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An Intelligent Protozoan White Spot Fish Disease Detection

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Abstract: Protozoan white spot disease is one of the leading causes in fish disease outbreaks in mariculture secotor in Malaysia. The outbreak induced by an active parasite, *Cryptocaryon irritans*, is hazardous as it could impair the production and the cultivation of diverse species resulting in a negative impact on the expansion of the aquaculture industry. As part of Industrial Revolution 4.0 in Malaysia, maximizing the use of Artificial Intelligence (AI) in the industry could be the key contributor as current technologies in disease detection could contain or slow the spread of infections among cultured fish. The advances of image processing in the underwater environment and deep learning techniques prove it is possible to ease the participation of human observers in fish disease detection. Hence, this study demonstrates a new procedure for white spot disease detection using underwater image, concerning on the development of integration between contrast-limited adaptive histogram equalization (CLAHE) and convolutional neural network (CNN). A total of 60 validated normal and infected underwater fish images have been tested in this study. The techniques used achieved 96.67% accuracy in protozoan white spot disease detection. Therefore, intelligent protozoan white spot fish disease detection could be served as an alternative to early detection of the disease, thus preventing secondary infection in mariculture fishes. The incentive offered could ensure the industry's anticipated growth as the sector plays a significant economic income for both country and farmers.

Keywords: Protozoan White Spot Disease, Mariculture, Disease Detection, Image Processing, Convolutional Neural Network

Abstrak: Penyakit bintik putih protozoa merupakan salah satu punca utama wabak penyakit ikan dalam sektor marikultur di Malaysia. Wabak yang disebabkan oleh parasit aktif, *Cryptocaryon irritans*, adalah berbahaya kerana ia boleh menjejaskan pengeluaran dan ternakan pelbagai spesies lain yang boleh mengakibatkan kesan negatif terhadap perkembangan industri akuakultur. Sebagai sebahagian daripada Revolusi Perindustrian 4.0 di Malaysia, memaksimumkan penggunaan Kecerdasan Buatan (AI) dalam industri boleh menjadi penyumbang utama kepada teknologi pengesanan penyakit yang boleh membendung atau memperlahankan penyebaran jangkitan dalam ikan ternak. Kemajuan pemprosesan imej di bawah air dan teknik pembelajaran mendalam membuktikan adalah mungkin untuk memudahkan pemerhati manusia dalam pengesanan penyakit ikan. Oleh itu, kajian ini menunjukkan prosedur baharu untuk pengesanan penyakit bintik putih menggunakan imej bawah air, berkaitan pembangunan penyepaduan antara kontras terhad penyamaan histogram adaptif (CLAHE) dan rangkaian saraf konvolusi (CNN). Sebanyak 60 imej ikan bawah air normal

dan telah sah dijangkiti diuji dalam kajian ini. Teknik yang digunakan mencapai ketepatan 96.67% dalam pengesanan penyakit bintik putih protozoa. Oleh itu, pengesanan penyakit ikan tompok putih protozoa pintar boleh dijadikan alternatif kepada pengesanan awal penyakit ini, sekali gus mencegah jangkitan sekunder pada ikan marikultur. Insentif yang ditawarkan dapat memastikan pertumbuhan industri kerana sektor tersebut menyumbang sumber pendapatan yang signifikan untuk kedua-dua negara dan penternak.

Introduction

Aquaculture sector in Malaysia has contributed significantly as source of foods and income to the nation. Since fish is recognized as a great source of protein that is easily digested by the human body, the demand continues to grow as the global population increases (FAO, 2019). According to the National Transformation 2050 vision for Malaysia's smart communities by 2050, this sector has developed into a fast-growing food industry due to the technology revolution, putting Malaysia among the top 15 global producers with an estimated 521,000 tonnes of total aquaculture production annually (Waterland, 2016)hand-holes, dram doors, etc. present very unique sealing and assembly challenges. Unlike other conventional gasketed connections, the majority of the gasket compression forces are developed during operation, and not during assembly. This creates several critical issues that must be understood and overcome in the original gasket selection process and the assembly itself. Even if considered and addressed in the original gasket selection and assembly process, these internal sealing manways will likely still require a post start-up retorque. The timing of the re-torque is of critical importance in ensuring worker safety and continued equipment reliability and uptime. Copyright © 2013 by ASME.”,”author”:[{“dropping-particle”:””,”family”:”Waterland ”,”given”:”A. Fitzgerald”,”non-dropping-particle”:””,”parse-names”:false,”suffix”:””}],”container-title”:”FAO, (Food and Agriculture Organization. Besides, fish consumption per head is expected to be 59 kilograms per year, making it one of the world's biggest seafood demand countries (FAO, 2020). Furthermore, Malaysia is heavily reliant on fish production as it is also considered as a way of providing employment and investment opportunities for the nation. Hence, considerable effort should be expanded on aquaculture fish management and production to ensure the sustainability of fish production to meet the country's 30.75 million population demand.

