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# An Effectual Underwater Image Enhancement using Deep Learning Algorithm

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*Abstract*—**Digital image processing domain is growing day-by-day by introducing novel technologies to provide assistance for several applications such as robotic activities, underwater network formation, and so on. In particular, underwater image processing is considered as the crucial task in image processing industry due to the flow of light waves that are not in the specific and expected range under the water level. While image restoration technology can adequately consider removing this same haze from source images, they need to obtain several images from a certain place that prevent it from being used in a real-time system. To overcome this issue, a deep study approach is developed by providing excellent outcomes of deep learning approaches in several other image analysis concerns such as colorizing images or object identification. A convolution neural network (CNN) model is trained to de-haze the individual images with image restoration in order to perform further with an image improvement. The proposed approach can produce images with image restoration quality by including a standard image input and here, the neural network is evaluated by using images and features, which are obtained from separate areas to prove its capacity to generalize. The efficiency of the proposed approach is high when compared to other existing methods**

***Keywords— Underwater image processing, deep learning, classification, image dehazing, convolution neural network***

## I. INTRODUCTION

The most important issues in underwater robotic activity estimation is the management of underwater images. In addition to the well-known issues in the automatic interpretation of the image in sort to engage nearer to world, submarine robotics must address other problems caused by image degradation by transferring the light waves in water. Proper construal of the camera-input is essential for building independent robots, which are capable of moving and interacting in a mysterious background [1] [2]. In case of submarine robotic activities, the underwater industry has many applications and unfortunately there are possibilities for tragedies like ship wrecks, shore drips or flight upsets. Such approaches are frequently conducted by remote vehicles (RVs) with a femoral information sharing cable, which is regulated by utilizing highly qualified pilots. In last few decades, however, the much more independent infrastructure has built: Autonomous-Underwater-Vehicles (AUV) intervention [3] [4]. This architectural style offers many benefits, such as the non-existence of delays between orders and the reaction of vehicles. In general, the first step in such systems is to process the input of the cameras, to locate the system, navigate carefully as well as to recognize the objectives of attention. As a result of the underwater nature of the transmission of light, mentioned in [5] [6], images dilapidation possessions such as diffusion, dispersion, sea flurry or vignette. Those same activities make it a difficult task to interpret the scene. Absorption reduces the light level while the robot leaves the camera, colors fall one by one belonging on the wavelengths. This consequence causes the bluish color of the underwater pictures because the medium is least enhanced by this wavelength. The diffracted outcome shifts the orientation of the brightness to the camera creating a typical veil that surpasses the picture and conceals the picture which blurs the entities [7-10].

In addition to this effect, the effect of various underwater image processing such as sea snowfall also raises the quantity of dispersed light is a significant thing. Finally, in intensity in the image corners due to the symmetry of the lens and often the lens housing, vignettes are a light fade-out [11][12]. Therefore, a pre-processing step is required to change the current color schemes and improve the image for further handling. It could be dealt with from two viewpoints. Image restoration aims to retrieve a wavelet coefficient using a model of degradation and the acquired image. The preferred method, the improvement of the image, involves the use of contextual individual characteristics to make an image more pleasant. Both methods have their own advantages and disadvantages, but the principal difference is that image restoration results produce more realistic results, but needs several parameters to be estimated or measured [13-15]. In this work, a hybrid solution is proposed to learn an image improvement function from image restoration techniques with a deep learning architecture. To train a convolutional network, a dataset of groups of processed and reestablished images can generate images from diminished inputs.

## II. MATERIALS AND METHODS

This paper estimates the processing of a deep-learning underwater image based on the training and testing procedures carried out with regards to the Convolutional Neural Network [16] and the Support Vector Machine algorithms [17].

**Sample preparation group 1**

20 RGB underwater image subset milk and deep blue

(Sony RX100 VI Compact cameras 100 meters)

**Sample preparation group 2**

20 RGB underwater image subset chlorophyll and blue

(Sony RX100 VI Compact camera 100 meters)

The following tables, Table-1 and Table-2 illustrates the sample group size and the study parameters of the proposed learning model in clear manner.

