FOREX Publication
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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 4 | Pages 932-938 | e-ISSN: 2347-470X

# An Adaptive Technique for Underwater Image Enhancement with CNN and Ensemble Classifier

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**ABSTRACT-** Image Restoration is a significant phase to process images for their enhancement. Underwater photographs are subject to quality issues such as blurry photos, poor contrast, uneven lighting, etc. Image processing is crucial in the processing of these degraded images. This research introduced an ensemble-based classifier based on the bagging approach to enhance UW images. The support vector machine and random forest classifiers serve as the ensemble classifier's main classifiers. Additionally, to complement the feature optimization technique, the proposed ensemble classifier leverages particle swarm optimization. The feature selection method for the classifier is improved by the feature optimization process. To validate results, underwater images are collected by the Kaggle repository. In this process, Extreme Learning (EL) and Convolution Neural Network (CNN) are compared with suggested algorithms. The simulation results indicate that the proposed algorithm outperformed the existing work.

**General Terms:** Underwater Images, Classification, Image Restoration.
**Keywords:** Image Enhancement, CNN, Ensemble Classifier.

**ARTICLE INFORMATION**
**Author(s)**: Yogesh K. Gupta, Khushboo Saxena;
**Received:** 14/06/2022; **Accepted**: 30/08/2022; **Published**: 10/11/2022;
**E- ISSN:** 2347-470X;
**Paper Id:** IJEER220617;
**Citation:** 10.37391/IJEER.100430
**Webpage-link:**
https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100430.html

**Publisher's Note:** FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

## 1. INTRODUCTION

Computer vision accepts a huge part in legitimate assessment, resource examination, and other submerged applications. Regardless, it encounters the outrageous concealing bending, which is achieved by the scattering and maintenance of light in the water. In this paper, a hybrid submerged picture system is proposed to get the educational assortment including concealing ruined pictures and relating ground truth [1-3]. Due to the scattering and weakening of light into the water, the submerged picture appears with concealing bending, clouded nuances, and low separation. To determine these issues, a sharp two-stage submerged picture convolutional neural net (CNN) along with structure decomposition is taken into account for submerged picture improvement. Specifically, the rough submerged picture is rotted into high-repeat and low-repeat reliant upon theoretical examination of the submerged imaging [4-7]. To additionally work on the brilliance and differentiation of submerged pictures, a histogram extending calculation in light of the red channel is given [9,13]. To confirm the effectiveness of the proposed combination calculation, trial submerged pictures are treated. Results show that the nature of submerged pictures is improved essentially, both in terms of abstract special visualization and objective assessment [11].

In this paper, submerged picture handling methodology is proposed with additionally contrasted and a few well-known procedures. Examination results show the upside of the proposed methodology over others [9]. Despite the fact that many researchers have made progress with regard to various sonar images, there is still plenty of room to optimize the solution or improve the overall picture quality because each calculation has a cap in that the goal of the actual image is corrupted or the picture of the article is difficult to remove clamor [13].

(a) (b)
**Figure 1**: Submerge picture before & after processing

*Figure 1* presents the *(a)* submerged haze picture (the first caught picture) and *(b)* submerged picture (handling of the methodology). The caught submerged pictures experience the ill effects of shading cast and murkiness impact brought about by assimilation and dispersing. Most existing learning-based techniques for submerged picture improvement (UIE) treats the corrupted cycle overall and overlook the association between shading rectification and de-hazing. Along these lines, they frequently get unnatural outcomes. To this end, we propose a clever hybrid method to enhance the after-effects of shading adjustment and de-hazing in numerous emphases [14]. The combination of put-together strategies centers on the weighted mix of numerous pictures in light of the necessary highlights from those specific pictures. Besides, combination-based strategies require less time when contrasted with advancement-based or learning-based methodologies [15].

This paper is organized into six sections, the first section provides an introduction, the second chapter provides the imaging model in the underwater scenario, the third section focuses on the literature survey or background, the fourth section provides the proposed methodology and the fifth and sixth section presents the simulation results and conclusion of the research work respectively.

