An Impirical Approach for Underwater Image Quality Enhancement and Object Detection using Deep Learning

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Abstract:

Underwater image quality assessment before object detection is a very emerging trend in image processing. In the past several years, a batch of new algorithms for improving underwater images have been presented. But these algorithms are mostly assessed on different datasets or a few picked photographs from the current world. However, it's hard to say how well these algorithms will perform on real-world images or how we can monitor their development. The first complete perceptual investigation and analysis of submarine images Object detection is another important task of underwater images. Due to noise images or lower light intensity, it's hard to detect such objects in an accurate manner. In this paper, we propose using deep learning techniques to improve the quality of underwater images and detect objects. The data contains some noisy data. By using data pre-processing and normalisation techniques, filtration has been done. The balanced data feeds to CNN and executes the convolutional and pooling layers for the extraction of features. Finally, the dense layer classifies the entire data set based on the trained module. The VGG-16 and RESNET-101 deep learning frameworks have been used for classification. Extensive testing has shown that CNN with RESENT gives 96.50% accuracy, while VGG-16 CNN gives 95.80% accuracy on the sonar dataset.

Keywords: image processing, Underwater data analytics, sonar signal analysis, supervised classification, machine learning, deep learning

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Introduction

Most researchers find underwater imaging to be a challenging field. There is an increasing requirement for underwater images, as well as images that would otherwise be impossible to capture on land or above the surface of the water. Due to light dispersion caused by the substance, underwater images are often more ominous than those taken on land. As a second example, frequency retention is known to induce a loss of shading in the resulting images, a phenomenon that is seldom seen in the air. Third, the sediment in the water will affect high-resolution images in addition to electronic clamour. Another problem is that photographs taken below the surface are often lit with false illumination, resulting in poor quality.

With submerged images data, light intake and the inherent design of the water are two of the key obstacles. The results of dimming underwater photographs are also examined in this study. The sea's design has a significant impact on the amount of light reflected. Due to its ability to reduce shimmer and so help capture deep tones that would otherwise be impossible to see in the water, vertical polarisation is an important feature of reflected light since it allows it to penetrate the water in a vertical direction. Deep-sea photography also raises the question of water density, which has been shown to be greater than that of air on several occasions. As a result, light that travels from the air to water is partially reflected and begins to penetrate the water halfway through. When we go further into the ocean, the amount of sunshine that gets into the water decreases. In addition, a specified quantity of light is absorbed by Water particles. As a result of the increasing depth, the images taken underwater are becoming opaquer and hazier. When travelling far into the water, not only does the quantity of light drop, but the colours are also affected by the tone frequency. The initial red tone, for example, disappears at a depth of 3 metres. Furthermore, as we go, the orange tone fades away. 5 metres deep, the golden tone will likewise disappear. Third, at a depth of 10 metres or more, the majority of the yellow tones disappear, as do the pink and orange hues.

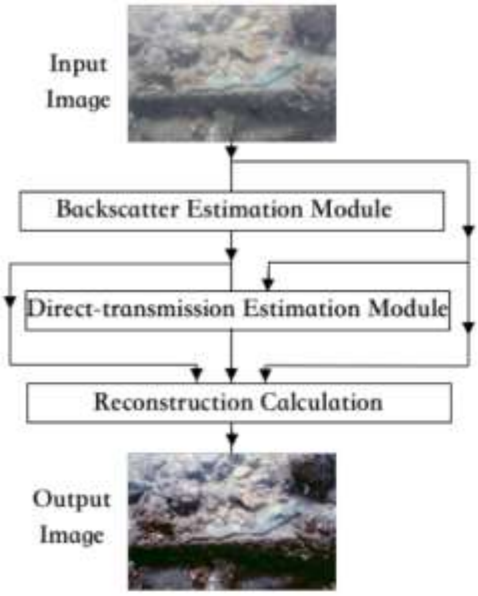

Figure 1 : Process of quality enhancement of underwater images

CNN is generally acknowledged as the quickest detection technique in many ways in many research areas employed CNN approach to deal with classification issue earning the champion of ILSVRC, which reduced the top 5 error rate to 15.3 percent, deep CNN has been extensively implemented since then. The Region as RCNN achieves 66 percent mAP by merging the Region Proposal Network with CNN algorithms, as shown on Pascal VOC 2007.

