Int. J. Nonlinear Anal. Appl. 13 (2022) 1, 1977-1984
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.5839

Fish diseases detection using convolutional neural network (CNN)

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(Communicated by Madjid Eshaghi Gordji)

Abstract

The fishing industry has become an important income source in the world. However, the fish diseases are considered as a serious problem among the fishermen as it tends to spread quickly through the water. In decades, fish diseases have been diagnosed manually by the naked eyes of experienced fish farmers. Despite being time-consuming since some lab works are required in determining the relevant microorganisms that cause the diseases, this classical method most often leads to an inaccurate and misleading result. Accordingly, a fast and inexpensive method is therefore important and desirable. Convolutional Neural Network (CNN) performance has recently been demonstrated in a variety of computer vision and machine learning problems. Thus, a study on fish diseases detection using CNN is proposed. A total of 90 images of healthy leaf and two types of fish diseases which are White spot and Red spot was tested. The application of CNN to a variety of testing datasets returned good detection accuracy at 94.44%. It can be inferred that the CNN is relatively good in detecting and classifying the type of diseases among infected fishes. Regardless, a study with a better number of datasets could be done in the future to improve the detection performance.

Keywords: Fish diseases, Detection, Classification, Convolutional Neural Network (CNN).

1. Introduction

Globally, aquaculture activities, specifically the fishery sector, play a critical role in supplying the major protein, as well as being a significant contributor to food security and the general economy.

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Received: September 2021 *Accepted:* November 2021

Scientists recently discovered 25,000 fish species that can be identified, with an additional 15,000 species that may potentially be recognized. As the world's population grows and the benefits of fish as an animal protein source become more widely acknowledged, fish demand continues to climb. Fish consumption has exhibited a significant trend in recent years in both developed and developing countries. In response to rising global demand, the aquaculture industry is gaining prominence as a more sustainable way of ensuring a steady fish supply. As a result, it is critical to ensure that the aquaculture industry is economically and ecologically viable [11, 4].

One of the challenges facing by the fishery sector that restricted the ability in sustaining the production, as according to [8], fishes are prone to diseases. In any event, all fish can suffer from numerous illnesses as they carry diseases and parasites like other living animals. Water temperature, which varies from season to season as well as contaminated water, are both important factors in the spread of fish diseases. The fish disease is seen as a severe issue among fishermen as it spreads swiftly through water [3].

To rule out a diagnosis, an invasive and time-consuming histopathological analysis of the skin and gills of the infected fishes need to be done [12]. Fish diseases have traditionally been diagnosed by an experienced fisherman or a fishery department expert. The accuracy of such a final diagnosis, on the other hand, is ultimately dependent on the individual's skill, experience, and knowledge [3]. This implies that the final diagnosis may be biased and inconsistent. Therefore, modern large-scale fish farming could be greatly benefited from technology tools, particularly those that allow remote monitoring of enormous populations of fish [5].

An image-based approach, image processing can be a valuable tool that can automate the processes of analyzing and detecting the diseases of fish [8, 9]. In this regard, numerous studies have been conducted particularly in agriculture and fisheries. An intensive review has been done by [16] on the application of the Deep Learning (DL) approach for smart fish farming. DL is found to be able to automatically extract features without compromising the precision of the output. DL also is expected to contribute to fish disease diagnosis. A classification of Epizootic Ulcerative Syndrome (EUS) disease into EUS infected and Non-EUS infected fish has been done by [9]. On the enhanced EUS diseased fish images, various edge detection approaches were used, followed by feature extraction utilizing various feature Descriptors such as Histogram of Gradient (HOG) and Features from Accelerated Segment Test (FAST). Afterward, the images are classified using Machine Learning Algorithms, and the classification accuracy is determined using a Classifier. Salman et al. [13] estimated and monitored fish biomass and assemblage in water bodies using a Region-Based Convolutional Neural Network. A novel approach was used to train the neural network, which used motion information from fish in underwater videos via background subtraction and optical flow, then integrated the results with the raw image to generate fish-dependent candidate regions.

One of the most widely used deep neural networks is known as Convolutional Neural Network (CNN). CNN is crucially significant in image-related applications, such as image classification, image semantic division, object recognition in images, and many others, due to its outstanding performance in a variety of computer vision and machine learning problems [15]. It is recognized by their low input variability and low pre-processing requirements [2]. The layers include the convolutional layer, non-linearity layer, pooling layer, and fully-connected layer. The convolutional and fully-connected layers do have parameters, whereas, the pooling and non-linearity layers do not [1]. Since CNN can reduce the quantity of parameters and can give better precision of classification comparatively, hence it is the most appropriate technique for image classification.