## 2. IMAGING MODEL IN THE UNDERWATER SCENARIO

Light is scattered and absorbed as it passes through water. Different wavelengths of light are absorbed in water in different ways. When submerged, Red light attenuates the quickest and vanishes at a depth of about 5 m. Blue and Green light attenuates more slowly, while blue light vanishes at a depth of around 60 m.
Three components can be used to model an underwater image taken by a camera: the direct component, which represents the light reflected by the object; the forward scattering, which causes the light to diverge from its original direction of propagation; and the backward scattering, which is made up of the light reflected by particles between the object and camera. The characteristics of the medium, the light, and the polarization all have an impact on the scattering process. Figure 2 shows the Imaging model in the underwater scenario [3].

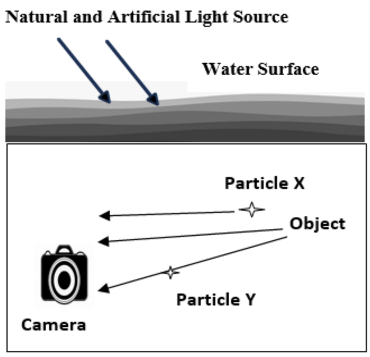


**Figure 2:** Underwater Imaging Model [3]

According to a model for underwater imaging, the direct, forward scatter, and backscattered components of the total illuminance that enters the camera are superimposed linearly.

$$I_r = I_{dir} + I_{fwd} + I_{back} \quad \dots\dots\dots\dots (1)$$

The components of direct irradiation, forward scattering, and backscattering are represented in *equation 1* by $I_{dir}$, $I_{fwd}$, and $I_{back}$ respectively.

Underwater captured images typically appear blue-green and have an apparent fog-like quality because water bodies absorb and scatter incident light. Low contrast, color fidelity, restricted visual range, hazy details, and increased noise are also predetermined issues that lower the quality of underwater images. The perception of human eyes is incompatible with low-quality images. The vision enhancement technique efficiently addresses the above issues in the original underwater hazy images. For future visual tasks, enhanced pictures are advantageous since they enhance visual perception. Many researchers have published their work on underwater image enhancement and restoration. New techniques, particularly those based on deep learning algorithms, must be updated over time to generate better quality pictures. This research paper intents to encompass related deep learning methodologies to focus on underwater enhancement and restoration and proposed an adaptive technique for Underwater Image Enhancement with CNN and Ensemble Classifier.

## 3. LITERATURE SURVEY

D. Estrada et al. present, a technique for mimicking degraded information for preparing likewise introduced. This LiDAR strategy was approved utilizing LiDAR information caught by the UMSLI framework inside Florida Atlantic College's Harbor Branch Oceanographic Organization (FAU-HBOI) optical test office and at the Marine and Beach front Exploration Lab impediment at the Pacific Northwest Public Research facility (MCRL-PNNL). This picture improvement method can be promptly stretched out to other submerged LiDAR frameworks [1].

Kai Hu et al. evaluate the underwater picture imaging concept, the causes of the images' deterioration in quality, and provide a basic classification of the many practices now in use. It also emphasizes the widely used deep learning technology for improving underwater image quality. Additionally, it introduces several common video image assessment indexes, underwater picture-specific indexes, and standard underwater data sets. Finally, this study considers potential future improvements in this field, including improved robustness and adaptability, creating a dataset of underwater photographs that is more extensive. the underwater video and picture quality assessment system should be improved, and Boost study on underwater video enhancing technology and real-time performance [2].

M.L. Thariq Hussan et al. combined real-time object detection and recognition with suitable deep learning methods dedicated to visually challenged users. Deep Neural Networks were utilized to predict the items, and Google's renowned Text-To-Speech (GTTS) API module was used for the predicted voice output, all while the image and video processing algorithms were created to take real-time inputs from the camera. By comparing precision and frame rate, the experiment outcomes of CNN, SVM, YOLO2, and YOLO3 were compared. Yolo3 outperformed the competition with a maximum of 18 frames per second and a precision that is 46.8% greater than the competition. With a portable solution, it will make mobility and object identification less of a problem without requiring the user to bring any more gadgets specifically for it [4].