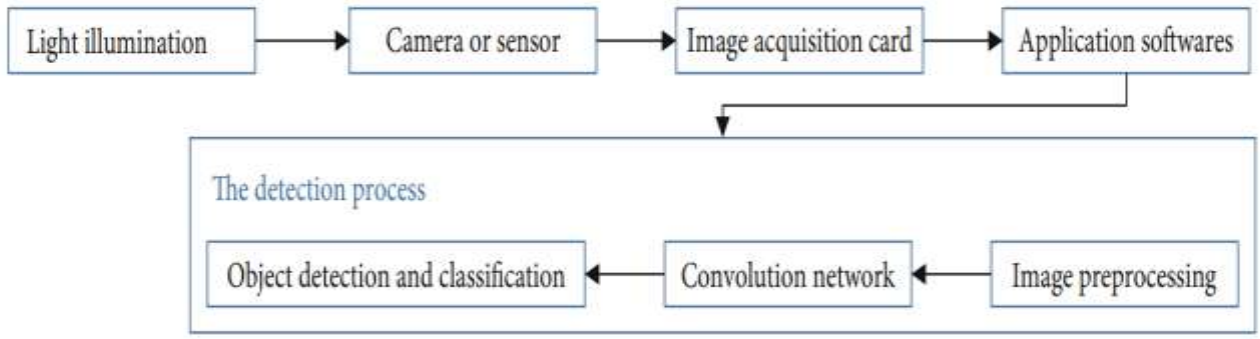

Figure 2 : Framework of object detection of underwater image using CNN

The above figure 2 demonstrates an object detection of underwater image using CNN. In first section it deals with image pre-processing and normalization techniques and later demonstrates detection methodology in underwater image.

The rest of the paper is arranged as follows: Section 2 provides a short summary of recent research, section 3 describes suggested work, section 4 discusses observations, section 5 discusses research contribution, section 6 discusses BCI sentiment categorization applications, section 7 discusses future scope, and section 8 concludes. These are divided into two categories: lexicon-based and machine-learning-based algorithms. Machine learning methods include neural networks, bayesian networks, support vector machines, nave bayes, and maximum entropy. Lexicon-based algorithms include semantic and statistical approaches.

Literature Survey

There are several resources to be found in the water. While this is true, it has yet to be fully used by humans, particularly in the undersea realm. For example, underwater archaeology, environmental monitoring, device maintenance, item detection and search and salvage all rely on underwater image processing. Underwater optical pictures are of poor quality, with faults such as colour distortion, low contrast, and even blurred features due to the suspension of particles and light attenuation in water. As a result, improving and restoring the deteriorated underwater photos is necessary in order to gather additional data about the underwater environment. Histogram equalisation, wavelet transform, and the Retinex algorithm are some of the most used methods for improving underwater photos [1–4]. However, each of these algorithms has its own drawbacks. Histogram equalisation, for example, might result in the loss of picture detail and the over-enhancement of the image. The wavelet transform's processing power is restricted when working with photos taken in shallow water. The halo effect is a problem for the Retinex algorithm when the brightness difference is substantial. [5–7] gives many instances of combining several of these improvement strategies in order to overcome these drawbacks. Fusion algorithms have been shown to be more effective in improving images in all aspects.

An imaging model is needed for underwater picture restoration.. Chiang and Chen [8] give a typical model. When utilising this model, it is essential to calculate the transmission map and the overall ambient light. In recent years, a large number of scholars have worked on developing methods for estimating these variables. Research may be divided into two broad categories: priori-driven and data-driven.

Approaches that rely on priors or assumptions in order to extract the transmission map and the atmospheric light environment are called prior-driven. The DCP (Dark Channel Prior) approach is a common one [9]. As a consequence of the red light's rapid absorption in water, the DCP regulations are often broken, leading to an unbalanced signal. Using just the blue and green channels, Drews et al. [10] suggested an Underwater Dark Channel Prior (UDCP) to improve upon the DCP approach. Galdran et al. [11] developed the Red Channel Prior (RCP), which uses the connection between the red channel's attenuation and the DCP to provide a reliable transmission diagram. Modifications like this increase the estimate of transmission map accuracy, but only somewhat because of the loss in dependability. According to Carlevaris-Bianco et al. [12], the attenuation difference between the red and green and blue channels may be used to infer depth in a scene based on the attenuation difference. In order to get a depth map from deteriorated underwater photos, Wang et al. [13] devised a novel technique known as maximum attenuation identification (MAI). This was done by minimising the amount of information that was lost in an area of red channel. Due to relying only on hue, these priors undervalue the transmission of green and blue coloured items. According to Berman and colleagues, the hazy line assumption may be used to estimate transmission and the gray-world assumption can be used to estimate attenuation coefficient ratios. However, if the ambient light is substantially brighter than the picture, this approach may fail since most pixels will point in the same direction, making it impossible to distinguish the haze lines.

