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A Study on Fish Classification Techniques using Convolutional Neural Networks on Highly Challenged Underwater Images

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Abstract
Underwater Fish Species Recognition (UFSR) has attained significance because of evolving research in underwater life. Manual techniques to distinguish fish can be tricky and tedious. They might require enormous inspecting endeavors, but they can be costly. It results in limited data and a lack of human resources, which may cause incorrect object identification. Automating the fish species detection and recognition utilizing technology would assist sea life science to evolve further. UFSR in wild natural habitats is difficult because the images open natural habitat, complex background, and low luminance. Species Visualization can assist us with deep knowledge of the movements of the species underwater. Automation systems can help to classify the fish accurately and consistently. Image classification has been emerging research with the advancement of deep learning systems. The reason is that the convolutional neural networks (CNNs) don't require explicit feature extraction methods. The vast majority of the current object detection and recognition mechanisms are based on images in the outdoor environment. This paper mainly reviews the strategies proposed in the past years for underwater fish detection and classification. Further, the paper also presents the classification of three different underwater datasets using CNN with evaluation metrics.

Keywords: marine environment, underwater objects, classification, CNN, deep learning.

1. Introduction

Few marine applications like monitoring fishes or commercial fisheries can instant detect and localize fish and classify the same in the images captured underwater. This system can be applied in monitoring activities as evaluating populations, classifying the types of fishes prevailing in that locality and fish migration [1]. In fishing tasks, the application can parameterize the fish and estimates its types and distribution effectively. Through this, catch and discard rates can be evaluated and therefore provide a choice for the commercial fisheries to find fishes group before considering any fishing quotas officially [2]. Recognition of underwater images is a trending research domain due to the mass availability of underwater data from multiple observations such as CANADA, VENUS, etc. Identifying species of fish will be helpful to researchers, ocean scientists and biologists [3]. It also helps to determine the levels of biomass and geological changes in the ocean. Various computer vision approaches are recommended for classifying the species of fish precisely through fish species detection. Fish species are categorized under three application domains according to their scope: (i) Finding fish species on dead fish [4], (ii) Finding fish species in unnatural habitats (for ex: water tanks, aquarium etc.). Many researchers focus fish identity on a dead fish [5] and a fish outside the water [6] or in an aquarium. But no significant research work is done underwater as there is an unlimited natural habitat in the sea. The videos captured underwater are of poor quality, low luminosity and complicated backgrounds**.** Making the fish species visualizing will assist us in gaining depth knowledge about the movement and tasks of species as a whole. Image classification is a trending research domain with the application of deep learning methodologies. Many available systems for object detection rely on grounded images. Different industries and personnel need to find fish by considering the fish features. An intensification in fish population influences environmental aspects like global warming, climatically changes and pollution, overfishing and sustainable exploitation of natural resources of marine [7]. These effects further motivate creating a standard, cost-effective, and trustworthy approach for monitoring the fish across habitats [8].

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It is challenging to apply manual methods for fish detection since they consume more time also need more effort during sampling. They are also cost-effective, and not many fish specialists are involved as it leads to incorrect detection. The frameworks which are automated will consistently help in accurate fish classification. There is a great demand in deriving benefits from electronic monitoring and reporting and artificial intelligence in fish detection for improvising the present techniques. These approaches are effective, non-destructive and portable and provide the best quality and best resolution pictures at reasonable costs [9]. ML methods give us the means to instant-process an image and perform fish detection and classification in an efficient manner [10, 11]. Recent automation techniques comprise various learning protocols and characteristics like colour, shape and particular landmarks. Specifically, the applied learning protocols are principal component analysis, SVM (multiclass), ANNs and CNNs. It is noticed that deep learning methods attain the best performance, particularly CNNs, which is quite successful [12] as it needs the availability of huge datasets. Their accuracy is contingent on the extent and training data quality. There is a chance to reduce these problems through the application of transfer learning and augmentation. In this paperwork, we preferred a methodology proposed by Rathi et al. (2018) [13] to generate a CNN model for the image classification of fishes. Firstly, gathered from the video captured underwater and later from a provided dataset of nature conservancy. Our work aims to build a CNN that is useful for applying the datasets gathered from research centres like Nature Conservancy and finding fishes for research and fisheries purposes.