M Rahul et al. introduced a hybrid approach to recognize emotion from different facial images with a pose, occlusion, and illumination. This model can label each of the publicly accessible datasets like EMOTIC, FER13, and FERG with high accuracy and decent outcomes with fewer training datasets. In

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comparison to the accuracy of the FERG and EMOTIC datasets, which are 68.10% and 72.64 respectively, the hybrid model's performance for the FER13 dataset is best, at 94.8% [5].

K. Wang et al. proposed a joint framework to together enhance shading rectification and dehazing. By gaining change coefficients from dehazing highlights, shading elements and essential elements of crude pictures are continuously refined, which keeps up with shading adjusted during the dehazing system and further develops the clearness of pictures. Test results show that our organization is better than the current cutting-edge approaches for UIE and gives further developed execution to submerged article identification [8].

W. Luo et al. shows that the nature of submerged pictures is improved essentially, both in term of abstract special visualization and objective assessment. The proposed submerged picture handling procedure is likewise contrasted and a few well-known methods. Examination results demonstrate the benefit of the proposed methodology over others [9].

AS. Bhadoria et al. proposed an improved single haze removal technique with a weighted median (WM) filter and gaussian-Laplacian. Different kernel sizes of the gaussian and laplacian filters are used to weight each point in the filter window image. The haze-free outdoor photos are statistically represented by the dark channel prior; this model directly calculates the haze thickness and recovers a high-quality haze-free image [10].

S. Dhar et al. the proposed network is interpretable as in crafted by the four capacities are effectively justifiable and they can proficiently upgrade a different piece of a submerged picture. The CNNs are utilized to tune the boundaries of the capacities relying upon the preparation information. The exhibition of the proposed technique is very proficient in contrasted with the late distributed strategies on standard datasets [11].

S. Song et al. present the pre-prepared model to recognize UW creatures. It is a hybrid method to merge MSRCR and Mask R-CNN to achieve a mean average precision of more than 90%. The proposed model emphasis on three steps, first to take 84 augmented enhanced images by MSRC, the second step is pre-examined on COCO dataset to reduce training time and the third step to transport UW dataset [12].

A. S. Parihar et al., present a point-by-point examination of picture improvement methods given multi-combination. It gives an understanding of the calculation utilized in every strategy, alongside its execution structure. At long last, an examination is drawn between the different methods in light of different boundaries [13].

J. Kim et al. performed sonar picture sound diminution with the auto-encoder calculation in light of convolutional neural organization, which as of late has been standing out. With the calculation, they acquired sonar pictures of predominant quality with just a solitary picture. In this paper, researchers use a huge load of sonar pictures in a neural organization of auto-encoder constructions, and afterward, they could get the outcomes by infusing the first sonar pictures [14].

J. Kim et al. applied the advanced method to the object-location calculation to the specialist vehicle framework. The quick item discovery calculation given neural organization can satisfy the continuous location and show momentous legitimacy. It implies the submerged robot can start the route under its input. Through experience, the proposed technique can distinguish and follow the specialist in the progressive sonar pictures [15].

X. Cao et al. present an original profound learning system for submerged target characterization. In the first place, rather than separating highlights depending on master information, autoencoder (AE) is used to gain invariant elements from the phantom information of submerged targets. Second, stacked autoencoder (SAE) is utilized to get significant level elements as a profound learning strategy. Finally, the joint of SAE and SoftMax is proposed to characterize the submerged targets [16].

H. Berg et al. described four conventional AI calculations on sonar information with a high measure of incorrect alarms problems along with manufactured submarine reverberations. It is shown that a portion of the calculations can beat straightforward sign to commotion proportion (SNR) thresholding by a critical sum, yet that the presentation is profoundly reliant upon the boundary values picked for every calculation. These boundaries are in this manner explored to decide their relative importance [17].