Fish disease has been extensively examined in attempt to establish the reason and the remedy for problems in the country (Sayuthi, 1993). Furthermore, fish disease outbreaks are one of the obstacles to the production and the cultivation of a species, which might limit the sector's development and expansion (Fathi et al., 2018). In Malaysia, a parasitic disease known as Protozoan white spot disease or cryptocaryoniasis caused by active *Cryptocaryon irritans* in saltwater has been a major source of disease outbreaks since mariculture introduced. The parasite attaches to the fish's body and moves beneath the skin, where it feeds on skin, gills and eyes diminishing the functionality of these body parts. Infected fish would suffer small white patches, skin discolouration, mucus hyperproduction and appear thin (Yanong, 2012)reduce "work in progress" and improve the dimensional accuracy of the cast parts and the final products used in the market. Since then chemists, engineers and metal casting experts have developed new cold box (CB. In even serious cases, sloughing skin causes fish to become fatigued and linger just below the water surface, along with corneal haziness and ragged fins. The disease became the primary focus of the research as the disease showed rapid increase in mortality over several days, restricting the ability to cope with regular histopathological analysis. For that reason, there is a need for a robust and immediate early detection approach.

In conjunction with the Fourth Industrial Revolution's emerging technology, intelligent detection of white spot disease is deemed critical for preventing outbreaks from worsening. The incentives could contain the outbreak by discovering the slight change on the fish bodies shortly. Besides, the strategies of using image processing on underwater images could ease the classification's process, which would effectively detect white spot fish disease in an early stage. It is believed that the integration approach could successfully use Artificial Intelligence (AI) for disease detection, while ease the participation of fish experts in protecting the aquaculture provision.

Artificial Intelligence (AI) has emerged as a vital force in the Industrial Revolution 4.0 in Malaysia. It has the potential to significantly increase global income levels by increasing productivity, adaptability and agility across all industries through intelligent manufacturing (Peres et al., 2020) On that account, to broaden the use of AI in the fisheries sector, research has been made to support the idea of creating an automated detection system for fish disease through underwater images. Therefore, underwater image datasets are critical for the development of underwater detection systems. After all, most of the existing fish studies are focusing on fish identification, fish species classification, fish behaviour detection as well as fish counting. Thus, there is limited dataset specified for fish disease.

Several researchers used their own datasets, which they gathered using self-designed underwater equipment for months (Siddiqui et al., 2018; Villon et al., 2018)yet it remains difficult and time-consuming. In this paper, we present a method to assist the identification of fish species on underwater images, and we compare our model performances to human ability in terms of speed and accuracy. We first tested the performance of a convolutional neural network (CNN. Researchers have also made use of several publicly available databases of real-world underwater images which includes the Fish4Knowledge dataset, the Underwater Image Enhancement Benchmark Dataset (UIEB), as well as ImageCLEF, National Oceanic and Atmospheric Administration (NOAA), LifeCLEF2014 (LCF-14). However, available datasets usually have insufficient data with degradation features characteristics due to limited scenes and poor environment of the water medium (Mohd Azmi et al., 2019).

Image processing is a subfield of AI used to enhance data collected by cameras, x-ray machines, microscopes, radar and satellite sensors (Gonzalez & Woods, 2017). An effective underwater image enhancement is needed as degradation of the underwater images could lead to failure for any visual detection of the images. This action is critical to improve original underwater image quality before training the classification model. Enhancement techniques generate a clearer output image than the original underwater images, making it much easier to visualize the targeted objects in a complicated environment. Subcategories of image enhancement including contrast enhancement, colour correction and hybrid approaches could process the degraded images by restoring the blurred images, enhancing the contrast and removing the unwanted noise (Raveendran et al., 2021).