TABLE-1: SAMPLE GROUP SIZE SPECIFICATION

| | |
|---|---|
| Group-1 | 20 |
| Group-2 | 20 |
| **Total** | **40** |

TABLE-2: STUDY PARAMETERS

| | |
|---|---|
| Incidence, Group-1 | 25.6% |
| Incidence, Group-2 | 0.2% |
| Alpha | 0.05 |
| Beta | 0.2 |
| Power | 0.8 |

Image enhancement techniques plays a vital role in enhancing the quality of the image. The enhanced output image is always better than the given input image. In this paper, an underwater image enhancement process is designed with deep learning principles and also analyzes the accuracy levels with the comparison of proposed CNN logic with classical SVM scheme. And the resulting scenario is applies to the software testing tool designed by IBM called Statistical Package for the Social Sciences (SPSS) to identify the stability of the proposed design as well as the sustainable accuracy metrics are acquired from the tool. The overall limitations identified over the approach are it process the image with low contrast and such color casting consumes more time for processing. The number of groups (datasets) are used in this application to train the model is two as well as the sample size consideration for those datasets are 40. These variations of datasets are trained with CNN and SVM to create a proper model for analyzing the underwater images accordingly. The following scenario shows the sample dataset training or preparation process.

## III. PROPOSED SYSTEM METHODOLOGIES

A convoluted neural network is used in this work to learn to convert raw images to amplified images so that they're used as input for other image processing. Using clinical analysis, 20 sample size estimated for group 1 and group 2, totally 40 samples for 2 groups with alpha value 0.05, threshold 90 % and pretest power 80%. The images are already analyzed by using method in [1] to train and improve the processes. In different real underwater interventions, the images used for training the neural network are taken by an underwater camera mounted on an autonomous underwater vehicle. The images were divided into six sets according to the qualities of the images as shown in the following figure, Fig-1.

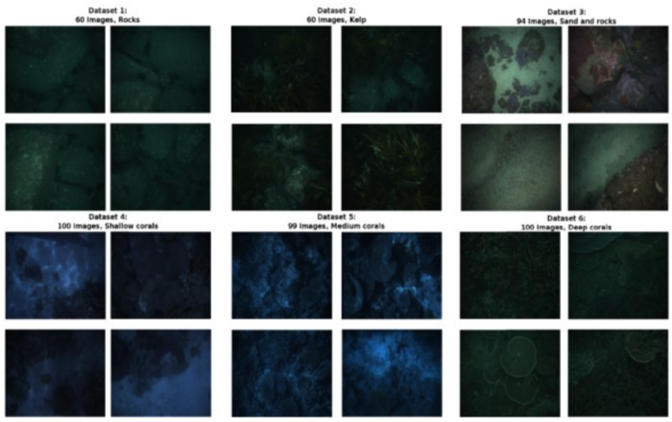


Fig.1 Diverse Underwater Image Datasets utilized in this approach

In addition, images were identified to offer a wide range of colors at various depths to train color features. This division of the data set allows you to train some images and reinforce the neural network with pictures from a different procedure. This allows the system to be tested in the event of a different intervention. In addition, each data set has been organized in a randomly selected training and test set with images to measure classification performance. There are various architectures tested to train the system, but Figure 2 shows the one proposed. As one can see, the CNN takes the entire image as an input and takes 6 convolutionary steps. The first reduces the image size in a further pooling step, which collects the far more essential variables. In addition to this, that each convolutionary step but the latter includes an Activation Function Rectifier Linear Unit (ReLU). Also every convolutionary layer affects the rate of extracted features from the first three steps of the unprocessed image (RGB) to 55. At this point, the functionality is found to create a matrix of 3 standards for assessing to the recovered image in the last step of the neural network. The trained Model, a conjugate gradient method, was used as a reduction function in required to train the boundary conditions in the neural network. The L2 Euclidean distance is a common function, which calculates the squared sums of the dissimilarities between some of the estimated value of x and quantitative measurements y:

$$\mathbf{L}_2 \in \sum_{i=0}^{n} (\mathbf{vi} - \mathbf{x}_i)^2 \quad (1)$$

In this case, lessening the L2 lost opportunity includes reducing the intensity differences between the proposed method and the neural network estimates. As a result, the neural network can carry out the same transformation using the restore methodology. The refurbishment method used to train however appears to require a depth map and a complete dataset of images, and only one image must be used in the neural network.

## IV. Results and Discussion

There have been two experiments to assess the accuracy of neural network estimates. In the first case, all the datasets were used for training and evaluation using the test images. Nevertheless, this is not really a real scenario because training images are usually not available at the treatment site. This is why the current study approximates the above circumstance preparing for only yet another dataset used for system validation. In order to assess the accuracy of the neural network predictions, the images are improved by two common techniques and compared to the approach proposed. The first, contrast enhancement, investigates the processed image histogram and moves it to adopt the optimal material. The contrast enhancement most frequently used in this paper changes the image features to a normal distribution of each channel. The second algorithm to be compared is an Automatic Color Enhancement, as mentioned in literatures and also shown in underwater environments. This technique improves the image on the basis of a simple human visual system model, inspired by specific methodologies such as grey world evolution, white picking, transverse inactivation and application based adaptation. This technique's main disadvantage is that it is computationally expensive, with a Geforce 960GTX requiring an image of about 1.5 seconds in an i5 with an image of about 0.013 seconds. The following table, Table-3 shows the performance analysis estimation ratio based on perceptual Quality due to scattering of light with the training samples.