M. Chuang et al. present, an unaided bunching approach that creates a paired class-ordered progression, where every hub is a classifier. To take advantage of data from questionable pictures, the thought of fractional characterization is acquainted with allocating coarse names by enhancing the advantage of hesitation made by the classifier. Tests show that the proposed structure accomplishes high exactness on both public and self-gathered submerged fish pictures with high vulnerability and class irregularity [18].

Diya Dong et al. present a smooth and safe way at a very quick speed of predicting underwater images. Initial a Voronoi preprocessor is utilized to make the mark of obstacles in the way and produce a harsh way associating the underlying and the objective positions. Because of the property of nonlinear isolating surface as well as quick learning speed, ELM is then applied to recover and smooth the way to guarantee that the vehicle drives consequently and securely. Related tests likewise approve the presentation of our proposed technique true to form. More investigation and a few potential limits are likewise talked about [19].

H. Qin et al. described NEPTUNE and VENUS as cabled observatories to offer every minute of everyday presence, bringing about phenomenal volumes of visual information. The examination of submerged symbolism forces a progression of remarkable difficulties, which should be handled by the PC vision local area in a joint effort with scholars and sea researchers. In this paper, we present how profound learning, the cutting-edge AI method, can help submerged symbolism understanding at the time of enormous information [20].

Tingting Sun et al. present the most commonplace and normal strategy for RL utilized in applications is Q realizing, which can produce the legitimate approach for AUV control. Also, RELM is proposed as an adjustment of ELM, which can ensure the speculation execution and work with persistent states and activities. The enactment results have shown that AUV effectively tracks and follows the moving objective by the proposed technique [21].

A. Carrera et al. present an analysis of various techniques and relying upon the assessed water flow; independently duplicates a consolidated system to play out the assignment. The p-LbD calculation as well as transaction with the other modules assists in the proposed system. It also presents outcomes on a free-drifting valve turning task, utilizing the Girona 500 I-AUV furnished with a controller and a modified end-effector. They got results showing the attainability of the p-LbD calculation to perform independent mediation errands consolidating the learned procedures relying upon the climate conditions [22].

Y. Tan et al. present a challenge to rescue quantitative data from the pictures produced from these cycles, especially for the discovery and extraction of data on the articles inside these pictures. This paper proposed a calculation for programmed recognition of submerged objects in side-examine pictures in light of AI utilizing versatile support. Exploratory outcomes show that the technique produces steady guides of the ocean bottom [23].

J. Osaka et al. achieve this Research and development objective, situating AUV precisely is required, so they are attempting to foster the procedure which limits the mistake of situating, utilizing an independent surface vehicle (ASV) that tracks AUV and studying its outright situation by really short-benchmark (SSBL) strategy. Being developed of following ASV, it is critical to foster the controlling algorism which orders ASV to guide steadily and control satisfactorily its speed as indicated by the aftereffect of SSBL situating of the AUV [24].

C. Spampinato et al. present a programmed framework for the ID of anomalous fish removed by handling submerged film. Our methodology takes advantage of HMM to address and analyze directions. Multi-faceted Scaling (MDS) is applied to extend the directions onto a low-layered vector space while saving the similitude between the first information. Regular or ordinary occasions are then characterized as a set of directions grouped, on which well are prepared and used to check whether another direction matches one of the typical occasions, or can be named as abnormal [25].

M. L. Seto et al. approved specialist is particularly successful for the situation read up for an energy deficiency coming about because of expanding the overviewed region by a component of 2, for a variable of 2 drop in energy. A specialist that successfully screens and rethinks ideal missions with energy contemplations, particularly for side sweep sonars, is very novel and expands the functional choices of AUVs on lengthy organizations [26].

S. Fefilatyev et al. present a classifier on the information acquired during one of the main explorations travels to the site of the deep-water skyline oil slick. Suspected oil drops were outwardly recognized in SIPPER pictures by a specialist. The characterization precision of the speculated oil drops is accounted for and examined. This methodology dependably observes oil when it is available. It additionally orders a few particles (air pockets and some marine snow), up to 3.3%, as oil in clear water [27].