The advanced approaches for classification that widely used is known as Machine Learning (ML). Yet, in the recent years, revolutionary technology has raised deep learning (DL), a subset of ML that has gained increasing interest due to outstanding performances in various industries. In 2015, research was conducted to detect and to recognize fish species using classification model namely Convolutional Neural Network (CNN). Fast R-CNN (Region-based Convolutional Neural Network) were applied to the domain-specific underwater environment as a faster object detection technique and has successfully proved that CNN detects 80 times faster than the previous technology (Li et al., 2016). Another research has developed CNN-based technique known as YOLO (You Only Look Once) network to detect fish underwater (Sung et al., 2017). The classification accuracy reached 93%. Hence, the great processing capabilities of CNN have demonstrated that this method is effective for problems classification.

Materials and Methods

All the processes involved in the automated protozoan white spot disease detection system are described in detail. Figure 1 demonstrates the system's architecture which consists of the activities for each phase.

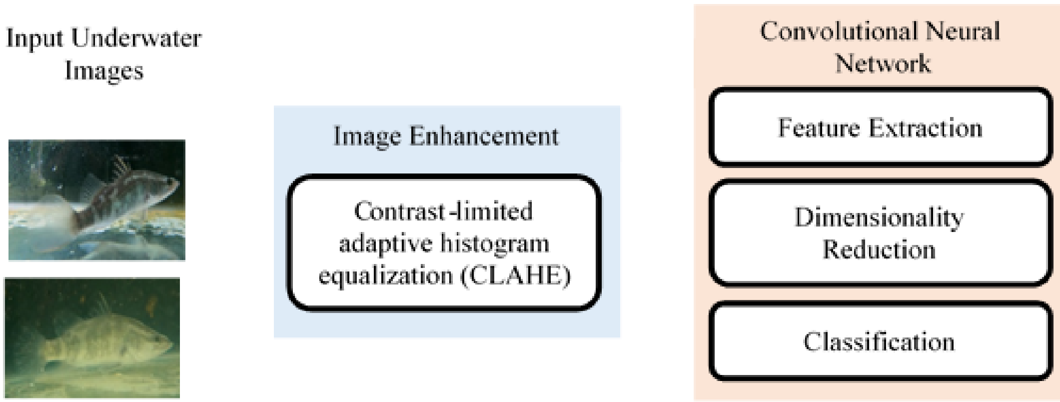


Fig. 1. Architecture of automated protozoan white spot disease detection system

Underwater Image Acquisition

Underwater fish image datasets were prepared from the 4K footage shot taken using GoPro camera at National Fish Health Research Center (NaFisH), Batu Maung Fisheries Research Institute, Penang. Images were extracted from the shot to create the datasets. The extracted images were screened and any images containing no fish were discarded. The datasets contained images of normal and protozoan white spot infected fish in their natural state, without artificial light or filters as displays in Figure 2.

