PAPER DETAILS

TITLE: The Impact of Image Enhancement and Transfer Learning Techniques on Marine Habitat

Mapping

AUTHORS: Ehab SHAKER,Mohammed Rashad BAKER,Zuhair MAHMOOD

PAGES: 592-606

ORIGINAL PDF URL: https://dergipark.org.tr/tr/download/article-file/1886932

The Impact of Image Enhancement and Transfer Learning Techniques on Marine Habitat Mapping

Ehab Hashim SHAKER[1] [iD] , Mohammed Rashad BAKER[2, *] [iD] , Zuhair Norii MAHMOOD[3] [iD]

[1]Ministry of Education General Director of Education, Kirkuk, Iraq.
[2]Department of Computer Techniques Engineering, College of Information Technology, Imam Ja'afar Al-Sadiq University, Baghdad, Iraq.
[3]Department of Computer Science, College of Computer Science and Information Technology, Anbar University, Anbar, Iraq.

Highlights
• This article investigates the impact of image enhancement and DCNN on marine habitat mapping.
• Various image enhancement techniques have been tested, and CLAHE stands out the most.
• DenseNet-169 and MobileNet as two different Neural Network models applied for classification.
• Overall, DenseNet-169 with CLAHE method had the highest accuracy across all four datasets examined.

Abstract

Marine habitat mapping is primarily done to monitor and preserve underwater ecosystems. Images captured in a marine environment suffer from acidification, pollutions, waste chemicals, and lighting conditions. Human beings are progressing fast in terms of technology and are also responsible for the degradations of ecosystems, both marine and land habitats. Marine biologists possess a lot of data for the underwater environment, but it is hard to analyze, and the task becomes tiresome. Automating this process would help marine biologists quickly monitor the environment and preserve it. Our research focuses on coral reef classification and two critical aspects, i.e., Image enhancement and recognition of coral reefs. Image enhancement plays an essential role in marine habitat mapping because of the environment in which images are taken. The literature contains many image enhancement techniques for underwater. The authors want to determine whether a single image enhancement technique is suitable for coral reefs. Four image enhancement techniques based on an extensive literature review are selected. We have used DenseNet-169 and MobileNet for image classification. It has been reported that DenseNet-169 has excellent results for coral reefs classification. Histogram techniques combined with DenseNet-169 for classification resulted in higher classification rates.

1. INTRODUCTION

Ecosystem-based management (EBM) approach manages the entire ecosystem. EBM includes human beings in decisions regarding resource management and real interaction within the ecosystem. Large oceans and ecosystems use EBM that considers the overall impacts of marine ecosystems due to the challenges faced by the environment.

In ecology, a habitat is an underwater ecosystem in which organisms' dwell. Habitats protect organisms from predators, provide food, and help them reproduce. Habitat consists of both physical and biological characteristics. There are two types of habitats: terrestrial and marine. For example, swamps, forests, and lakes are habitats [1]. As human activity increases, marine ecosystems deteriorate and are damaged, which we have only recently identified. Therefore, habitat mapping is used to assess the health of maritime ecosystems and their current distribution. A habitat map illustrates the geographic distribution of habitats throughout time, assisting marine scientists in evaluating the strength of locales and developing a strategy for their preservation [2]. Habitats mapping supports the EBM directly and plays a massive role in assessing ecosystems. Marine habitat mapping is the first step in conducting domestic and international waters surveys. On the other hand, individual habitat mapping projects are not frequently associated with EBM.

*Corresponding author, e-mail: mohammed.rashad@sadiq.edu.iq

Marine habitat mapping is typically done using underwater imagery. However, it suffers from image quality degradation due to factors, such as haziness of water, marine litter, the stableness of the equipment during the image time to prevent blurriness, to name a few. Underwater and Aerial imagery are cost-effective measures for underwater objects monitoring their health, type, abundance and distribution [1]. Due to their proximity to the target throughout the image capture process, they achieve a higher spatial resolution than other technologies, such as airborne and boat-based sensors. The indicator of species diversity is computed using underwater images [3]. Coral colony growth and destruction caused by bleaching or illness can be tracked over time.

Humankind is constantly changing the earth's surface and ecosystems. This process is not new - it has been happening for a long – however, it has drastically reached a dangerous level recently. Consistent destruction of the planet, ecosystems, and environment are at the top of all the things being the victim of humankind. Marine habitats are still at risk on a local scale. Overfishing, marine garbage, anchoring, and divers are only a few concerns. In addition, global concerns are causing havoc on these delicate ecosystems. These risks include ocean acidity, climate change, etc. All these threats and consistent activities from humankind result in the demolishment of ecosystems.

The proposed research work focuses on coral reefs marine habitat ecosystem. Coral reefs, primarily found in clean and shallow water, are the essential ecosystems for marine life and human beings. A recent survey showed that 40% of coral reefs are being threatened. Thus a direct result of climate change, air and water pollution and change in oceans' temperatures [4]. Coral reefs have an extensive taxonomy and are regularly updated as more information is obtained. The European Nature Information System (EUNIS) is a standard where the taxonomy of habitats is mapped and assigned to species. In addition, the site data is maintained to support management decisions such as protected area design under the Natura 2000 programme of the European Commission. Coral reefs provide beauty to the ocean. They minimize the effects of hurricanes on shorelines and provide tourism opportunities to approximately 500M people. Coral reefs are also used in the treatment of cancer and other diseases. The coral reef covers just 2% of the seabed and provides shelter to about 30% of marine organisms. These organisms live and die by the coral reef, and their relations are inseparable [5]. Coral reefs provide wide biological diversity and are also referred to as rainforests of the sea [6].

Due to the vast hierarchical taxonomy of habitats, the classification of coral reefs is a tiresome task. In addition, the same external similarities of coral reefs and different internal characteristics make the classification task even harder for marine biologists. Automation of this process would require little effort from marine biologists, and they can keep their focus on the main problem. The literature work on coral reef classification focuses on automating the task. However, no single approach exists among researchers who concentrate on image quality loss due to the marine environment and using state-of-the-art deep neural network features. Deep learning has recently taken over the attention of researchers due to big surges in the automation process, such as visual recognition and detection. Deep learning applications are critical in modern life. Ecosystems are not immune to this wave of deep learning across all domains. Global concerns such as environmental degradation, climate change, and growing demand for ecosystem services necessitate improved ecological forecasting. Recent advances in data availability, process comprehension, and computer capacity have increased the focus on ecosystems in deep learning [1,5,6].