TABLE-3: PERFORMANCE ESTIMATION

| | SVM | CNN |
|---|---|---|
| True Positive | 50 | 78 |
| False Positive | 8 | 4 |
| False Negative | 10 | 5 |

The following table, Table-4 illustrates the accuracy level estimations of the proposed approach in comparison with the classical model Support Vector Machine.

TABLE-4: ACCURACY LEVEL ESTIMATION

| Algorithm | Accuracy Ratio (%) |
|---|---|
| SVM | 86.20 |
| CNN | 95.12 |

The following figure, Fig-2 illustrates the processing accuracy levels of the proposed approach in comparison with the classical SVM logic.

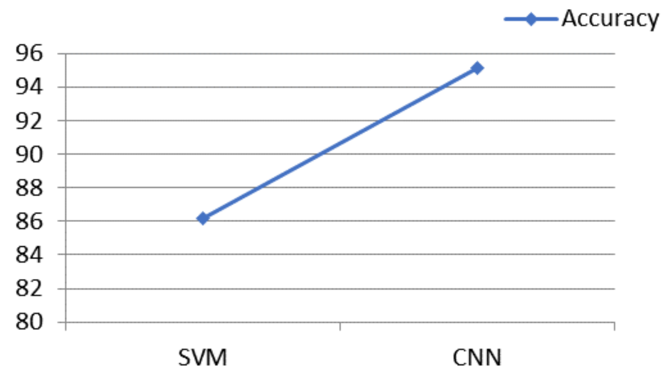


Fig.2 Accuracy Level Estimations

The following figure, Fig-3 illustrates the performance analysis estimation ratio based on perceptual Quality due to scattering of light with the training samples of 40 images.

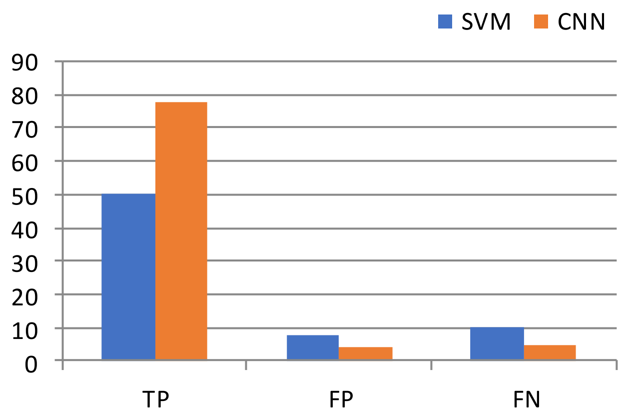


Fig.3 Performance Estimations

The following figure, Fig-4 illustrates the estimation ratio of True Positive rates of the proposed approach, in which it is cross validated with the existing SVM approach.

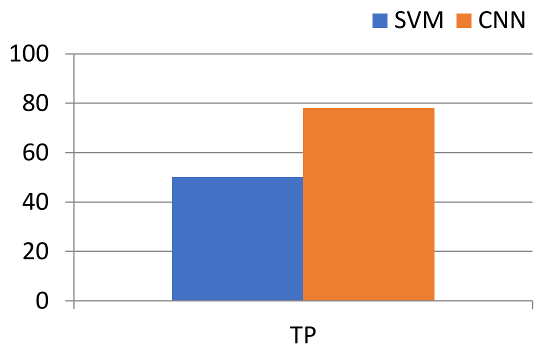


Fig.4 True Positive Rate Estimation of Proposed CNN and Existing SVM Algorithms

The following figure, Fig-5 illustrates the view of resultant image acquired form MATLAB simulation tool for underwater image enhancements, in which it process the image based on several pre-professing metrics and provide the final outcome like the following figure. The given input image was enhanced twice and adaptive histogram equalization performed to obtain the enhanced output image.