2. Related Works

Finding fish species in restricted habitats is challenging because the background and noise in images are complex. For the last few years, the researchers have been working on the same and also applied the best methodologies for classifying the species of fishes in natural habitats.

Leilei Jin et al. [14] introduced a system that can employ a minimum sample size of underwater fish species detection. The pre-processing can be done for the sample images with the best median filter that differs from the conventional median filter. A ConvNet is utilized that is pre-trained with a huge ImageNet dataset. Later it is fine-tuned and trained with sample pictures from the Fish4Knowledge dataset and achieved 85.05 % accuracy. [15] introduced a system that receives a low-resolution picture and transforms it into a picture with high resolution by considering a single image super-resolution method [16]. Machine learning mechanisms extract features, namely PCA-Net [17] and Network-In-Network (NIN). The dataset chosen is FishCLEF2015, and the PCA-Net has achieved 77.27% precision and NIN with a 69.84% accuracy rate.

Katy Feature extraction involves two PCA convolutional layers in a deep learning network, which includes binary hashing and block-wise histograms in the pooling layers. A spatial pyramid pooling follows these to extract pose invariant data. Classification is done by linear SVM. This system reached a 98.64% accuracy rate upon the Fish4Knowledge dataset. Salman et al. [18] suggested CNN with an ensemble feature combinational model to explore species-dependent features and variability. The FISHCLEF 2014 and FISHCLEF 2015 datasets are taken into sight and achieved 97.41% accuracy. Mohammed et al. [19] introduced SVM architecture followed by feature extraction methods for classifying fish. SIFT and SURF are the mechanisms applied for extracting the features of a picture and attained optimal results. The earlier stated systems applied machine learning methodologies to classify the fish species. In contrast, other systems applied conventional techniques to do the same. Moniruzzaman et al. [20] presented a survey about various techniques utilized for fish species classification.

In the literature [21], classifying fish species is done based on deep neural networks. A multi-layer NN is used as a classifier to process the already extracted features from a fish image. These features rely upon existing parameters like fish size and shape. The current methods can be taken as feature extractors of an input image and classifiers for those extracted features. In [22], proposed approaches to the entire process to detect and localize a fish in the images and characterizing the distinguished fishes into their particular species by using state-of-the-art object detectors based on deep R-CNNs. In the literature, underwater fish detection and classification is done for non-intrusive platforms, i.e. the camera system is installed according to the specified position. The key targets for the species classification are done based on the already existing large-scale fish dataset [23], which mainly has the best quality video of tropical fish species and does not focus on selected species outside of this scope. The common challenges of such automated frameworks of fish recognition and fish classification are scalability and reliability. Conventional image processing ways may sometimes fail in generalizing outside the scope of which it was developed. Hence, it becomes a challenging one when applied under new platforms, noise and many poor situations. Large-scale data-driven models try to remove the effects of those variations in information. Still, in turn, it needs huge annotated datasets and has greater demand on processing power.

The mechanisms of FC, including classification algorithms, are represented in Table 1. The table includes the algorithms employed for three steps called pre-processing, extraction of features and classification. Pre-processing methods include

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resizing a fish picture, anchor points, and image cropping. To extract the features, frequently utilized ways are measuring distance, SIFT, and SURF. Many feature extraction approaches on features combinations like integrated extracted shape, size, texture, and colour signature features. In Fish Classification, the highly applied algorithms are SVM, Bayesian classifier, and CNN. Among these methods, SVM is giving better results in most of the datasets.

Table 1. Recent works on fish classification by numerous researchers

Author	Pre-processing Method	Feature extraction method	Classification algorithm
[24] (2016)	GMM	PHOW	SVM
[25] (2017)	Detecting anchor points	Computing Distance between the objects	KNN
[26] (2017)	Segmentation, resizing	VGG	CNN
[27] (2017)	Pose estimation	Image and instance level	CNNs
[28] (2018)	Fish detection	Fish-Cam monitoring system	CNN
[29] (2018)	Normalization	Plotting, filtering	CNN
[30] (2018)	Filtering	Wrapper	Ensemble method
[31] (2019)	Cropping Filtering	Feature extraction	PNN
[32] (2019)	Segmentation	Computing distance between the objects	MA-B Classifier
[33] (2019)	Resizing, Histogram generation	Feature extraction	SVM
[34] (2019)	-	HLBP	SVM
[35] (2020)	-	VGG16 (pre-trained)	Ensemble method

3. Results and Discussion

The proposed framework is stimulated under the Keras framework and tensor flow backend. The system configuration includes i5, a 9th generation processor, 8 GB RAM, and NVIDIA 8 GB GPU.