The purpose of this manuscript is to focus on coral reef classification adhering to the EBM context. Underwater imagery suffers quality loss and obfuscation by marine species and litter. The objectives of this research work are as follows:

- Image enhancement and restoration techniques play an essential role in classifying marine things. Coral reefs are no exception; the coral reefs' environment may contain other species and litter during capture. Therefore, the proposed research work targets four publicly available datasets and test various underwater algorithms to test the performance of the approach.
- After conducting the literature (See Section 2), it can be observed that various approaches have not exceeded 90% on large datasets of coral reefs [7,8]. Therefore, the proposed research work also focuses on improving performances by training state-of-the-art deep neural networks from scratch.

This article is organized as follows. In Section 2, we discuss the background study in this field. In Section 3, a description of the proposed methodology is provided. The experimental setup and the results with analysis are described in Section 4. Finally, the discussion and conclusions are placed in Section 5.

2. LITERATURE REVIEW

A marine ecosystem has many zones. Coral reefs, lagoons, and other marine life can be found along the beach. The littoral zone is defined as the area between high and low tides. Invertebrates live in the benthic zone. Fish and other species live in the ocean zone [2]. Habitat mapping is mainly done to assess the health of delicate marine ecosystems. This task is difficult since the images are taken underwater and are prone to image quality loss due to various marine environment factors. Sonar imagery and Camera imagery are used in marine environments, but sonar imagery is costly; hence, camera imagery is used chiefly [9].

Autonomous Underwater Vehicles (AUVs) is mainly used to monitor the marine environment, studying the different parameters (both physical and chemical) to assess the health of endangered ecosystems and species [10]. AUVs perform this task automatically as they have a power source and an intelligent control system. The navigation system of AUVs is more robust in the marine environment than inland environments due to the lack of connected networks. AUVs Imagery is an alternative to towed cameras, trawl nets, and grabs for assessing the marine environment. A workflow towards endurable and renewable marine image analysis using a multi-terabyte deep-sea data set acquired by autonomous underwater vehicles (AUVs) is presented. The proposed data acquisition, curation and management workflow [10].

On the other hand, due to the recent development surges in neural networks, especially Deep Learning (DL), the visual recognition systems achieve excellent performances. Computer vision (CV) has significantly improved the field of object localization and detection [11,12]. Deep learning popularity is attributed to its high-speed parallel computing using graphics processing units (GPUs) that can handle massive volumes of data reliably and build various machine learning algorithms that result in ideal solutions. The applications are widespread, including financial (e.g., revenue forecasting, OCR) [13], business (e.g., discovering insights and trends)[14], medicine (e.g., tumor diagnosis and segmentation, virtual nursing)[15], automation (e.g., robotic A.I., robotic vision)[16], military applications (e.g., estimating missiles trajectory)[17], communications (speech recognition, data encryption and compression)[18] and numerous others [19,20].

Coral reefs classification poses an issue for converging machine learning models [6]. The following cases discuss the nature of marine data: 1) The global habitat structure is not included; 2) There is a high degree of inter-class similarity. 3) The spatial borders are hard to identify between different classes. Most of the literature on coral reef classification employs hand-engineered feature extraction techniques [9-14]. These research works include Scale Invariant Feature Transform (SIFT), Local Binary Pattern (ILDP), Maximum Response (MR) filter bank, RGB histograms, Discrete Wavelet Transforms (DWTs), Octa-angled Pattern for Triangular subregion (OPT) and Color Median Robust Extended Local Binary Pattern (CMRELBP), Co-occurrence CMRELBP (CCMRELBP) and Local Distribution Transform (LDT). In addition, the authors proposed an enhancement technique called Color Channel Stretching (CCS) using LAB color space for enhancement [21–26].

Moreover, the manual feature extraction technique Maximum Response (MR) filter bank and Support Vector Machines (SVM) have obtained an overall accuracy of 74 % on the Moorea Labeled Coral (MLC) dataset [21]. A novel feature extraction technique OPT and a novel classifier named Pulse Coupled Convolutional Neural Network (PCCNN) is proposed in research work. It is faster on coral datasets than CNNs, SVMs and KNNs [24]. Another research suggested CMRELBP and CCMRELBP, two novel feature descriptors, combined with LBP classifier to achieve higher classification rates [25]. A fusion of LDT feature descriptor with rotation invariant LBP and local variance (VAR) features obtained a set of robust-to-noise features. These features can detect uniform and non-uniform patterns. The authors claimed to have outperformed many feature descriptors by achieving higher classification rates [26]. Another fusion method consisting of color histograms, SIFT feature descriptor and Gabor filter response combined with a voting-based classifier for corals and macroalgae achieved satisfactory results [22]. The authors used discrete

wavelet transform combined with KNNs to classify benthic substrates using patches in another effort. The results are promising, but their dataset is too small (16 images) for scalability.

Transfer learning has been employed in [11] to extract features from deep residual neural networks [27] pre-trained on the ImageNet database [28]. The authors extracted features from different layers and combined them to form a feature vector to classify coral reefs. In other efforts [19,29], the authors used the Local-SPP approach for feature extraction using deep neural networks. Local-SPP generates scale-invariant features to represent efficient representation of neighborhood data points. These works targeted the MLC dataset [21] and achieved higher classification rates. VGG [30] have also been used as a feature extractor for the binary classification of coral reefs [31]. In another work from the same authors, sub-categories of coral reefs are classified using combined hand-crafted features and CNN based features. The authors have used the Maximum Response filter bank [21] and SVM to classify coral reefs with excellent accuracy [31].

Necessary adjustments made in an image for better quality, restoration, and analysis are called image enhancement. For instance, an image contrast sharpness is adjusted to make its features enhanced and visible. It is the most common preprocessing step in computer vision applications. Image enhancement needs to be done not to lose critical information in the image. For instance, in medical imagery, contrast is used to increase the quality of an image. Depending on the type of image, color or grayscale, a specific enhancement technique is used. Machine learning and computer vision require high-quality input images to generate meaningful output. However, images are often taken in specific conditions, like images taken in the underwater environment. Therefore, the images need to be preprocessed in machine learning and computer vision algorithms. In general, the image enhancement technique "corrects" an idea for a specific purpose to make it suitable for machine learning and computer vision algorithms [32].

