ISSN 2515-8260 Volume 07, Issue 11, 2020

RECOGNITION OF MAN-MADE OBJECT IN UNDERWATER USING TRANSFER LEARNING AND DEEP LEARNING

Dr.C. ANNADURAI and Dr. I.Nelson

Associate Professor, Department of ECE, Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam, Chennai , Tamilnadu, India. Pin: 603110.
Email Id: annaduraic@ssn.edu.in , nelsoni@ssn.edu.in

Abstract
Underwater image processing has always been a promising and thrilling task due to the natural condition and the lighting effect for taking the image requires good artificial lights. While taking underwater images lots of difficulties are faced by photographers such as the shadows, non-uniform lighting, color shading, etc. Recognizing the object underwater is very difficult in order to the environmental condition. Man-made object recognition was made with underwater optical sensors to capture underwater images that have gained more attention from the users. Deep learning methods have demonstrated impressive performance in object recognition tasks from natural images. Anyhow it is hard to collect all the labelled underwater optical images for training the model. It is possible to acquire labelled images. Based on the assumption that it is possible to acquire sufficient labeled in-air images, the proposed work leverages a combination of deep learning and transfer learning to develop a novel recognition system for the man-made object from underwater optical images. The extracted features from the proposed network have high representative power and demonstrate robustness in both in-air and underwater imaging modalities. Therefore, our proposed framework has the ability to recognize underwater man-made objects using only labeled in-air images. The results of experiments on simulated data demonstrate that the proposed method outperforms traditional deep learning methods in the task of underwater man-made object recognition.
Keyword: Underwater optical image, man-made object recognition, deep learning, transfer learning, unsupervised domain adaptation.

1. Introduction

Recognization of underwater images is very useful and helpful for several purposes like pipeline maintenance, used in mining, monitoring of species in the ocean, and also used for military purposes. Light travel with the speed of 20 m in clear water, its traveling speed is little less in the turbid and coastal water [1]. The visibility of light underwater is very low and the speed of entering inside water rapidly decreases. When the underwater image is captured at the very low quality then it becomes difficult for recognizing the object. Underwater images are captured at a depth level, so there is a possibility of it being poor in quality [2]. Underwater image capturing is not always done by the human being because it is captured at a deep level inside water so in that case Autonomous Underwater Vehicle the AUVs are used for exploring the images. The artificial lights from the AUV give brightness to the light for capturing, and it also causes turbidity while driving inside the water bodies resembles as a noise. The underwater images must undergo pre-processing for better recognization. The aim of image pre-processing is to increase image quality by enhancing distortion and image features. It helps to improve image recognition [3]. Much research has been conducted on this though it seems to be a challenging one.

Object recognition is a computer-based visual idea for recognizing objects in an image and videos, which includes identifying a similar target with a different image [4,5]. The idea behind the recognization of an object is to identifying it from the image and then guiding computers to understand as humans do to understand it. The recognization of the image is done from various viewpoints like front, side, and back.

The object is recognized from various shapes and sizes when partly being blocked for the viewers [6]. There are many kinds of object recognization that include text, face, lane line, voice, etc [7,8]. Almost two 3rd of the earth is covered by water bodies but not a lot of technologies to study the marine life has been completely discovered. Especially marine safety includes shipwrecking, navy battle, etc. is an important aspect for object recognization to be used in marine life surveillance [9]. There are 2 steps of marine object recognization: feature extraction and classification. Four geometric features were derived artificially before recognizing surface ships [10]. The marine problems such as marine disaster prevention, target detection, emergency rescue, tracking, and recognition can be solved by learning the marine life clearly [11]. Deep cleaning methods are used for a marine system like marine data reconstruction, data classification, data prediction. As a part of a deep learning algorithm, it consists of 2 layers of learning which include 2 conventional and fully conventional layers to understand complex layers through conversations and it also stimulates the object characterization [12]. The traditional vector machine highly supports the object recognization and classification when compared to that of the conventional neural networks the CNN due to the hyper-parameters [13]. The restricted Boltzmann machine the RBM when integrated into the deep learning method the framework for learning has been developed significantly. When the powerful GPU with computer access has a great capability in boosting the deep learning methods in the process of deep belief network the DBN [14].