3.1 Datasets

The three most challenging underwater image datasets are considered in this paper (Croatian dataset, Life CLEF fish dataset, Fish4Knowledge). Croatian dataset contains a total of 794 images with 12 categories of fish. The second dataset is a Fish CLEF dataset that contains more than 3000 images with 15 categories of fish. The third dataset, Fish recognition Ground-Truth data, contains 27370 images with 23 categories of fish. These fishes are categorized based on dependent characteristics like several fins, shapes, etc. The entire dataset is partitioned into 90% training and 10 % testing since the dataset is not balanced properly, and the less frequent species contains only 17 images. The sample images of each of these three datasets are shown in Figure 1.

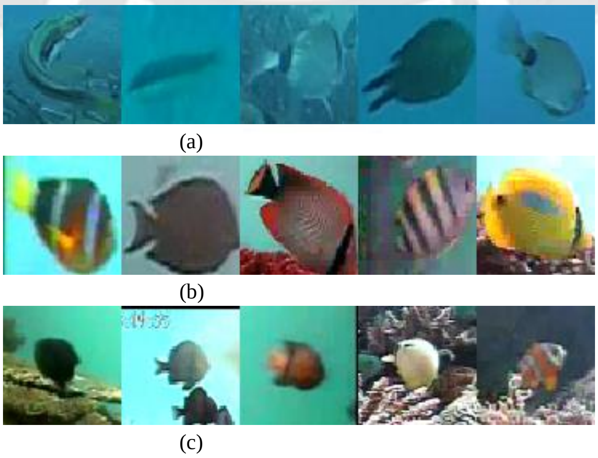

Figure 1: Sample images. (a) Croatian dataset (b) Fish CLEF (c) Fish4Knowledge dataset.

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The CNN model is used for classifying the fish species in this paper. Similar to Neural Network, CNN comprises convolutional layers, hidden layers, and output layers. The structure of the proposed model is shown in Figure 2. The input is an image or set of images. To get the final output, a series of conv+pooling layers were applied to the input images. Figure 3 represents the architecture of the proposed CNN. The model is sequential, and the architecture includes convolution layers, pooling layers trailed by a dense layer. The model utilized three layers of convolutional layers followed by a max-pooling layer. The softmax activation function is used at the end for getting the probabilities. Each CONV+RELU block helps shrink the image. Input images are normalized and are of similar size (i.e. 32 X 32). Convolutional layers in the models provide output 32 feature maps that imply some features in the image identified by the convolutional layer. The convolutional layers and max-pooling layers have a part size of 3 x 3 pixels. The kernel matrices are utilized in separating the neighboring features. The activation function ReLU is utilized over tan-h and sigmoid activation functions. The activation function of ReLU is given in Eq. (1)