Ocean floor surveys are often conducted using Autonomous Underwater Vehicles (AUVs) equipped with acoustic sensors for enhancing remote sensing. This combination is often used for image and video analysis for short-range operations. However, image and video quality suffer from floating particles in the ocean, causing blur and haze in the captured image [33]. When such quality images and videos are used to train a neural network or machine learning model, this results in lower performances of such models. Thereby, underwater image enhancement is an essential preprocessing step for analysis.

Underwater images by nature have permeability, low contrast, blurry, low divergence and lessening hues [34]. Also, unsupervised digital image color equalization is used [35]. Histogram techniques are also used to increase the quality of an underwater image [36–38]. However, histogram techniques are limited because they over-enhance and under-enhance the input image based on gray levels. Some algorithms also decrease underwater perturbations and increase image quality [39–41].

Adaptive Histogram Equalization (AHE) is a popular technique that focuses on enhancing local information by convolving a kernel sequentially over the image and improving the pixels falling under it. However, higher computation power is required, enhancing the noise locally due to the overlapping effect of kernel convolving [42]. Contrast Limited Adaptive Histogram Equalization (CLAHE) [43] removes the impact of AHE by splitting the image into non-overlapping sections and computing histograms over them. A clip limit is also specified for desired contrast expansion, and a transforming function is used to perform the grayscale mapping. For edge smoothing, bi-linear interpolation is done at the end. However, small ring blobs have emerged at the edges, and over-enhancement at flat regions are expected.

A preprocessing filter is proposed to minimize underwater disturbance and improve image quality. This technique consists of several preprocessing steps containing various filters. However, the contribution of filters is not defined [39]. A fusion technique is proposed to overcome this issue. A weight measure is used for each filter, which considers degraded versions of the image [44].

In an underwater environment, quality is affected by light scattering and absorption, resulting in one color domination in the image. A slide stretching approach [36] begins with contrast stretching to balance the contrast, followed by saturation and intensity pulling of the HSI to disclose the proper color and eliminate

lighting issues. A novel gamma correction is proposed in [45], which increases the overall contrast by decreasing the pixel values at low grayscale, increasing at high and maintaining at middle grayscale.

3. PROPOSED METHODOLOGY

Figure 1 illustrates the proposed strategy. The authors mapped MLC, EILAT, EILAT2, and RSMAS four publicly-accessible habitat datasets. MLC dataset has three variants corresponding to three years in which images are captured in a marine environment.
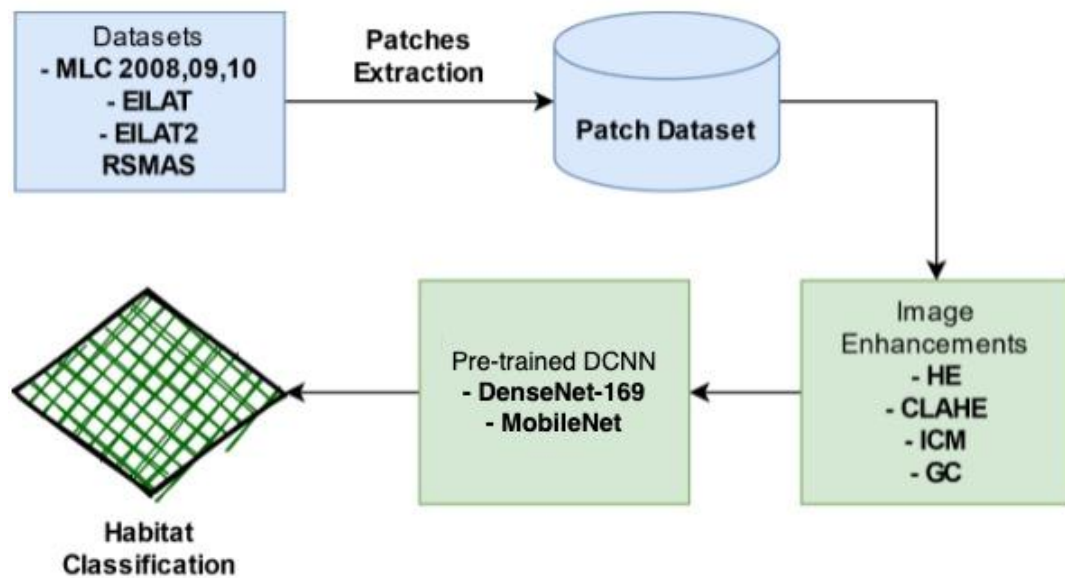

Figure 1. *The Proposed Approach*

The patches are extracted from these datasets based on the ground truth pixel location and its respective label. These patches are extracted from four datasets, resulting in four distinct patches for each dataset. The patches have variant sizes for each dataset, as mentioned in Table 1. The patch-size difference among datasets is due to the nature of coral reefs classes that they represent. Some classes can be easily distinguished, and some classes need more information to be classified. The MLC dataset has the highest image resolution compared to other datasets, as it is the dataset with lower accuracies in the literature [3,11,23]. However, the datasets are different in capturing the environment and the coral reef class they represent. EILAT and EILAT2 are relatively easy for the model to learn compared to the other two datasets, namely, RSMAS and MLC. Image enhancement techniques are applied to all the datasets, resulting in four datasets per single image enhancement algorithm. The proposed approach tackles the habitat mapping issue through pre-trained deep neural networks and training from scratch on Densenet-169 [46]. The output layer neurons are changed according to the number of classes in the dataset.

3.1. Datasets

The relative performance of image-enhancing methods has not been evaluated to the best of the author's knowledge on standard datasets. Therefore, we propose evaluating four datasets (MLC, EILAT, EILAT2, and RSMAS) that depict various demanding scenarios to address this issue. Table 1 summarizes the image datasets used in this study.

Table 1. Datasets Information

Datasets	Number of Classes	Number of Images	Image Resolutions	RGB?
MLC	9	18, 872	312 x 312	Yes
EILAT	8	1,123	64 x 64	Yes
EILAT2	5	303	128 x 128	Yes
RSMAS	14	766	256 x 256	Yes

3.2. Image Enhancement

After carefully conducting the literature review for underwater image enhancement, the authors have used four image enhancement techniques. These techniques include *Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction (GC) and Integrated Color Model (ICM)*.