CNN along with RNN and AE when used in the process of object recognition gives great results in exploring deep learning architectures [15]. The robust training algorithm enables object recognization without the use of artificial factors [16]. The non-linear information is obtained from the CNN properties such as shared weight, pooling, local connection, and multilayers [17].

The success of AlexNet on ImageNet Large-Scale Visual Recognition Challenge the ILSVRC deep learning is connected to the CNN method with VGGNet and the ResNet. Hence the results from the deep CNN are capable enough of achieving large accuracy and data on the deep learning process [18-20]. The DNN has succeeded in the industrial and

academic community in deep learning when reviewed [21]. A specific object recognization has been processed in 3D, visual, and object segmenting recognition [22].
In the past years, many deep learning and architectures for marine life objects have been proposed but still the advantage, and disadvantages of these ideas are not evolved and it is not clearly understood [23]. Because of it, many challenges in identifying them are still found. In this research, the deep learning process of marine life is time-based and it also includes both the theoretical and practical importance in the marine engineering community.

Figure 1. Object recognition using multiple images.

2. Optical Imaging

The optical and sonar-based system are the 2 main modules used in the image models in the process of underwater vision navigation. In the underwater imaging system, the recognization of the man-made object plays an important role in research under the concepts of ocean object identification, mining, navy and pipeline setting, etc.

Figure 2. Underwater image with low resolution

When compared to sonar imaging the optical imaging has a better ability to capture details such as colors, and underwater object recognization. The development in the underwater optical sensor and the man-made object recognization from underwater have been highly used in ocean engineering and image processing. Poor image quality is the biggest challenge or task in the image optical image analysis. The visibility of light underwater is very low and the speed of entering inside water rapidly decreases which makes the quality of the image decrease.

Only a few studies have been done in the man-made object recognization from underwater optical images among that Hou et al identified a color-based and shape object recognization technique from the man-made underwater object.
An underwater man-made object recognization combined a pipeline of image processing ideas including edge and line detection, pre-processing, Euclidean shape prediction. A system for the man-made object was detected using an unconstrained subsea video [24]. The deep learning method has illustrated a powerful performance in the object recognization of natural images, so, realistically, deep learning methods can be used for object recognization of optical images. Certain challenges are faced in the deep learning method especially the availability of the large-scaled labeled data for the estimation of parameters in the training phase. Both the training and the testing phase follows the same image processing.
In this research simpler methods have been used in acquiring sufficient training samples of the man-made object from in-air images. It is very simple to capture the multiview of images before the man-made object gets submerged in water. Based on assumptions obtained a framework using both deep and transfer learning has been proposed in this paper. During the training phase, where the large scale data of the labeled in-air image is combined with the unlabelled man-made object. During the testing phase, the ability of the trained model to categorize the underwater man-made object with robustness is displayed. The main contribution of our work is a system which can use in-air images to effectively classify man-made object from underwater optical images.

3. Methods

3.1. Underwater datasets generation

He et al research on underwater images is generated based on the depth of field analysis and simulation of the underwater environment. It is challenging and costly to collect the depth field analysis for simple optical acquisition devices so a simple method has been proposed in this research for deep information of field images.
Color is a significant factor in the underwater image. Nguyen et al used a color transfer method based on illumination and 3D gamut on manipulating the color values of the original image with the same appearance. The turbidity simulation on the top color transfer is obtained for the better representation of the image. Hence this is applied in this paper. The result of the signal is obtained with 2 components: direct transmission

$$D = I_{color} e^{-\eta z}, \qquad (1)$$

where Icolor is the image obtained through color transfer,
η is the coefficient of diffusion attenuation obtained from a given real underwater patch,
z represents the adjustable distance between Icolor and the reference underwater image, with a higher value of z representing higher turbidity.
backscattering:

$$B = B_{\infty}(1 - e^{-\eta z}), \qquad (2)$$

where B∞ is the backscatter in the line of sight (LOS) which extends to infinity in water.
The resulting signal of an underwater image combining the direct transmission and backscattering as follows:

$$I_{underwater} = D + B - D \cdot B, \tag{3}$$

and · represents the element-wise multiplication.