$$h = \max(0, x) \qquad (1)$$

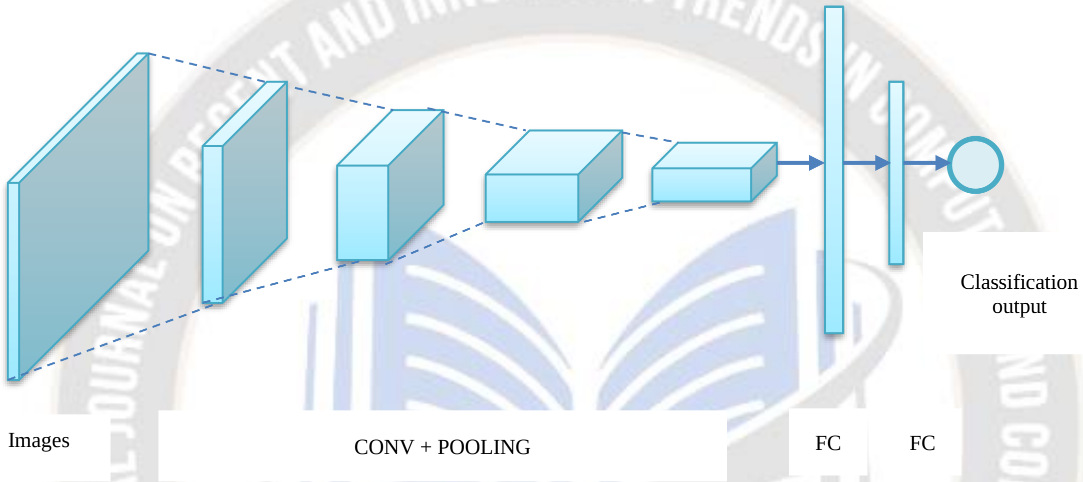

Figure 2. The architecture of CNN

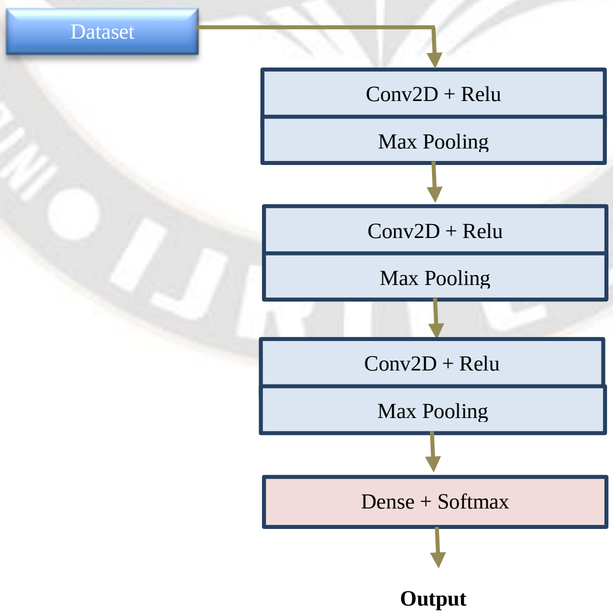

Figure 3. The Proposed model used for training the dataset(s).

Later, the matrix is flattened into a vector. In this work, the model is developed with the help of Keras API on Tensor

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Flow that performs backpropagation instantly. Models are employed through sparse categorical cross-entropy loss and the Adam optimizer. To implement, we verified many combinations of EPOCHs, learning rates and batch sizes. The number of EPOCHs we utilized varied from 50 to 200, with a learning rate of 0.001 and a batch size of 32. The experiments are conducted on three different benchmarks underwater image datasets for 50, 100, and, 200 epochs and the results are analyzed. We utilized accuracy, Precision (P), recall (R) and f-score (F1) for performance analysis. The equations for these are as follows:

$$P = \frac{t_p}{t_p+f_p} \quad (2)$$

$$R = \frac{t_p}{t_p+f_n} \quad (3)$$

$$F1 = 2 * \frac{P*R}{P+R} \quad (4)$$

Here t_p and t_n are true positive and true negative, f_p and f_n are false positive and false negatives computed from the confusion matrix. Along with this matrix, accuracy is also computed during training and testing. The evaluation metrics on the Croatian dataset are shown in Table 2. The evaluation metrics on the Fish4Knowledge dataset are shown in Table 3. The evaluation metrics on the Fish recognition ground truth dataset are shown in Table 4. The accuracy of the model for different epochs on three datasets is shown in Table 5. The results are analyzed based upon the training and testing loss, and the results are shown in Figure 4. The Croatian dataset gives more testing loss than the other three datasets because the model is overfitting.

Table 2. Evaluation metrics on Croatian dataset for EPOCHS (E = 50, E=100, and E=200)