- Histogram Equalization (HE)

Histogram brings the distribution of discrete intensity levels of an image within the range [0, L-1]. The distribution is a discrete function *h* associated with each intensity level: *rk* the pixel number with this intensity: n_k. Histogram Equalization adjusts the contrast of an image by changing its intensity distribution. Essentially provides a linear trend to the cumulative distribution function (*cdf*) associated with the input image. The *cdf* is a cumulative sum of all the probabilities lying in its domain and defined by:

$$cdf(x) = \sum_{k=-\infty}^{x} P(x). \tag{1}$$

The new image is obtained using the following equations:

$$S_k = (L-1)cdf(x). \tag{2}$$

- Contrast Limited Adaptive Histogram Equalization (CLAHE)

Adaptive histogram equalization (AHE) differs from ordinary HE in that the adaptive method computes several histograms, each belonging to a different section of the image. It uses them to redistribute the lightness values of the image. It is therefore used local contrast enhancement and edges sharpness. However, it tends to over-enhance the noise in homogenous regions of an image. CLAHE is a subclass of adaptive histogram equalization that circumvents this by reducing the amplification. The gradient of the transformation function determines the contrast enhancement in the neighborhood of a pixel value in CLAHE. CLAHE avoids excessive amplification by clipping the histogram at a specified value before computing the CDF. The value, referred to as the clip limit, is based on the histogram's normalization and, thus, the neighborhood region's size. Common values limit the resulting amplification to between 3 and 4.

- Gamma Correction (GC)

Gamma Correction (GC) control the overall brightness of the image. The image that is too dark or bleached out can be changed by varying the amount of gamma parameter. It does not only correct brightness changes but also the ratios of red to green to blue.

- Integrated Color Model (ICM)

Contrast stretching is used to equalize the contrast, followed by saturation and intensity pulling of the HSI to expose the proper color and resolve lighting problems. The contrast stretching algorithm scales the pixel values linearly. Each pixel is scaled as follows:

$$P_0 = (P_i - c) * \frac{(b - c)}{(d - c)} + a \tag{3}$$

where *Po* denotes the normalized pixel value, *Pi* the considered pixel value, a minimum value of the desired range, *b* the maximum value of the chosen range, *c* the lowest pixel value currently present in the image, and *d* the highest pixel value now current in the image.

After contrast stretching, each channel is extended using the same scaling to maintain the correct color ratio. Next, RGB is transformed into HIS in the second step to increase brightness and accurate colors. To achieve this, stretching saturation and intensity values using the transform function is done. Finally, the saturation parameters are used to obtain the correct color for the underwater image. Figure 2 illustrates a selection of images from each dataset and four resultant images from image enhancement algorithms for each dataset.
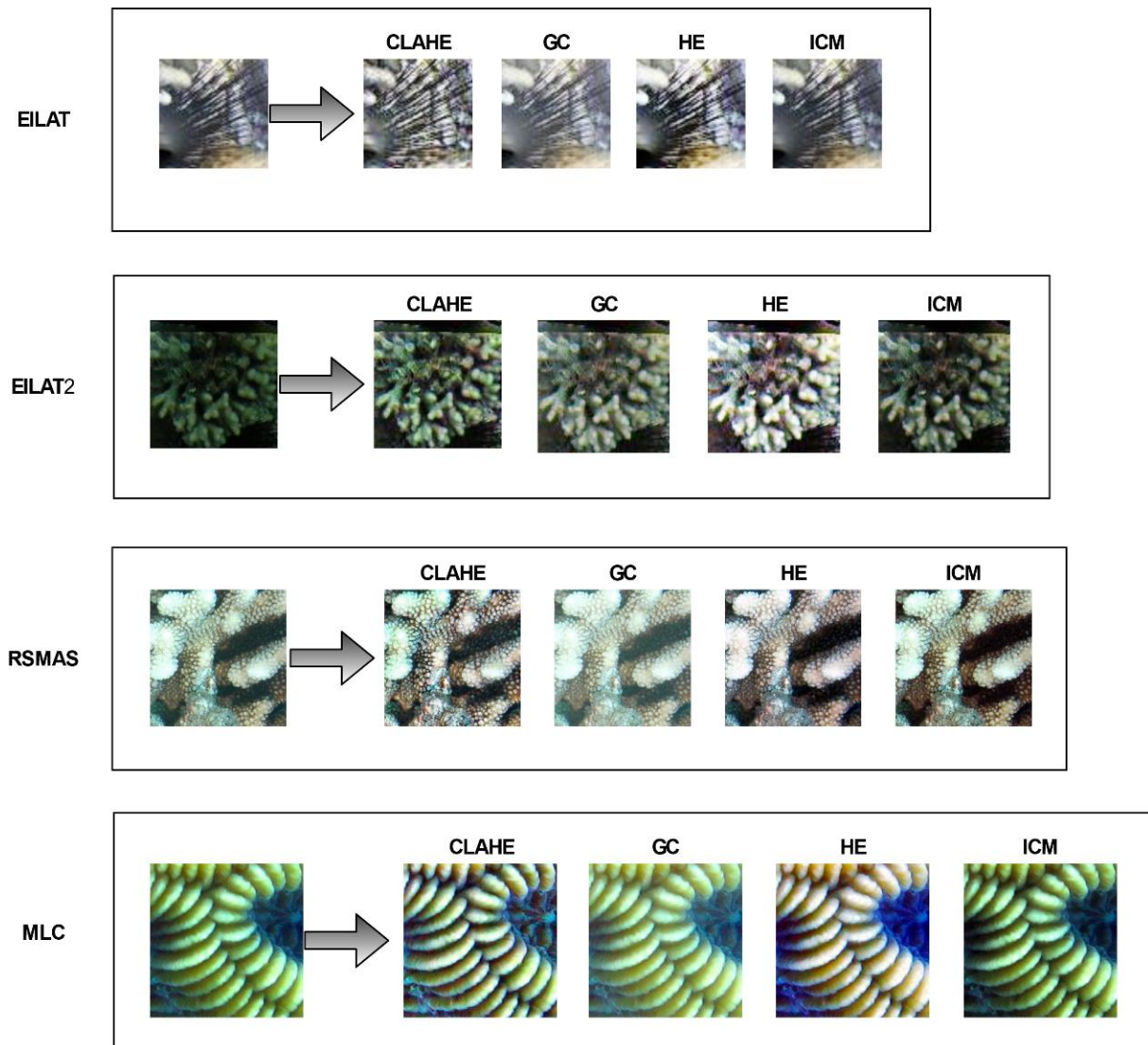

Figure 2. *Samples of EILAT, EILAT2, RSMAS and MLC datasets with image enhancement applied*