Normal

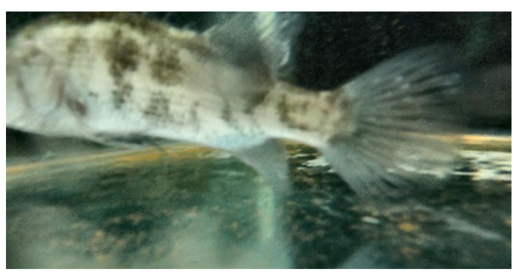
Infected fish

Figure 2: Sample images of normal and protozoan white spot infected fish

Image Enhancement

The detection procedure begins with image processing to enhance the image degradations as an input for the classification to ease the detection process. Contrast enhancement is considered as an important technique for improving image quality and helps recover lost information in images. The vision processing approach often used to improve contrast is the contrast-limited adaptive histogram equalization (CLAHE) algorithm, an extension of adaptive histogram equalization (AHE). CLAHE improves contrast while equalizing the image histogram when compared to the standard histogram equalisation (HE) (Pramunendar et al., 2018)such as varying light intensity levels and varied wavelengths. Low quality of underwater images is one of the major problems in identification of fish species during monitoring of underwater ecosystem. Improving the quality of underwater images is important for accurate fish identification. Some researchers introduce various methods that address colour-correction problem for underwater images. However, previous researches do not consider the noises produced during the implementation of the image processing techniques. To deal with this problem, we propose a novel method called novel contrast-adaptive colour-correction (NCACC. This is because noise amplification issues arising when using HE can be avoided by using CLAHE (Sharma et al., 2019; Suharyanto et al., 2021)besides that light can be absorbed by seawater, as well as the turbidity level of seawater, so special techniques are needed to get clear underwater imagery. In underwater environmental conditions, the images obtained are usually of very poor quality. Backlight and attenuation will occur this is due to water conditions, objects that dissolve easily in water, and other particulate matter so that there is the degradation of the underwater image. Because it is very important if the image is improved in quality to facilitate the process of describing objects. Image matching techniques to determine the key points of image pairs are needed in three-dimensional reconstruction research. Speeded Up Robust Features (SURF. As a result, the enhanced image could highlight the image's important features before moving on to the classification step. Figure 3 shows the conversion of original to enhanced image.

Original



Enhanced

Figure 3: Sample images of original and enhanced image of protozoan white spot infected fish

Classification

Enhanced images were processed using CNN to detect the presence of white spot disease. There were two sets of classes to be classified namely normal and infected. The datasets consisted of 60% infected fish images and 40% normal fish images, where 80% would be used for training and 20% for testing. In this study, CNN algorithm was chosen as classification method to classify white spot disease.

During the training process, CNN began by acquiring the enhanced image from the previous stage as the input layer. These pixel values were analysed using multiple connected layers to identify features of white spot disease. Convolution operations were executed in the convolutional layer to extract features such as edges and corners using numerous independent kernels or filters. Each kernel interpreted the input images pixel by pixel and consequently produces a feature map. Then, the rectified linear unit (ReLU) operations were adapted to the feature maps to add nonlinearity in the network. In the pooling layer, the size of input images was reduced using max pooling. After that, the pooled feature map was flattened into a long vector before going into the fully connected layers. During the fully connected layers, the set of features were combined to predict the classes either infected or normal. The error was estimated in each cycle and backpropagated until the network was well-trained. Subsequently, during testing process, CNN was able to generate the output indicating whether the image included the protozoan-infected fish or the normal fish. The overview of classification using CNN is shown in Figure 4.

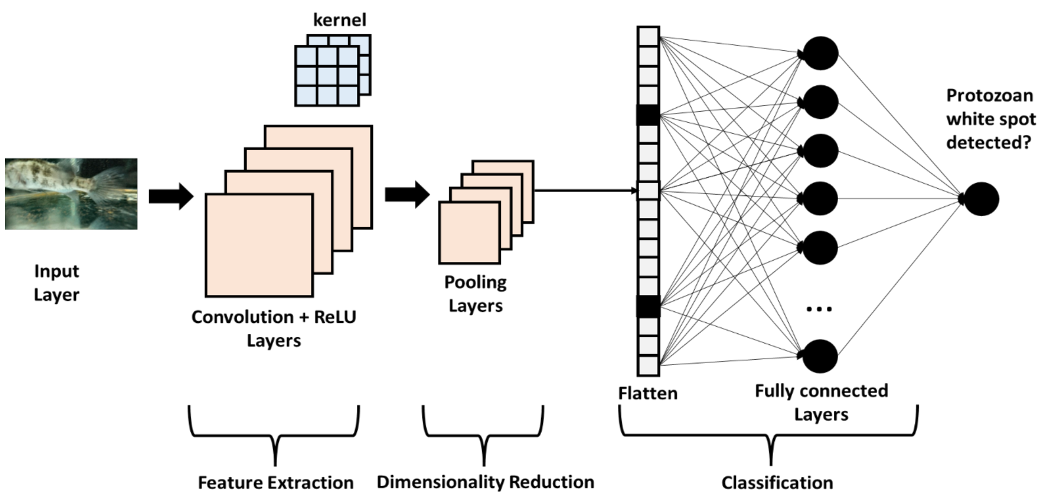


Figure 4: Overview classification process using CNN

Performance Evaluation

The performance of the system would be evaluated according to confusion matrix as presented in Figure 5. A confusion matrix is made up of four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The terms TP and TN indicate true predictions respectively. Meanwhile, positively false predictions are denoted by FP, whereas negatively false predictions are denoted by FN. Based on the confusion matrix, accuracy of the proposed model was computed by applying the formula as shown in Equation 1. Accuracy measures the proportion of specifically classified images over the total number of images in the test dataset.