## 4. PROPOSED METHODOLOGY

The process of the proposed algorithm is shown in figure 3. The proposed algorithm is described in two sections, 1st section describes the process of underwater image-based feature extraction and feature optimization using particle swarm optimization [1], and 2nd section proposes an ensemble-based classifier.

Feature extraction is the primary phase of underwater image enhancement. The discrete wavelet transform applies for the extraction of texture features of the images dataset and after feature extraction preserved the coefficient in detail and after that process, the low-frequency layers are approximated. The estimated feature coefficients of the underwater images are in equations 2 and 3. The coefficient of features is estimated as the mean and standard deviation of underwater images.

Let {F1, F2, F3……., FN} be the level of low frequency as level 1, 2………………., N.

The estimation of the mean as

$$\mu = \frac{\sum_{i=1}^{N} Fi}{N} \dots\dots\dots\dots.(2)$$

The estimation of standard deviation as

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (Fi-\mu)^2}{N}} \dots\dots\dots\dots..(3)$$

The extracted features in terms of horizontal, vertical, and diagonal coefficients combined and form a matrix are called the feature matrix of images [12]. This feature matrix further process for the optimization is called feature optimization process, feature optimization process increases the selection possibility of the relevant feature of underwater Image. The applied optimization algorithm is PSO [13].

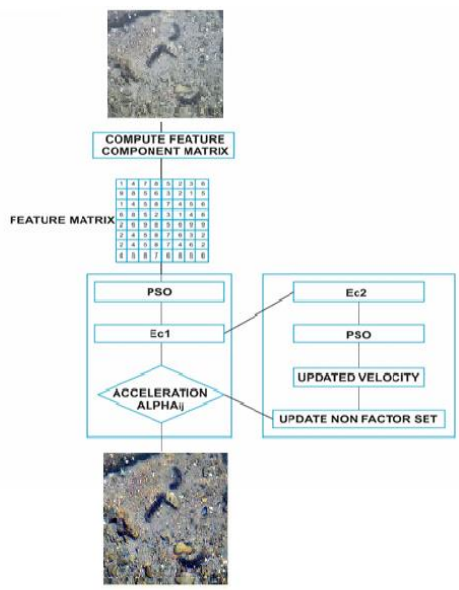


**Figure 3:** Work Process of the proposed algorithm

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Here is a description of the feature optimization procedure.

Consider the particle of features $x_1, x_2, x_3, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots x_n$ and level of features as $y_1, y_2, y_3, \ldots\ldots\ldots\ldots\ldots y_n$.

The relation between the symmetric features as

$$Su\,(xi, yi) = 2\frac{H(xi) - H(\frac{xi}{yi})}{H(xi) + H(yi)} \quad \ldots\ldots\ldots\ldots (4)$$

Now estimate the probability of optimization feature selection as

$$Pi = \frac{Su(xi, yi)}{max_{j=1\ldots\ldots D}\,(Su(xj, y))} \quad \ldots\ldots\ldots\ldots\ldots (5)$$

The process of the optimization algorithm

1. R is a random number with a range [0,1]
2. D1 is a set of remaining features after the optimization process
3. Measure the selection possibility of features using equation (4)
4. For i=1:H do
5. Form the level of H1 particle
6. For j=1: D1 do
7. Form the level of D1-
8. If Pj>rand then
9. Xij=1;
10. Else
11. Xij=0
12. End if
13. End for
14. End for

The proposed ensemble classifier is using the random forest as an optimal feature selection for the main classifier support vector machine. The random forest classifier collects the optimal features of the underwater image dataset and maps these features in space of the support vector machine [14]. The random forest classifier (RF) gives the weight value of each feature and is mapped with support vectors. The description of algorithm describes as

RF – Random Forest
SV- Support Vector
Wi – Weight of optimal features [i=1,2, 3, n]
Yi= Mapped feature space
EC1- Ensemble 1
EC2 – Ensemble 2

The dataset is divided into two different parts, one for the training and another for the testing phase. The training part consists of 70% image data and the testing part consists of 30% of the image data. The system learns from the training image and performs in the testing image. The performance parameters can be calculated using the standard formulas.