3.3. Transfer Learning in CNNs

Transfer learning refers to the fact that knowledge learned in one setting is transferred to another setting for error reduction in the new setting. Figure 3 shows where knowledge learned on a model trained on ImageNet [28] dataset is transferred to another model with a small but similar dataset. Knowledge transfer means transferring values of parameters that a network learns, i.e., *weights(w)* and *bias(b)*. In most cases, it is undesirable to train a Convolutional Neural Network (CNN) model from scratch. It requires vast amounts of data, and data may not be enough to train a CNN model, or if the data is available, it may be imbalanced. Transfer learning is done in supervised learning, where inputs are related and labels are different. For instance, we may have learnt visual representations, such as cats and dogs in one setting, and then learn different visual representations, such as tiger and wolf, in another setting. Transfer learning helps reduce time and resources as training a CNN model requires high processing power and time [19].
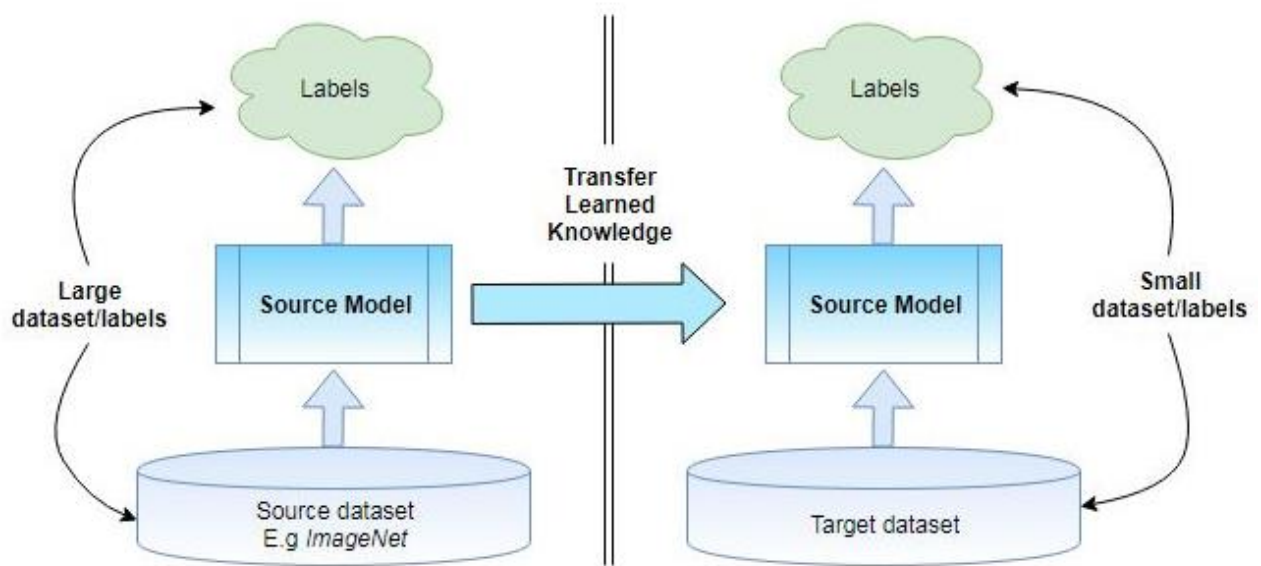

Figure 3. *Transfer Learning Idea*

There are three transfer learning approaches: Full Train, Fine Tuning, and F*eature Extraction.*

- Full Train

In this approach, a pre-trained CNN model architecture is adapted. It has achieved adequate results in performing tasks similar to the one at hand and training it from scratch by randomly initializing all weights. We capitalize on this approach when there is a large amount of data available, different from the data on which the pre-trained CNN model was trained [11,19].

- Fine Tuning

In this approach, a pre-trained CNN model is adapted on a new dataset by continuing backpropagation on the last few layers of the network. Since initial layers of the network learn low-level features, such as lines and curves, which are the same in almost every dataset, they are kept as they are. Therefore, it is common to start with a lower learning rate value. We capitalize on this approach when there is a small amount of data available and low similarity to the source data. Another common scenario is when data is large and have high similarity. In this case, the model is retrained on original architecture along with its weights to suit the task better [11,19].

- Feature Extraction

In this approach, classification layers are removed from a pre-trained CNN model and used as a feature extractor for our task. After this, a different classifier is trained on extracted features to classify them into different classes relating to the task at hand [11,19].

3.4. Marine Habitat Classification Using Transfer Learning

The authors have used transfer learning for marine habitat classification by employing DAG-Net (cyclic) model. DenseNets [46] introduced the idea of feature reuse. They do not sum the output feature maps, as in ResNets; instead, they concatenate them. The idea behind DenseNets is that it may be useful to reference features from earlier layers, allowing the network to leverage features from earlier layers (See Figure 4a). There are three sub-versions, namely DenseNet121, DenseNet169, and DenseNet201. Since each layer has direct access to the original input signal and gradients of the loss function, this helps train deep neural networks easily. The authors of the DenseNets refers to the number of filters in every convolutional layer as *growth rate, k,* since each layer will have k more feature maps than the previous one. DenseNets uses a transition layer that contains 1x1 convolution followed by 2x2 average pooling for size reduction. Figure 4a is shown a 5-layer Dense block with k = 4. A minimal, faster and efficient neural network architecture is proposed in [47].
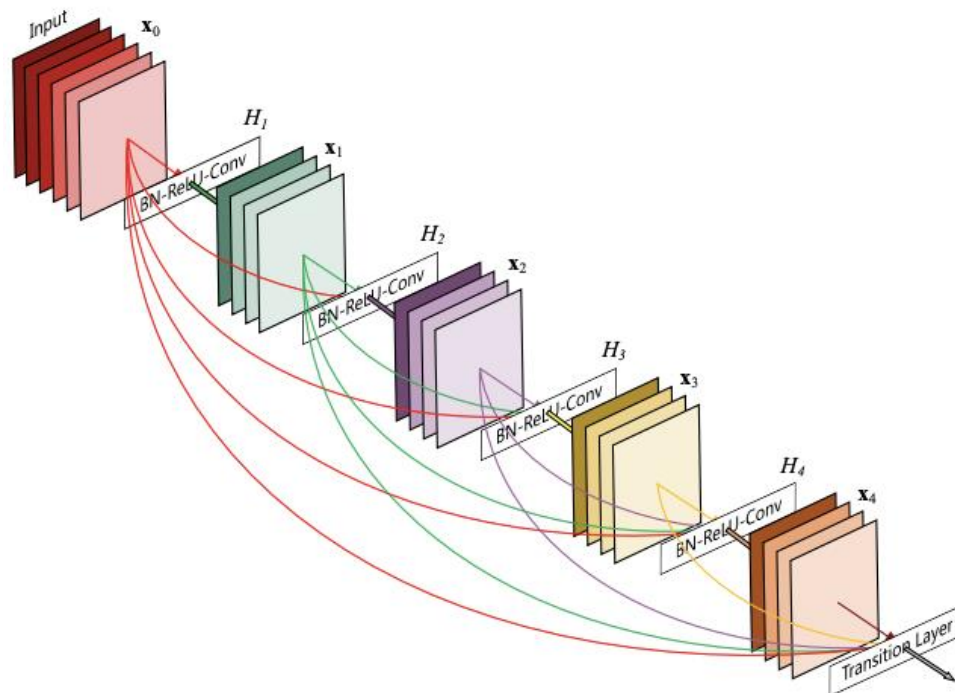

