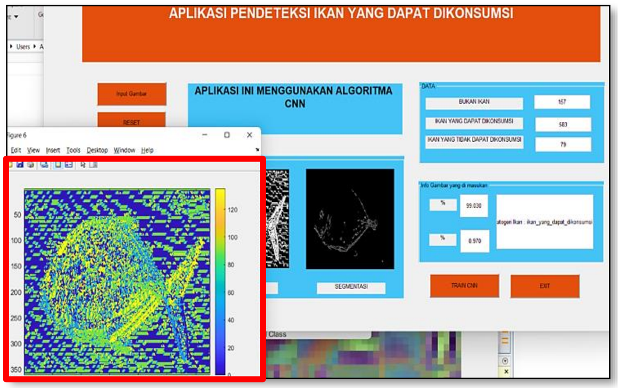

Figure 20 The Segmented Image

Figure 21 showed the test result of the input features of the fish image along with the accuracy of image classification using a confusion matrix.

Figure 21 The Classification Result

After processing the input image using the CNN process, the classification result revealed that the input image was a consumable saltwater fish that are residing in the coastal area of Likupang.

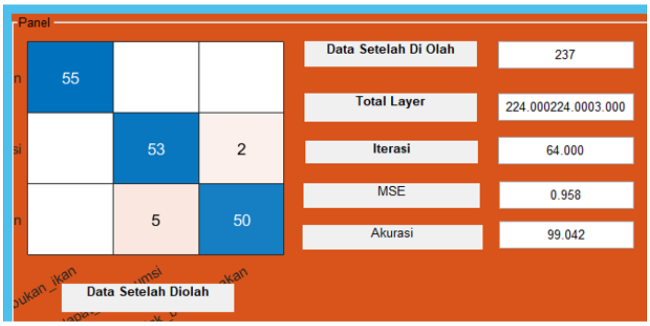

Figure 22 The Performance Evaluation.

The classification of types of saltwater fish in the coastal area of Likupang was done using the CNN method which used two convolution layers, the ReLu activation function, and several other parameters. The parameters used were filter=3, stride=1, channel=3, and padding = 0. The use of the pooling layer can reduce the dimensions of the feature map, thereby speeding up computation because fewer parameters need to be updated and overfitting.

The test dataset contained 237 images. After testing, it was found that the total layer, the total number of iterations, and the mean squared error (MSE), were 224.000224.0003.000, 64, and 0.958 respectively. MSE was used to check the estimate of how much the value of error in prediction. The value of MSE, 0.958, indicated that the margin error for predicting the type of fish from the uploaded image is less than 5%. This implied that the classification model labeled the images more accurately and timely.

The test accuracy in identifying and classifying images of consumable fish, non-consumable fish, and non-fish images were 94%, 98%, and 95% respectively.

This application can detect the type of saltwater fish and whether this fish was consumable. Also, it can successfully detect when the user uploads a non-fish image.

Conclusion

The following conclusions were made regarding this research.

1. This application can implement the CNN method to detect and classify whether the input image is a consumable saltwater fish that resides in the coastal area of Likupang.
2. The number of datasets and the number of convolution layers on the CNN architecture affect the level of accuracy. The MSE was 0.958 while the accuracy in identifying and classifying images of consumable fish, non-consumable fish, and non-fish images were 94%, 98%, and 95% respectively.
3. When done on input with multiple channels, pooling reduces the height and width, speeds up calculations, and makes some of the features it detects more vigorously.

Several recommendations can be made as follows:

1. Further research is recommended to add an optimization function that can make the value of a parameter maximum or minimum.
2. Added a dropout function to avoid overfitting the neural network by enabling or disabling a neuron.

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