## 5. SIMULATION ANALYSIS

This section validates the proposed ensemble classifier for the detection of underwater details using python 3.7.

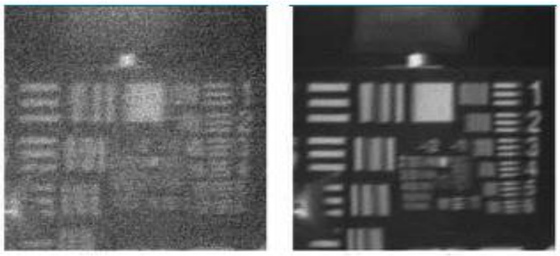
The performance matrix measures the value of prediction in terms of true positive (TP), true negative (TN), false negative (FN), and false positive (FP).

$$Sens = \frac{TP}{TP + FN} \times 100 \quad \ldots\ldots\ldots\ldots\ldots (6)$$

$$Spec = \frac{TN}{TN + FP} \times 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

$$Accu = \frac{TP + TN}{TP + TN + FN + FP} \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

*Table 1* shows simulation results with *dataset-1* (The Brackish *Dataset*: Bounding box annotated underwater image dataset) [28] in terms of accuracy, sensitivity, and specificity [17]. For this evaluation, the dataset is taken from the Kaggle machine learning website, and the enhanced value indicates better results. These results are also compared with existing methods such as EL and CNN. A few underwater photographs are provided in the first row of *figures 4-6* together with the findings produced using the approaches mentioned such as EL and CNN for comparison in order to qualitatively evaluate the proposed method.



(a) (b)
**Figure 4**: (a) Input Image (b) Recovered Image [1]

(a) (b)
**Figure 5**: (a) Input Image (b) Recovered Image [9]

(a) (b)
**Figure 6**: (a) Input Image (b) Recovered Image [11]

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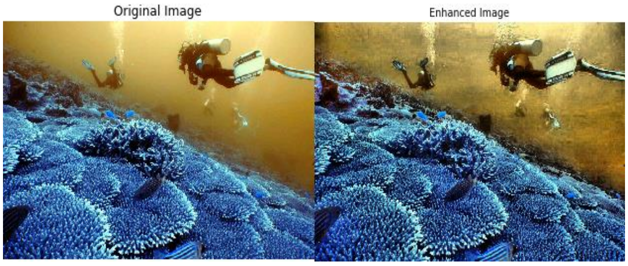
*Figure 7* is showing the original underwater image or input image for the proposed enhancement processing.




(a) (b)

**Figure 7**: (a) Input Image (b) Recovered Image from the proposed method

### Table 1: Simulation Results-I

| Algorithms | Accuracy (%) | Error rate (%) | Sensitivity (%) | Specificity (%) |
|---|---|---|---|---|
| EL [1,9] | 90.2 | 9.8 | 89.6 | 93.4 |
| CNN [11] | 93.7 | 6.3 | 89.5 | 91.6 |
| Proposed | 94.2 | 5.8 | 90.7 | 90.3 |