As depth rises, theoretically, transmission decreases and ambient light has a bigger effect on the picture quality. It's common to use the pixels with the greatest depth in a picture as a reference point for estimating ambient light. These reference pixels are often selected with more precision using one of two methods: one based on colour information and the other on edge information. Chiang et al. [8] used the pixel with the greatest brightness value in a picture to deduce the ambient light. Because the strength of the red channel is substantially lower than the intensity of blue and green, selecting red pixels as a reference is an alternate technique. However, objects of the same colour may interfere with the selection since the reference pixels are chosen based on colour information. Edge maps linked with smooth, non-textured regions may be used to estimate ambient light, according to Berman et al. [15]. For example, if the picture comprises a huge, smooth object, this approach is not appropriate. In addition, a picture may not have an ideal reference pixel. There may not be many pixels with depth in a picture taken from a low angle, for example. When the adopted priors are invalid, prior-based approaches produce substantial estimate errors. For prior-based techniques, the lack of accurate priors for generic underwater photos has become a key roadblock.

A data-driven technique known as deep learning has grown in popularity in the field of image processing in recent years. Using deep learning, it is feasible to prevent estimate mistakes owing to incorrect priors in the algorithm, since the system learns the link between pictures. Underwater image processing makes extensive use of the Convolutional Neural Network (CNN), a typical deep learning technology. Images, such as those seen in [16–19], are often used to estimate transmission. In order to regress transmission and produce more refined restored pictures than standard approaches, these CNN-based models are trained using synthetic data. For example, in [20–22], there are applications that deal with both the transmission and the ambient light. These techniques, however, only partially address the dispersion problem since they assume that all three channels have the same transmission. Color deviance can't be fully fixed, despite the enhanced contrast. It was originally utilised to estimate the blue channel, then red and green channels were calculated using the connection between channels to recover underwater pictures in Wang et al. [23]. Li et al. [24], Sun et al. [25], and Uplavikar et al. [26] directly employ a data-driven end-to-end network to learn the mapping link between underwater degraded photos and clear images. Training data quality is well-known to have a significant impact on the success of data-driven approaches. Synthesis is often used to create underwater pictures for training, and these may be created with or without colour variation (e.g., [16–18]). (e.g., [20]). As a result, only varying shades of blue or green may be seen in underwater photos owing to the complexity of the undersea ecosystem. These photos were created using Generative Adversarial Networks (GANs) to increase the quality of the synthetic data collection. However, when compared to genuine underwater photographs, the recovered images are still lacking.

When it comes to underwater picture processing, each enhancement or restoration approach has its own set of drawbacks. You can get high-quality underwater images by using a combination of algorithms in which one module performs well and its deficit is compensated for by another module. A fusion method is presented in this work. Color balancing is accomplished using the CIE Lab's colour model, defogging is accomplished using the foggy training set, and brightness is equalised. The mapping connection between the underwater blurred picture and the clear image may be established in this manner without synthesising the data set of the underwater image. Inaccurate mapping may also be avoided owing to the lack of actuality in the synthetic pictures. To create colour harmony, the colour channel's channel value redistribution is used by the colour balancing algorithm. Defogging employs deep separable convolution instead of regular convolution to minimise the number of parameters in the computation. To further lower the depth of the primary network, the defogging module incorporates a subnetwork. The CNN uses the Basic Attention module, which consists mostly of the Channel Attention block (CA) and Pixel Attention block (PA). ' (PA). PA records the difference in haze weight across pixels, while CA tracks the distribution of fog throughout channels. A pooling pyramid module is introduced to the network model that provides global information by aggregating distinct contextual information of pictures. To ensure the integrity of edge data, cross-layer connections are used. An adaptive histogram equalisation approach in the L channel (the Luminance channel in CIE Lab colour model) is used to balance overall brightness in the brightness equalisation module.