Figure 4a. *A 5-layer Dense block with k = 4* [46]

The architecture is named MobileNet because of its faster inference time and usage in mobile and embedded vision applications. The main idea behind MobileNet is using depth-wise separable convolutions (See Figure 4b) and two hyper-parameters (width and resolution multiplier). Depth-wise separable convolutions focus on feature maps resulting from each kernel channel instead of all kernel channels, leading to fewer computations. Hyper-parameters allow for faster, smaller and faster MobileNets at the expense of lower accuracy. The authors have used it to demonstrate the power of deep neural networks and compensate for lower computation resources availability.
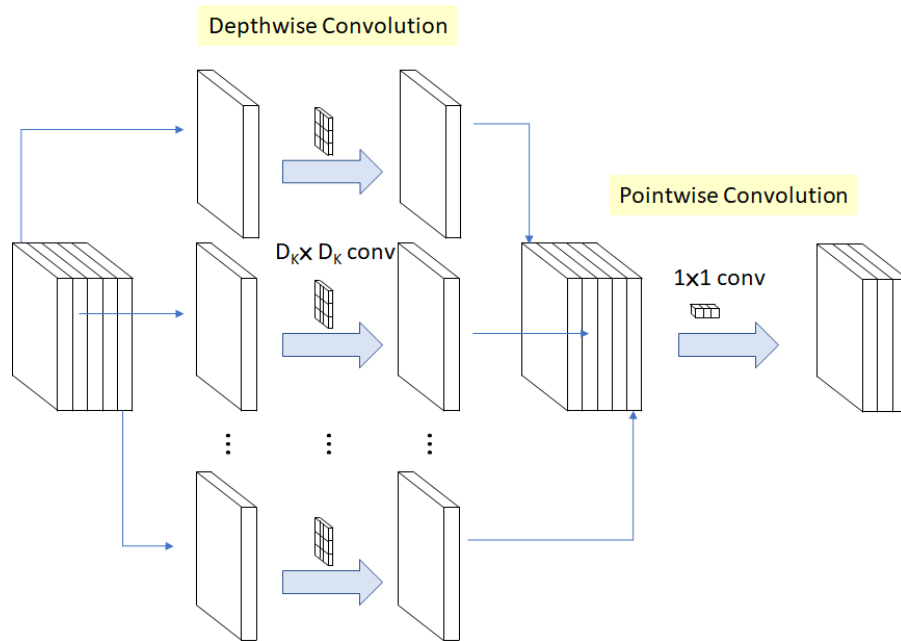
Figure 4b. *Depth-Wise Separable Convolutions* [47]

4. EXPERIMENTAL RESULTS

80% of images are used for training throughout all experiments, and 20% are used for testing in all trials. The results are presented using k-fold cross-validation, with k =10. We have used accuracy as a performance metric.

The authors have used four coral reefs datasets, namely EILAT, EILAT2, RSMAS and MLC2008. We have adopted the architecture of DenseNet-169 [46] by getting inspiration from [19]. We have also used MobileNets [47] to demonstrate the power of transfer learning on deep neural networks. We have first applied four image enhancement techniques on each of these datasets, resulting in four new datasets for each dataset. We then resized the images to 224 x 224 x 3 to match the input size requirement of both neural network architectures. Finally, the model is trained using a fine-tuning technique with DenseNet-169 and MobileNet using hyper-parameters from Table 2. Epochs in Table 2 are different for MLC as it is the most challenging dataset to learn for the model. The reason is the nature of the classes that it represents. Also, the batch size is smaller for MLC than other datasets. The default MLP classifier is used for classification by changing output neurons in the last layer.

Table 2. *Hyperparameters for DenseNet169 and MobileNet*

Hyperparameter	Value
Optimizer	Adam
Loss	Categorical Cross Entropy
Epochs	50 for EILAT, EILAT2 and RSMAS. 150 for MLC2008
Data Augmentation	Yes
Batch Size	16 for EILAT, EILAT2 and RSMAS. 8 for MLC2008
Input Size	224 x 224 x 3

The overall results are presented in Table 3. The authors have conducted sixteen experiments using four image enhancement algorithms. As shown in Table 3, Histogram techniques have better performance than all others. Contrast Limited Adaptive Histogram Equalization (CLAHE) has outperformed all other techniques regarding the model's accuracy because it works locally and enhances the image using multiple histograms. Since the underwater images have low contrast and brightness, CLAHE fixes these locally by specifying a kernel size and clip limit for the histogram. In the RSMAS dataset, Histogram Equalization (HE) outperformed CLAHE in terms of accuracy because to the fact that RSMAS images are quite clear

already in terms of image quality. As a result, CLAHE over-enhances a portion of the image. It is not the case with HE, which performs global image improvement. We have used two deep neural networks for the experiments, namely, DenseNet and MobileNet. We have inspired DenseNet in the literature section and used MobileNet to show that even faster models work efficiently for marine habitat mapping. Among the two, DenseNet performed better when paired with CLAHE as an image enhancement technique. The number of parameters and slow training time for DenseNet allowed it to learn better on the dataset. However, MobileNet did not perform too worse for its size and number of parameters. We can increase the performance of MobileNet further by tuning its two hyper-parameters (width and resolution multiplier). However, we did not fine-tune due to limited resources and high training time.