Therefore, in this research, CNN is proposed for fish diseases detection. A fast, non-invasive and accurate computer-vision assistance is proposed by utilizing CNN to classify fish diseases. The remainder of this paper is organized as follows: the image datasets and CNN structure are described

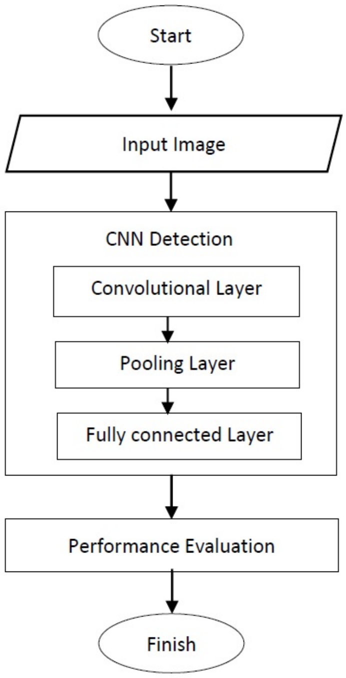

Figure 1: Proposed process flowchart for fish disease detection

in Section 2, as well as our research method. Our findings and discussions are presented in Section 3. Finally, in Section 4, we present our conclusion.

2. Method

The in-depth process flowchart for fish disease detection using the CNN technique is shown in Figure 1. It begins with the input image which is the fish image. The image will then go through the CNN detection process which consists of three-layer processes: convolutional, pooling, and fully connected layer processes. The third step is performance evaluation, which is used to assess how well the CNN detects diseases in fish images.

2.1. Input Image

A total of 90 images of fish diseases were collected. The healthy fish and two types of fish diseases are White spot and Red spot. The salt-grain-like White spot can be seen on skins, fins, and gills of fishes is one of the contagious diseases caused by parasites called Ichyophthirius multifilis. The parasite induces bacterial and fungal infections in the fish tissue [8, 14, 17]. When the fish begin to swim around repeatedly or rub their bodies against the net surface, they lose scales, become irritated, and decay [6]. Following that, the fish lose their appetite and become thin, their movement slows, and their eyes turn white and cloudy. Since the gill tissues have been severely wounded and damaged, the fish will eventually die of suffocation [10].
On the other hand, the Red spot disease can be seen when a skin lesion that looks like an ulcer can be spotted [9]. It is also known as EUS disease, which is caused by a fungal pathogen of Aphanomyces invadans. This lesson may range from tiny red spots to severe dermal ulcers [7]. Later, fishes with this disease will experience issues in breathing, losing their appetite, and become lethargic. Finally, when the gills and body decay, death will occur [10]. The sample images of the healthy and fish diseases are tabulated in Table 1.

Table 1: Sample of Datasets

Type of Fish Diseases	Sample Image	Total no. of images
White spot		30
Red spot		30
Healthy		30

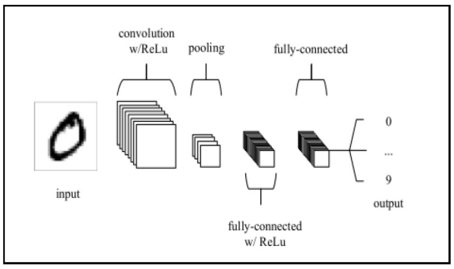

Figure 2: CNN layers

2.2. *CNN Detection*

The CNN is made up with concatenated separate blocks that perform different task. In a CNN, these building blocks are known as layers. CNN is used to identify and classify the images of fishes into three classes, which are white spot disease, red spot disease, and healthy. The image is fed into a network via an image input layer, which is then normalized. The image height, width, and channel size were set to 200, 200, and three (Red Green Blue) correspondingly. Figure 2 shows the layers associated with CNN.

2.2.1. *Convolutional Layer*

Subsequently, the convolutional layers encode a variety of lower-level features into more discriminative features in a spatially-aware manner. The convolutional layer can be thought of as a series of filters that transform an input image into other featuring patterns. In this study, the convolutional layer was used to extract features from the input images, which were fish images. The raw pixel values filtered image was then taken to the RGB colour channel, and the dot product between the filtered pixel and input pixel was then measured. The weight matrix for extracting certain features from images was set to a 3×3 matrix. The CNN learns the values of these filters on its own throughout the training phase. The layer after the convolutional layer is the non-linearity layer. It can be used to modify or disable the output. This layer is used to saturate or limit the generated output. The Rectified Linear Unit (ReLU) was adopted as it offers simpler function and gradient definitions. Each element of the input was subjected to a threshold operation, in which any value less than zero was set to zero.

2.2.2. Pooling Layer

Following then, the pooling layer begins the process of reducing the size of a fish image data set. The pooling layer also focuses on improving the feature position invariance in image processing. The subsampling approach used in most CNNs was max pooling. Max pooling divides the output data from the convolution layer into a few small grids, subsequently obtains the maximum number of each grid to create a reduced image matrix. The use of a pooling layer on CNN is solely to reduce image size. In this sense, a convolution layer with the same stride value as the associated pooling layer might essentially change it. Pooling can also be used in conjunction with non-equal filters and strides to improve efficiency. The pool size was set to $[2, 2]$, which yields two as the maximum value in the height and breadth. Pooling layers scan horizontally and vertically over the input in step sizes which we can specify with the 'Stride' name-value pair argument. The pooling regions will not be overlapped if the pool size is less than or equal to the stride.