Proposed System Design

In this investigation, a hybrid kind of deep learning methodology will be used to design and implement an emotion recognition system. In this paper, we demonstrate how a CNN-LSTM may collaborate to effectively identify sonar data. As a consequence of this, the purpose of our research is to investigate and analyse the efficacy of various deep learning (DL) and machine learning (ML) algorithms for the classification of SONAR data. Our objective is to develop a Convolutional Neural Network method for the purpose of feature extraction by making use of a number of different deep learning framework called RESNET-101. Using characteristics extracted from Convolutional Neural Networks, the objective of this research is to provide a technique for the categorization of long-term and short-term memories that may be used for unit testing and training. As a consequence of this, one of our goals is to develop a hybrid deep learning model that is able to forecast and categorise an epileptic state in real time. In order to investigate the whole system using supervised learning strategies in the research that was carried out, the first step was to gather information from the mind in the form of SONAR data signals. In order to develop the trained system and extract a wide variety of characteristics from the data, Seth makes use of both the CNN-LSTM methods. ECG data will be used in an effort to diagnose epileptic disease as the program's primary focus. Display the effectiveness of the procedure while categorising each piece of input data in the testing system so that it corresponds to its own tag.

The below figure1 provides an illustration of the proposed architecture for the system including the quality enhancement and object detection.

Figure 1. Proposed Systems Architecture for underwater object detection using Deep learning

Deep learning Classifier (CNN+LSTM)

Deep Learning includes the Convolutional Neural Network (CNN). Too far, CNN has shown to be a highly efficient and successful method of achieving handwriting recognition. Convolutional Neural Networks are neural networks that employ multiple layers of filters to extract information from images.

1: Convolutional Layer: It's the foundation for constructing a CNN model. This layer conducted mathematical calculations on the picture that was used as input, as well as resizing the image into the M* M format. This layer's output describes the image's features, such as edge and corner mapping, also known as a feature map. The information was then added to the following layer.

2: Pooling Layer: This is the layer that connects the convolutional and fully connected layers. This layer is used to decrease the network's parameters and computation. The maxpooling and average pooling methods are provided by this layer. The most frequent method is max pooling. The output of the preceding layer, the pooling layer, is sent to the fully connected layer. This layer is where the categorization process takes place.

In practice, input is given through a GUI. Now, for the GUI, we've built a new file in which we've constructed an interactive window in which we can draw characters on the canvas and identify them using buttons. The Tkinter package for Python was used to create the GUI. Tkinter is a standard Python GUI library. It allows you to build a GUI application quickly and easily. After giving the input, the model is loaded and stored, and predictions are made. h5 format. The supplied information is progressed further in order to resize in a certain format in order to get the real forecast. The resize picture is then passed on to the prediction model, where the provided input's features are extracted. The modelling then yields a prediction, which reflects the likelihood of the target variable based on the assessed importance of the input variables.

Algorithm Design

Input: Normalized training dataset *Train_Data[]*, Normalized testing dataset *Test_Data[]*, defined threshold *qTh*

Output: Result set as output with *{Predicted_class, weight}*

Step 1: Read all test data from *Test_Data[]* using below function for validating to training rules, the data is normalized and transformed according to algorithms requirements

$$\mathrm{test\_Feature(data)} = \sum_{m=1}^{n} (.\mathrm{Attribute\_Set}[A[m] \ldots\ldots A[n] \leftarrow Test\_Data)$$

Step 2 : select the features from extracted attributes set of test_Feature(data) and generate feature map using below function.

Test_FeatureMap [t……..n] = $\sum_{x=1}^{n}(t) \leftarrow$ test_Feature(x)

Test_FeatureMap [x] are the selected features in pooling layer. The convolutional layer extracts the features from input and passes to pooling layer and those selected features are stored in *Test_FeatureMap*

Step 3: Now read entire taring dataset to build the hidden layer for classification of entire test data in sense layer,

$$\mathrm{train\_Feature(data)} = \sum_{m=1}^{n} (.\mathrm{Attribute\_Set}[A[m] \ldots\ldots A[n] \leftarrow Train\_Data)$$

Step 4 : Generate the training map using below function from input dataset

Train_FeatureMap [t……..n] = $\sum_{x=1}^{n}(t) \leftarrow$ train_Feature(x)

Train_FeatureMap[t] is the hidden layer map that generates feature vector for build the hidden layer. That evaluate the entire test instances with train data.