Fish Category	E=50			E=100			E=200		
	P	R	F1	P	R	F1	P	R	F1
Chromis chromis	1.00	0.81	0.90	0.93	0.86	0.89	0.85	0.93	0.89
Coris julis female	0.56	0.67	0.61	0.73	0.53	0.62	0.79	1.00	0.88
Coris julis male	0.83	0.62	0.71	0.56	0.50	0.53	0.70	0.54	0.61
Diplodus annularis	0.71	0.63	0.67	0.63	0.79	0.70	0.72	0.72	0.72
Diplodus vulgaris	0.87	0.62	0.72	0.81	0.63	0.71	0.69	0.69	0.69
Oblada melanura	0.75	0.67	0.71	0.67	0.75	0.71	0.75	0.67	0.71
Sarpa salpa	1.00	0.60	0.75	1.00	0.50	0.67	1.00	1.00	1.00
Serranus scriba	0.42	0.56	0.48	0.59	1.00	0.74	0.71	0.92	0.80
Spicara maena	0.65	0.93	0.76	0.86	0.92	0.89	1.00	0.62	0.76
Spondyliosoma cantharus	0.62	1.00	0.76	0.76	0.87	0.81	0.44	0.50	0.47
Symphodus melanocercus	0.79	0.68	0.73	0.88	0.68	0.76	0.88	0.85	0.86
Symphodus tinca	0.38	0.71	0.50	0.44	0.80	0.57	0.80	0.80	0.80

Table 3. Evaluation metrics on Fish CLEF dataset for EPOCHS (E = 50, E=100, and E=200)

Fish Category	E=50			E=100			E=200		
	P	R	F1	P	R	F1	P	R	F1-Score
Abudefduf vaigiensis	0.92	0.91	0.92	0.94	0.94	0.94	0.94	0.97	0.96
Acanthurus nigrofuscus	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99
Amphiprion clarkii	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99
Chaetodon lunulatus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
Chaetodon speculum	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Chaetodon trifascialis	0.96	0.99	0.97	0.98	0.91	0.95	0.99	0.91	0.95
Chromis chrysura	0.99	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99
Dascyllus aruanus	0.99	0.99	0.99	0.98	0.99	0.98	0.99	1.00	1.00
Dascyllus reticulatus	0.99	0.99	0.99	0.99	0.99	0.99	0.98	1.00	0.99
Hemigymnus melapterus	0.97	0.89	0.93	0.97	0.90	0.94	0.97	0.81	0.88
Myripristis kuntee	0.98	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Neoglyphidodon nigroris	0.97	0.81	0.88	0.96	0.81	0.88	0.97	0.97	0.97
Pempheris Vanicolensis	1.00	0.75	0.86	1.00	0.80	0.89	1.00	0.89	0.94
Plectrogly-Phidodon dickii	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.99
Zebrasoma scopas	0.93	0.95	0.94	0.93	0.87	0.90	0.94	0.89	0.92

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Table 4. Evaluation metrics on Fish4Knowledge dataset for EPHOCS (E = 50, E=100, and E=200)

Fish Category	E=50			E=100			E=200		
	P	R	F1	P	R	F1	P	R	F1-Score
fish_01	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.99	0.98
fish_02	0.98	0.98	0.98	0.97	0.96	0.97	0.98	0.98	0.98
fish_03	0.98	0.98	0.98	0.97	0.98	0.97	0.97	0.97	0.97
fish_04	1.00	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99
fish_05	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00	0.99
fish_06	0.84	0.79	0.82	0.95	0.87	0.91	0.85	0.86	0.86
fish_07	0.96	0.99	0.97	0.95	0.95	0.95	1.00	0.97	0.98
fish_08	0.64	0.73	1.00	0.76	0.72	0.74	0.75	0.75	0.75
fish_09	0.93	0.82	0.87	1.00	0.85	0.92	0.89	0.87	0.88
fish_10	1.00	0.97	0.99	0.99	0.99	0.99	1.00	1.00	1.00
fish_11	0.81	0.76	0.79	0.91	0.70	0.79	0.91	0.80	0.85
fish_12	0.78	0.86	0.82	0.83	0.91	0.87	0.94	0.72	0.82
fish_13	1.00	1.00	1.00	0.98	1.00	0.99	1.00	0.98	0.99
fish_14	0.86	0.60	0.71	0.89	0.62	0.73	0.79	0.50	0.61
fish_15	0.94	0.89	0.91	0.89	0.89	0.89	1.00	0.91	0.95
fish_16	0.96	1.00	0.98	0.98	1.00	0.99	1.00	0.98	0.99
fish_17	0.83	1.00	0.91	0.75	0.90	0.82	0.80	0.86	0.83
fish_18	0.88	0.83	0.86	1.00	1.00	1.00	1.00	0.93	0.96
fish_19	1.00	0.89	0.94	1.00	1.00	1.00	1.00	0.67	0.80
fish_20	0.83	0.83	0.83	1.00	0.60	0.75	1.00	1.00	1.00
fish_21	1.00	0.50	0.67	1.00	0.33	0.50	1.00	0.50	0.67
fish_22	1.00	0.71	0.83	1.00	0.71	0.83	0.86	0.86	0.86
fish_23	1.00	1.00	1.00	1.00	0.88	0.93	0.86	0.86	0.86