Table 3. Results of overall experiments conducted. Computer Vision Algorithm column with "-" represents no preprocessing involved. The white rows represent the maximum accuracy achieved for a specific dataset

Dataset	Neural Network Model	Accuracy – Fine Tuning for Computer Vision Algorithms				
		Gamma Correction	Histogram Equalization	CLAHE	ICM	-
EILAT	DenseNet-169	96.103%	95.370%2	99.074%	96.296%	92.593%
EILAT2		80.111%	89.286%	96.429%	78.571%	81.351%
RSMAS		70.003%	92.647%	91.176%	73.529%	72.059%
MLC2008		78.040%	75.870%	82.143%	70.340%	71.660%
EILAT	MobileNet	91.334%	91.647%	93.008%	89.908%	87.121%
EILAT2		78.677%	86.000%	91.344%	84.988%	74.566%
RSMAS		81.980%	87.607%	90.001%	79.111%	78.648%
MLC2008		68.666%	73.988%	76.475%	69.890%	66.440%

After analyzing the results, the authors conclude that histograms are better suited to underwater image enhancement. Many histogram enhancement techniques exist, but CLAHE and HE stand out for underwater images.

6. CONCLUSION AND FUTURE WORKS

After conducting an extensive literature review, the authors have tested four image enhancement techniques. The results of the experiments outperformed the accuracies of existing systems. With DenseNet, we achieved an accuracy of up to 99 % on EILAT. DenseNet accuracy of 96 % was achieved using EILAT2 and RSMAS. With DenseNet, MLC achieved an accuracy of 82 %, the lowest of the four datasets. The reason is that the dataset's nature is highly imbalanced and has higher inter-class similarities among classes.

Among the four enhancement techniques, CLAHE outperformed on all four datasets. Using these techniques, we generated preprocessed datasets and used MLP for the classification. We can use the attention model with DenseNet and MobileNet for more accurate results for future work. DesneNet outperformed MobileNet. The reason is a tradeoff between faster training time and lower accuracy. In the end, the combo of a CLAHE technique with a deep neural network yields maximum performance. Thus it proves the hypotheses correct in terms of the impact of both (image enhancement technique and DCNN). Also, fine-tuning transfer learning techniques can check the resulting accuracy. Image enhancement plays a vital role in the classification of marine habitats; therefore, we can also check specific Neural Network-based image enhancement techniques to check the performance of these systems.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1]   Sun, Z., "A novel approach to coral fish detection and classification in underwater footage based on convolutional neural network", 2020 International Conference on Applied Physics and Computing (ICAPC 2020), Ottawa, Canada, 1-8, (2020).

[2]   Corrales, X., Vilas, D., Piroddi, C., Steenbeek, J., Claudet, J., Lloret, J., Calò, A., Di Franco, A., Font, T., Ligas, A., Prato, G., Sahyoun, R., Sartor, P., Guidetti, P., Coll, M., "Multi-zone marine protected areas: Assessment of ecosystem and fisheries benefits using multiple ecosystem models", Ocean & Coastal Management, 193(8): 1-12, (2020).

[3]   Shihavuddin, A.S.M., Gracias, N., Garcia, R., Gleason, A.C.R., Gintert, B., "Image-based coral reef classification and thematic mapping", Remote Sensing, 5(4): 1809–1841, (2013).

[4]   Chegoonian, A.M., Mokhtarzade, M., Valadon Zoej, M.J., Salehi, M., "Soft supervised classification: An improved method for coral reef classification using medium resolution satellite images", 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 2787–2790, (2016).

[5]   Politikos, D. V., Fakiris, E., Davvetas, A., Klampanos, I.A., Papatheodorou, G., "Automatic detection of seafloor marine litter using towed camera images and deep learning", Marine Pollution Bulletin, 164(5): 1-10, (2021).

[6]   Ariyasu, E., Kakuta, S., Goto, K., Sano, T., "Evaluation of coral reefs mapping in kerama islands by satellite-based classification", 2019 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2019), Yokohama, Japan, 2670–2673, (2019).

[7]   Purkis, S.J., Gleason, A.C.R., Purkis, C.R., Dempsey, A.C., Renaud, P.G., Faisal, M., Saul, S., Kerr, J.M., "High-resolution habitat and bathymetry maps for 65,000 sq. km of Earth's remotest coral reefs", Coral Reefs, 38(3): 467–488, (2019).

[8]   Hopkinson, B.M., King, A.C., Owen, D.P., Johnson-Roberson, M., Long, M.H., Bhandarkar, S.M., "Automated classification of three-dimensional reconstructions of coral reefs using convolutional neural networks", PLoS One, 15(3): e0230671, (2020).

[9]   Diegues, A., Pinto, J., Ribeiro, P., Frias, R., Alegre, D.C., "Automatic habitat mapping using convolutional neural networks", 2018 IEEE/OES Autonomous Underwater Vehicle Workshop (AUV), Porto, Portugal, 1–6, (2018).

[10]   Iqbal, K., Odetayo, M., James, A., Salam, R.A., Talib, A.Z.H., "Enhancing the low quality images using unsupervised colour correction method" 2010 IEEE International Conference on Systems, Man and Cybernetics, Istanbul, Turkey, 1703–1709, (2010).

[11]   Mahmood, A., Bennamoun, M., An, S., Sohel, F., Boussaid, F., "ResFeats: Residual network based features for underwater image classification", Image and Vision Computing, 93(1): 1–7, (2020).

[12]   Pierce, J.P., Rzhanov, Y., Lowell, K., Dijkstra, J.A., "Reducing Annotation Times: Semantic Segmentation of Coral Reef Survey Images", Global Oceans 2020, Singapore - U.S. Gulf Coast, 1-9, (2020).

[13]   Kratsch, W., Manderscheid, J., Röglinger, M., Seyfried, J., "Machine learning in business process monitoring: A comparison of deep learning and classical approaches used for outcome prediction", Business & Information Systems Engineering, 63(3): 261–276, (2021).

[14] Polak, P., Nelischer, C., Guo, H., Robertson, D.C., ""Intelligent" finance and treasury management: what we can expect", AI & SOCIETY, 35(3): 715–726, (2020).

[15] Caballo, M., Pangallo, D.R., Mann, R.M., Sechopoulos, I., "Deep learning-based segmentation of breast masses in dedicated breast CT imaging: Radiomic feature stability between radiologists and artificial intelligence", Computers in biology and medicine, 118103629, (2020).

[16] Pierson, H.A., Gashler, M.S., "Deep learning in robotics: a review of recent research", Advanced Robotics, 31(16): 821–835, (2017).

[17] Schubert, J., Brynielsson, J., Nilsson, M., Svenmarck, P., "Artificial intelligence for decision support in command and control systems", 23rd International Command and Control Research and Technology Symposium, Multi-Domain C, Stockholm, 1-17, (2018).