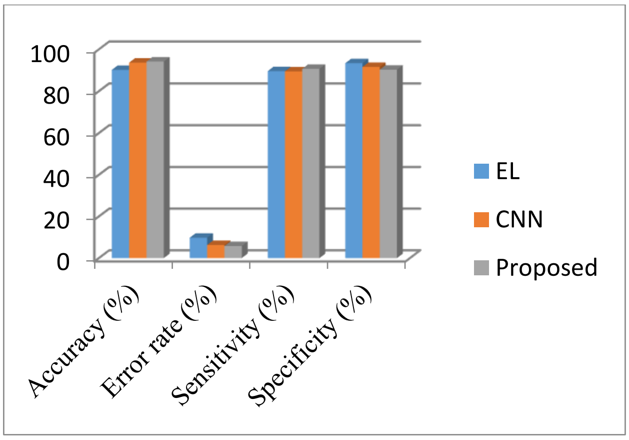
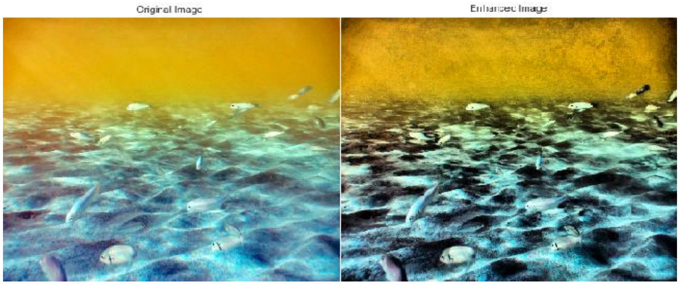



**Figure 6**: Result Comparison-I

*Figure 6* analyzed the results of dataset-1 in terms of calculated parameters, results show the improvement in accuracy and other instead of EL and CNN.

*Table 2* shows an analysis of the proposed algorithm done with dataset 2 (Learning to Sea: Underwater image Enhancement + EDA) [29] and existing algorithms EL, and CNN. Enhancing the value of parameters indicates better results in terms of accuracy, error rate, sensitivity, and specificity. To subjectively assess the suggested method, a few underwater images are supplied in the second row of *figures 4-6* along with the results generated using the indicated approaches, such as EL and CNN.

*Figure 8* is showing the enhanced image underwater image after the proposed enhancement processing.




(a) (b)

Figure 8: (a) Input Image (b) Recovered Image from the proposed method

### Table 2: Simulation Results-II

| Algorithms | Accuracy (%) | Error rate (%) | Sensitivity (%) | Specificity (%) |
|---|---|---|---|---|
| EL[1,9] | 91.5 | 8.5 | 91.3 | 91.2 |
| CNN[11] | 93.7 | 6.3 | 93.5 | 92.5 |
| Proposed | 94.2 | 5.8 | 94.3 | 90.4 |

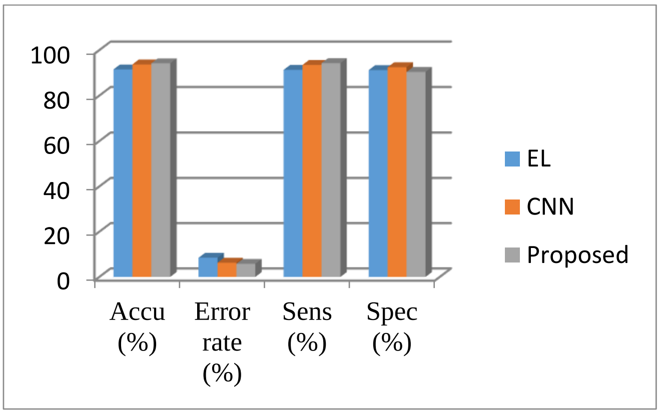



**Figure 9**: Result Comparison -II

*Figure 9* analyzed the results of dataset-2 in terms of calculated parameters, results show the improvement in accuracy and other instead of EL and CNN. Therefore, it is clear from the simulation results and discussion, that the novelty of the proposed algorithm is established and comparing it with existing work.

## 6. CONCLUSION AND FUTURE WORK

The proposed ensemble-based classifier applies for the enhancement of underwater images. It uses an SVM and RF classifier; in this RF classifier works as the optimal feature selector of image datasets. The particle swarm optimization reduces irrelevant samples of features and increases the classification algorithm's detection ratio. The proposed algorithm has two segments. 1st segment describes the feature extraction and optimization of extracted features and 2nd segment proposed an ensemble-based classifier. The comparative study of existing algorithms mentions in *Tables 1 and 2*. In the future, the hybrid techniques based on the deep learning algorithm will be implemented with significant improvement of the performance parameters and can derive multiple feature point selection algorithms for more enhancement and restoration of the underwater image.

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