Step 5 : After generating the feature map we calculate similarity weight for all instances in dense layer between selected features in pooling layer

$$\mathrm{Gen\_weight} = \mathrm{CalcWeight}\ (\mathrm{Test\_FeatureMap} \mid\mid \sum_{i=1}^{n} \mathrm{Train\_FeatureMap[i]})$$

Step 6 : Evaluate the current weight with desired threshold

$$\mathrm{if(Gen\_weight} >= qTh)$$

Step 7 : $\mathrm{Out\_List.add}$ **(**$\mathrm{trainF.class, weight}$**)**

Step 8 : Go to step 1 and continue whenTest_Data$==$ null

Step 9 : Return Out_List

Result and Discussion

Extensive experimental study has been carried out in python environment with RESNET-101 and VGG-16deep learning framework. The RESNET and VGG framework has been used for the utilization of recurrent neural networks and LSTM has been used for classification. In the experiment evaluation CNN highest accuracy than the conventional machine learning classifier. It provides around 94.00% classification accuracy on different class validation. The below figure to demonstrate the classification accuracy with various conventional machine learning algorithms as well as proposed hybrid deep learning algorithm. The below Table 1 demonstrates the performance evaluation of proposed 2 CNN models including other 5 deep learning modules.

Table 1 :Quantitative measurements comparison of several underwater image enhancing techniques

Method	Accuracy	PSNR	SSIM
DNN	92.90%	20.60	0.51
PNN	93.70%	21.30	0.49
RNN	94.10%	20.85	0.57

LSTM	92.10%	22.50	0.57
CNN	94.60%	19.95	0.69
CNN-LSTM (RESNET-100)	96.50%	19.20	0.86
CNN-LSTM (VGG-16)	95.80%	19.30	0.84

The above Table 1 describes a CNN-LSTM with RESNET with 101 convolutional layers that gives higher accuracy for object detection on SONAR data. The VGG-16 framework also obtains 95.80% detection accuracy, which is higher than conventional methods.

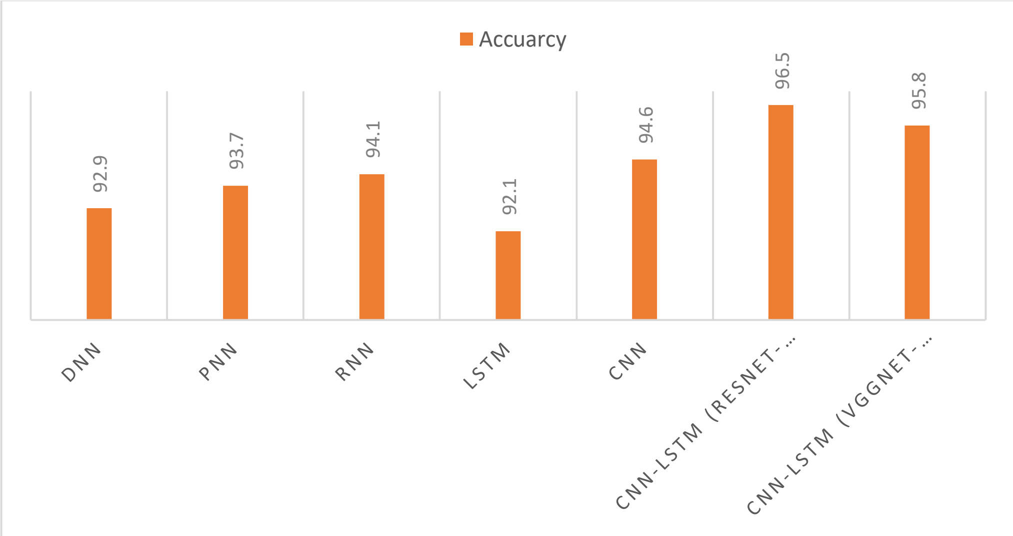

Figure 3 :Object detection accuracy for underwater image using proposed vs existing CNN