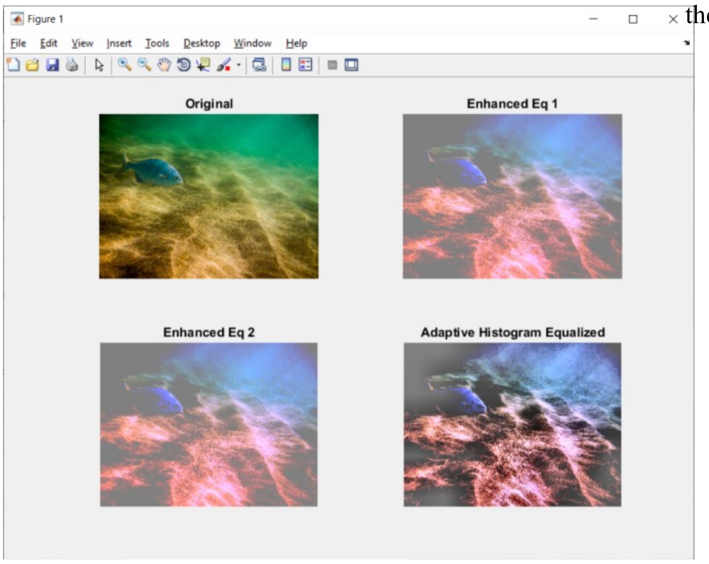


Fig.5 Resultant Perception

The following table, Table-5 and Table-6 illustrates the clear view of the proposed approach descriptive analysis as well as the resulting accuracy level estimations in terms of mean, standard deviation, error rates and so on in clear manner with maximum and minimum range specifications. In which these values are estimated based on the mean ratio of 95% confidence interval.

TABLE-5: DESCRIPTIVE ANALYSIS

| | N | Mean | SD | SE | LB | UB | Mi | Ma |
|---|---|---|---|---|---|---|---|---|
| **SVM** | 20 | 84 | 2.0 | 0.44 | 83 | 85 | 80 | 87.23 |
| **CNN** | 20 | 74 | 6.5 | 1.45 | 71 | 77 | 61 | 88.37 |
| **Total** | 40 | 79 | 6.8 | 1.08 | 77 | 81 | 61 | 88.37 |

Where SD indicates the Standard Deviation, SE indicates the Standard Error Rate, LB and UB indicates the Lower and Upper Bounds, Mi indicate the Minimum Ratio and Ma indicates the Maximum ratio.

TABLE-6: SIGNIFICANT ANALYSIS

| | SoS | DF | MS | F | Sig. |
|---|---|---|---|---|---|
| **Between Groups** | 941.57 | 1 | 941.57 | 40.512 | <0.001 |
| **Within Groups** | 883.18 | 38 | 23.24 | | |
| **Total** | 1824.7 | 39 | | | |

Proposed algorithm attained significant value $p<0.05$ from the SPSS analysis tool. Where SoS indicates the Sum of Squares, MS indicates the Mean Square.

The resulting units obtained from MATLAB is applied to the software testing tool designed by IBM called Statistical Package for the Social Sciences (SPSS) and attain the significant accuracy ratio, in which it is clearly specified with the graphical representations over the following figure, Fig-6.

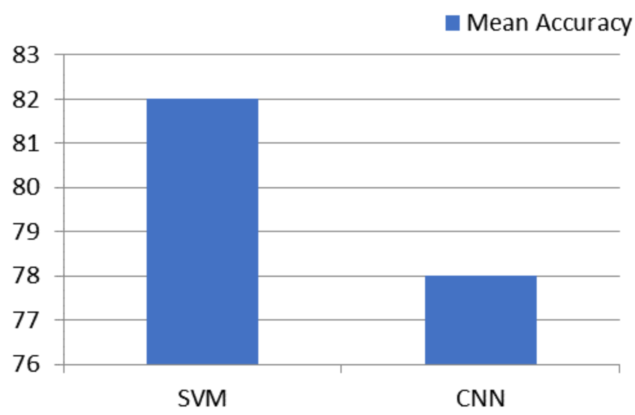


Fig.6 Comparison graph for Mean Accuracy

## V. CONCLUSION AND FUTURESCOPE

In this work, a novel Deep Learning approach Convolutional neural network is implemented for image dehazing, in which it is implemented in this piece in actual time and especially in comparison with classical SVM algorithm to prove the efficiency of the proposed approach. Only certain reconstruction algorithms are used to train the system and contain some many contributions so as to really be difficult to approximate mostly during interference. Once the framework is trained, however, it can properly unravel images in real-time with a core image as an contribution. The outcome process that the method can simplify and learn to dehaze images from a place and use them in a different location. The resulting performance estimations are clearly proved via the graphical results shown in resulting section as well as the proposed approach of CNN is far better than the classical SVM logic. Statistical analysis also performed, the results shows that the proposed algorithm perform well compare to the existing method and attained significant value $p<0.05$

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