		Prediction	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Fig. 5. Confusion Matrix

$$\text{Accuracy (\%)} = \frac{(\text{TP+TN})}{(\text{TP+TN+FP+FN})} \times 100$$

Equation 1. Accuracy

Results

A total of 30 normal fish images and 30 protozoan white spot infected fish images were tested. Table 1 and Table 2 demonstrate the accuracy of all the tested images. These accuracies determine the percentage of the prediction model to classify each tested image. Additionally, Table 3 presents the summary of confusion matrix that was constructed from the results obtained in Table 1 and Table 2.

Table 1: Normal fish detection

Image	Prediction	Accuracy
1	Normal	100
2	Normal	100
3	Normal	100
4	Normal	99.99957275
5	Normal	99.99991608
6	Normal	100
7	Normal	99.99995422
8	Normal	99.49093628
9	Normal	100
10	Normal	99.99997711
11	Normal	100
12	Normal	100
13	Normal	99.99797058
14	Normal	99.99393463
15	Normal	99.99990845
16	Normal	99.99998474
17	Normal	90.63188171

Table 2: Infected fish detection

Image	Prediction	Accuracy
1	Infected	100
2	Infected	99.94576263
3	Infected	99.9947052
4	Infected	99.99806976
5	Infected	99.99807739
6	Infected	99.99807739
7	Infected	99.99954987
8	Infected	99.57289124
9	Infected	99.57289124
10	Infected	99.99967957
11	Infected	99.7928009
12	Infected	100
13	Infected	99.97796631
14	Infected	99.9997406
15	Infected	99.84117889
16	Infected	99.99998474
17	Normal	96.03152466

18	Normal	100	**18**	Infected	99.91448975
19	Normal	99.9998703	**19**	Infected	99.97936249
20	Normal	99.95469666	**20**	Infected	99.99997711
21	Normal	99.97249603	**21**	Infected	99.83209991
22	Infected	82.51512909	**22**	Infected	97.74310303
23	Normal	99.99908447	**23**	Infected	99.99819946
24	Normal	99.99998474	**24**	Infected	96.77257538
25	Normal	99.72317505	**25**	Infected	95.992836
26	Normal	99.99891663	**26**	Infected	99.96543884
27	Normal	99.99998474	**27**	Infected	99.99993134
28	Normal	99.99982452	**28**	Infected	99.97146606
29	Normal	99.96932983	**29**	Infected	99.99976349
30	Normal	100	**30**	Infected	99.99976349

Table 3: Summary confusion matrix

		Detection	
		Infected	Normal
Fish Condition	Infected	29	1
	Normal	1	29

The values shown in the diagonal pattern of Table 3 accurately detected normal and infected fish images. 29 infected fish images were correctly detected while a single image was wrongly detected as normal. Meanwhile, a single normal fish was incorrectly detected as infected and the rest 29 were correctly detected as normal. According to Equation 1, 96.67% of accuracy has been achieved for protozoan white spot fish disease detection. The results demonstrated the potential of the proposed approach to detect protozoan white spot disease based on underwater images.

Discussion

The ocean covers seventy-one percent of the Earth's surface making it a complex task for diagnosing fish disease due to the challenges of underwater environment and it demands high level of expertise. As an alternative to the traditional method, the demand of fish disease detection study using new approach should be fulfilled to continuously sustain the productivity of aquaculture sector. As part of the efforts, this study strategized the use of image enhancement technique on the degraded underwater images successfully, making the classification process more accurate in detecting the contagious protozoan white spot disease. Combination of CLAHE and advances technology of CNN has showed the potential to detect the disease based on underwater images. 96.67% accuracy achieved in this study proved that this action could become the key to early prevention of the outbreak and this effort could ease the participation of fish experts in preserving the aquaculture sector.

Conclusion

This research aimed to develop more advanced algorithm for performing detection tasks based on underwater images. Even though most of the past research are not limited to fish disease detection, the major picture of the integration model has been demonstrated in this study as a way to discover fish disease outbreak in an early stage. The results achieved in this study could also become the standard reference for any future studies. Besides maximizing the use of AI in the sector, Malaysia's food security could be secured, which consequently will lead to the sustainable development of aquaculture.

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