[18] Hassan, M.D., Nejdet N.A., Baker, M.R., Mahmood, S., "Enhancement automatic speech recognition by deep neural networks", Periodicals of Engineering and Natural Sciences, 9(4): 921–927, (2021).

[19] Yasir, M., Rahman, A.U., Gohar, M., "Habitat mapping using deep neural networks", Multimedia Systems, 27(4): 679–690, (2021).

[20] Nadeem, U., Bennamoun, M., Sohel, F., Togneri, R., "Deep fusion net for coral classification in fluorescence and reflectance images", Digital Image Computing: Techniques and Applications, DICTA 2019, Perth, 1-7, (2019).

[21] Beijbom, O., Edmunds, P.J., Kline, D.I., Mitchell, B.G., Kriegman, D., "Automated annotation of coral reef survey images", 2012 IEEE Conference On Computer Vision and Pattern Recognition (CVPR), Providence, USA , 1170–1177, (2012).

[22] Pizarro, O., Rigby, P., Johnson-Roberson, M., Williams, S.B., Colquhoun, J., "Towards image-based marine habitat classification", OCEANS 2008, Quebec, Canada, 1–7, (2008).

[23] Mary, N.A.B., Dharma, D., "Coral reef image classification employing Improved LDP for feature extraction", Journal of Visual Communication and Image Representation, 49(8): 225–242, (2017).

[24] Stokes, M.D., Deane, G.B., "Automated processing of coral reef benthic images", Limnology and Oceanography: Methods, 7(2): 157–168, (2009).

[25] Sotoodeh, M., Moosavi, M.R., Boostani, R., "A structural based feature extraction for detecting the relation of hidden substructures in coral reef images", Multimedia Tools and Applications, 78(24): 34513–34539, (2019).

[26] Shakoor, M.H., Boostani, R., "Noise robust and rotation invariant texture classification based on local distribution transform", Multimedia Tools and Applications, 80(6): 8639–8666, (2021).

[27] He, K., Zhang, X., Ren, S., Sun, J., "Deep residual learning for image recognition", Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, USA, 770–778, (2016).

[28] Deng, J., Dong, W., Socher, R., Li, J.L., Ki, K., Fei, L.F., "ImageNet: A large-scale hierarchical image database", 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, USA, 248–255, (2009).

[29] Mahmood, A., Bennamoun, M., An, S., Sohel, F., Boussaid, F., Hovey, R., Kendrick, G., Fisher, R.B., "Coral classification with hybrid feature representations", 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, USA, 519–523, (2016).

[30] Simonyan, K., Zisserman, A., "Very deep convolutional networks for large-scale image recognition", III. International Conference on Learning Representations (ICLR 2015), San Diego, USA, 1409–1556, (2015).

[31] Mahmood, A., Bennamoun, M., An, S., Sohel, Boussaid, F., Hovey, R., Kendrick, G., Fisher, R.B., "Automatic annotation of coral reefs using deep learning", OCEANS 2016 MTS/IEEE Monterey, Monterey, USA, 1–5, (2016).

[32] Bhardwaj, N., Kaur, G., and Singh, P.K., "A systematic review on image enhancement techniques", Sensors and Image Processing, Springer, Singapore, 227–235, (2018).

[33] Duarte, A., Codevilla, F., Gaya, J.D.O., Botelho, S.S.C., "A dataset to evaluate underwater image restoration methods", OCEANS 2016 – Shanghai, 1–6, (2016).

[34] Gao, F., Wang, K., Yang, Z., Wang, Y., Zhang, Q., "Underwater image enhancement based on local contrast correction and multi-scale fusion", Journal of Marine Science and Engineering, 9(2): 1–16, (2021).

[35] Rizzi, A., Gatta, C., Marini, D., "A new algorithm for unsupervised global and local color correction", Pattern Recognition Letters, 24(11): 1663–1677, (2003).

[36] Iqbal, K., Salam, R., Osman, A., and Of, A.T., "Underwater image enhancement using an integrated colour model", IAENG International Journal of Computer Science, 32(2): 239–244, (2007).

[37] Kim, Y.T., "Contrast enhancement using brightness preserving bi-histogram equalization", IEEE Transactions on Consumer Electronics, 43(1): 1–8, (1997).

[38] Zhang, W., Pan, X., Xie, X., Li, L., Wang, Z., Han, C., "Color correction and adaptive contrast enhancement for underwater image enhancement", Computers & Electrical Engineering, 91(3): 1–14, (2021).

[39] Mahiddine, A., Seinturier, J., Boi, D.P.J.M., Drap, P., Merad, D., Long, L., "Underwater image preprocessing for automated photogrammetry in high turbidity water: An application on the Arles-Rhone XIII roman wreck in the Rhodano river France", 2012 XVIII. International Conference on Virtual Systems and Multimedia, Milan, Italy, 189-194i, (2012).

[40] Mathur, M., Goel, N., "Enhancement algorithm for high visibility of underwater images", IET Image Processing, 16(4): 1067-1082, (2022).

[41] Singh, P., Mukundan, R., De Ryke, R., "Feature enhancement in medical ultrasound videos using contrast-limited adaptive histogram equalization", Journal of Digital Imaging, 33(1): 273–285, (2020).

[42] Zhu, Y., Huang, C., "An adaptive histogram equalization algorithm on the image gray level mapping", Physics Procedia, 25: 601–608, (2012).

[43] Yadav, G., Maheshwari, S., Agarwal, A., "Contrast limited adaptive histogram equalization based enhancement for real time video system", 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Delhi, India, 2392–2397, (2014).

[44] Ancuti, C., Ancuti, C.O., Haber, T., Bekaert, P., "Enhancing underwater images and videos by fusion", 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence, USA, 81–88, (2012).

[45] Xu, G., Su, J., Pan, H., Zhang, Z., Gong, H., "An image enhancement method based on gamma correction", 2009 Second International Symposium on Computational Intelligence and Design, Changsha, China, 60–63, (2009).

[46] Huang, G., Liu, Z., Van Der Maaten, L., Weinberger, K.Q., "Densely connected convolutional networks", 2017 IEEE Conference On Computer Vision and Pattern Recognition (CVPR), Honolulu, USA, 2261–2269, (2017).

[47] Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., Adam, H., "MobileNets: Efficient convolutional neural networks for mobile vision applications", arXiv:1704.04861, (2017).