2.2.3. Fully connected Layer

The final fully connected layer integrates the features for image classification. The fully connected layer is organized similarly to neurons in a standard neural network, to change the information measurement such that it can be classified linearly. Every node in a fully connected layer has a unique relationship with each node in the preceding and subsequent layers. Every node in the pooling layer's last frames is connected to the main layer through a vector from the fully connected layer. These are the most commonly used parameters with the CNN within these layers, and they take some time to construct. As a result, the output size parameter in the last fully connected is equal to the number of classes in the target data, which is three (healthy, white spot, red spot). Since this procedure involves spatial information loss and is not reversible, the fully connected layer must be actualized at the end of the network.

Finally, the output consists of positive values that add up to one, which the classification layer can use as classification probabilities. Classification is the process of classifying an image into the type of fish diseases it belongs to. The classification layer computed the cross-entropy loss for multi-class classification problems with mutually exclusive classes. This layer assigns each input to one of the mutually exclusive classes and the probabilities supplied by the SoftMax activation function were utilized to compute the loss.

2.3. Performance Evaluation

The training and testing datasets are split in a 60:40 ratio, with each dataset weighing in at 18 and 12 respectively. The fish diseases detection testing results were presented using a confusion matrix. Based on the confusion matrix obtained, the classification accuracy, sensitivity, and specificity rate for each fish disease were computed using Eq. (2.1), Eq. (2.2), and Eq. (2.3) respectively. The accuracy is used to measure both true positive (TP) and true negative (TN) over the total values of TP, false positive (FP), false negative (FN), and TN rate. The sensitivity rate was calculated using the TP, whereas the specificity rate was computed by the TN rate.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2.1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2.2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2.3}$$

Table 2: Confusion matrix of CNN Detection

		CNN fish diseases detection		
		White spot	Red spot	Healthy
Actual fish diseases	White spot	10 (TRUE)	1 (FALSE)	1 (FALSE)
	Red spot	0	11 (TRUE)	1 (FALSE)
	Healthy	1 (FALSE)	0	11 (TRUE)

Table 3: Confusion matrix summary of CNN Detection

	White spot	**Red spot**	**Healthy**
True Positive	10	11	11
True Negative	23	23	22
False Positive	1	1	2
False Negative	2	1	1

3. Results

A total of 36 fish diseases images for healthy leaf and two types of fish diseases which are white spot and red spot were tested. The confusion matrix constructed from the results of accuracy testing is tabulated in Table 2.

The values represented in the diagonal pattern in Table 2 reflected the correct fish diseases detection. It can be observed that 10 White spot images were correctly detected as White spot, whereas two images were incorrectly detected as Red spot and Healthy. Next, 11 Red spot images were accurately identified as Red spot, while one image was wrongly detected as Healthy. Like Red spot, the healthy fish images were detected 11 times correctly and one time incorrectly detected as the White spot. As a result, Table 3 tabulates the confusion matrix summary for each fish disease. The computed percentages of accuracy, sensitivity, and specificity are then arranged in Table 4.

From Table 4, the Healthy were monitored to return the highest percentages for accuracy at 97.2%. It was then followed by the Red spot which returned 94.44% of accuracy. The White spot produced the lowest percentages of accuracy at 91.67% respectively. On the other hand, the Red spot and Healthy were observed to produce a similarly high percentage of sensitivity at 91.67%. The White spot however returned a slightly lower sensitivity rate at 83.33% due to a quite high number of false negative rate. For specificity, the White Spot and Red spot recorded promising percentages at 95.83% respectively. It was then followed by the Healthy at 91.67%. The overall mean percentage of accuracy, sensitivity, and specificity demonstrated a very encouraging accuracy which are 91.67%, 94.44%, and 97.2% correspondingly.

Table 4: Summary of Accuracy, Sensitivity, and Specificity Result

Fish disease	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
White spot	91.67	83.33	95.83
Red spot	94.44	91.67	95.83
Healthy	97.2	91.67	91.67
MEAN	**94.44**	**88.89**	**94.44**

4. Conclusion

A study on fish diseases detection using the Convolutional Neural Network (CNN) technique was presented. The Healthy, and two categories of fish diseases were investigated in this research. The application was successful on 90 different image datasets. A confusion matrix was used to evaluate the performance of fish disease detection. The overall mean percentages of accuracy, sensitivity, and specificity indicated promising performance at 91.67%, 94.44%, and 97.2%, correspondingly. It could therefore be deduced that the proposed fish diseases detection using CNN is successful.

Acknowledgment

The research was supported by Universiti Teknologi MARA Cawangan Melaka through the Teja Internal Grant 2021 (GDT2021/1-25).

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