Table 5: Accuracy of the model for different epochs on three datasets

Dataset	Epochs	Training Accuracy	Training loss	Test Accuracy	Test loss
Croatian dataset	50	80.34%	0.6384	71.36%	0.9950
	100	95.13%	0.2138	74.37%	0.9518
	200	100%	0.0140	76.88%	1.4441
Fish4Knowledge	50	99.87%	0.0211	98.77%	0.0877
	100	100%	0.0010	98.82%	0.0924
	200	100%	0.0009	98.73%	0.0873
Fish Recognition Ground Truth	50	99.83%	0.0049	97.82%	0.1278
	100	99.98%	0.0011	97.49%	0.1758
	200	100%	0.0002	97.73%	0.1728

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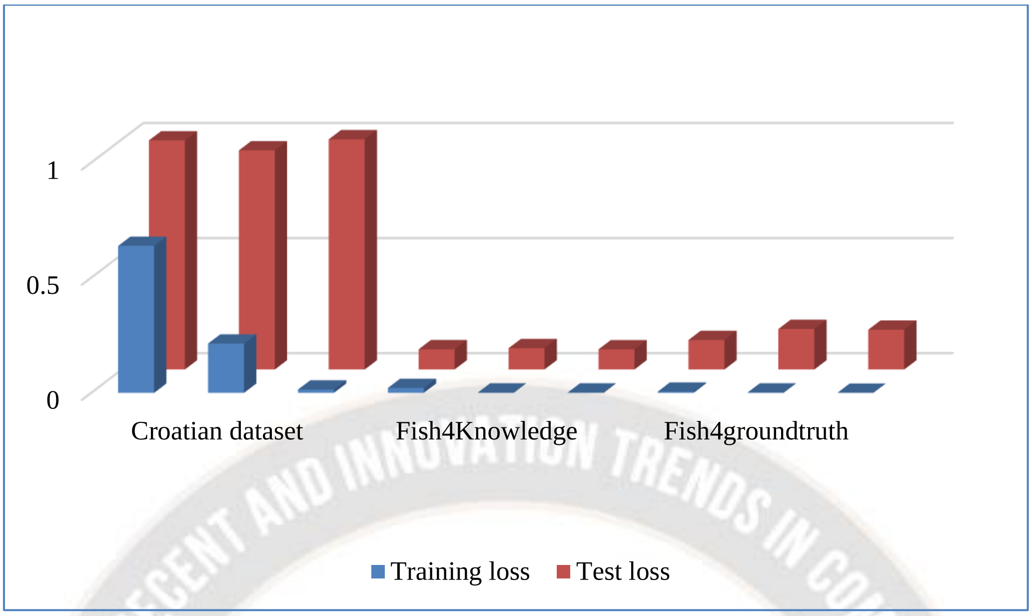

Figure 4. Training and Test loss on three datasets

4. Conclusion

Live fish species recognition is a difficult task because of its uncontrolled environment. Difficulties to the aquatic environment include helpless image quality, uncontrolled obstacles that are present in an image. This paper aims to suggest a way for automating the fish classification that is needed for marine biologists. A greater part of the accessible techniques focuses on the detection and classification of fishes outside of water because of not able to tackle the issues posed in the aquatic environment. Further, the systematic survey of underwater image enhancement techniques from conventional machine learning techniques to deep learning is missed in the literature. The detection and classification of fish images on different datasets by numerous authors in the past few years are presented in this paper. Further, a model is prepared to classify the fishes of different categories over benchmark datasets. Based on the statistical analysis of our experimental study, the model is suitable for real-time applications. But the strategy couldn't accomplish 100% accurate results (in terms of testing loss) because the model is trained on highly challenging real-time data. We intend to improve our method further by carrying out image enhancement procedures and data augmentation techniques using deep generative networks. In addition, fine-tuning the architecture of CNN by using the generalization techniques to improve the classification accuracy is considered future work.

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