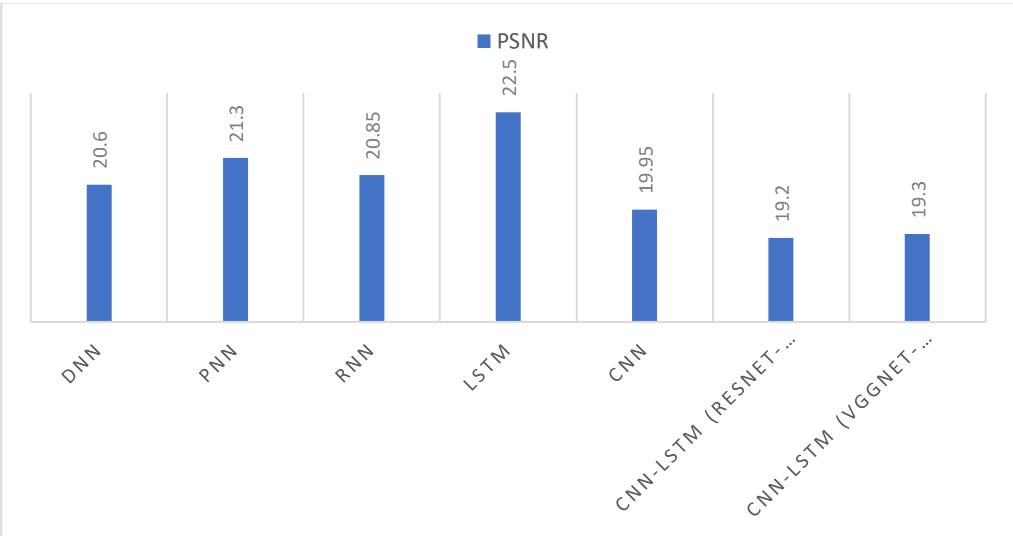

Figure 4 :PSNR calculation for underwater image using proposed vs existing CNN

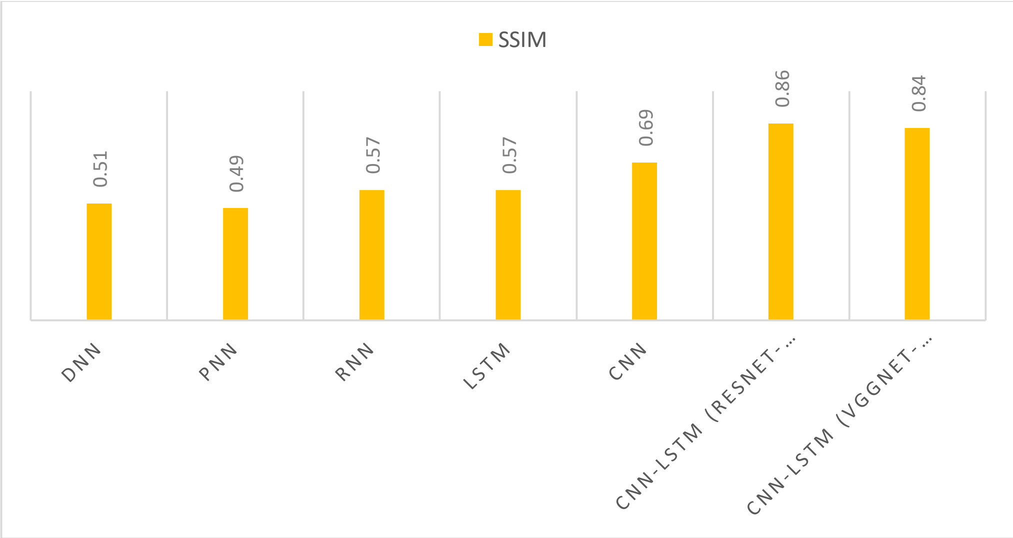

Figure 5 :SSIM of proposed model with conventional deep learning and proposed deep learning algorithm

In the experiment that was just described, the Figures illustrate both the correctness of the testing and the complete loss of the data set. The hybrid technique consisting of a recurrent neural network and an LSTM has been used for identification of sentiment. The pulling layer in the convolutional layer is responsible for the extraction and optimization of a variety of characteristics. The accuracy of the final classification may be predicted using many convolutional layers, followed by the same job and a dense layer. A real-time SONAR dataset is able to attain a detection accuracy of 94.00% with the help of the proposed hybrid technique.

Conclusion

This paper describes an underwaterimage quality enhancement and object detection in deep learning framework. This approach of image enhancement is based on deep learning and a framework for how images are formed. Compared to previous approaches, the suggested method provides better visual qualitative as well as quantitative measures on a number of datasets. Real-time processing requirements for an underwater robot platform may be met appreciations to a significant increase in computational performance. The suggested underwater picture enhancing approaches may also be used to help with high-level machine learning tasks in the future, according to testing.

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