3.2. Framework for underwater man-made object recognition

Figure.3 represents the flowchart of our proposed framework. The Alexnet is the CNN based deep learning method that has been implemented as the proposed framework of this paper. It consists of 5 evolution layer and 3 fully connected layers. The rectified linear unit ReLU is applied following the pooling operation on the layers of conv1, conv2, and conv5. The classifiers with a fully connected layer are connected at the end of the network. The vector generated in the last fully connected layers is proceeded with a soft-max, while the vector represents the final prediction of result in all categories. The maximum mean distance, the MMD is applied on both the fc7 and fc8 layers of the neural network as the transfer and regulated Learning method of the proposed framework. This minimizes the data distribution of the different image procedures of in-air images. In this theory, the source domain is the transfer learning, the labeled in-air images. While the target domain is the unlabelled underwater image.
The MMD has written in square form using kernel operations:

$$\begin{aligned} D_k^2(p,q) = & E_{x_p^s x_q^s} k(x_p^s, x_q^s) + E_{x_p^t x_q^t} k(x_p^t, x_q^t) \\ & - 2E_{x_p^s x_p^t} k(x_p^s, x_p^t), \end{aligned} \tag{4}$$

where E denotes the expectation,
$x^s p$ and $x^s q$ are two samples from the source domain,
while $x^t p$ and $x^t q$ are two samples from the target domain;
k is the Gaussian kernel function.

3.3. Data pre-processing

Image pre-processing plays an important step in marine object recognization with deep learning methods where the images and videos are the significant ones in this method. Xiong et al proposed a dark channel before the DCP theory in which the original image is automatically classified into 2 categories as the clear image and the fuzzy image. The image quality of the fuzzy image can be improved using the DCP defogging algorithm. Later the clear images are used for the training process in the AlexNet. When compared to the original image the underwater image taken from the underwater camera declines in its image quality created by the underwater noises.
In a median filter where only certain pixels are affected by the noises, the other pixels are processed [25]. By using an object recognition technique, the underwater videos transfer the parameters of the pre-trained AlexNet to the target domain by this the low quality and low-resolution images are not processed directly [26].

ISSN 2515-8260 Volume 07, Issue 11, 2020

The ConNet has shown an extraordinary quality of images and videos where the deep networks tolerate the noises. The DN framework permits the non-supervised hierarchical image which is used for low-level tasks such as the de-noising and also used for features of the marine identification of objects [27].

By using the DN distinguished features extracted from the low-light noisy underwater images the ED-Ne has been designed with high-resolution. The de-conventional layers were applied to remove the noise from the image [28]. FDCNet is the filtering deep conventional network was designed to classify the sea object. The UDCP is used for calculating the disparity which is the main factor in the underwater de scattering [29].

The unary and pairwise super-pixel of CNN is learned. The CNN and the UDCP are combined with the joint bilateral filtering to attain the classification task of the sea objects. In this research, the DA, deep learning, and transfer learning methods are used [30]. SAR-ATR is a multi-view deep learning framework that was also used. The image from SAR is obtained through a given ground surface as a target from various angles and intervals by the estimated SAR platform, where the raw SAR images are not used for this. The newly generated and raw data should not be treated equally [31]. Parallel network topology with multi inputs is essential so that the SAR images from various views can be obtained and fused layer-by-layer. The 4-view DCNN attained a better recognition than the SAR-ATR which works under a fixed operating condition [32].

The 360-panoramic images are generated by correcting the images which are taken by an underwater drone with a 360-panoramic camera. It has benefited for recognition of fish and has attained 87% of deep learning techniques [33].

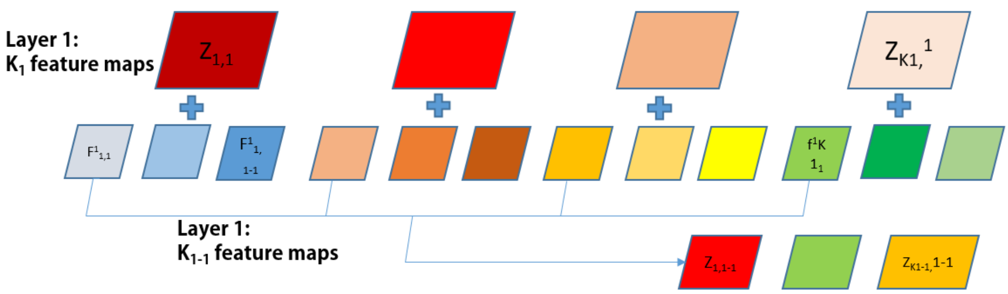
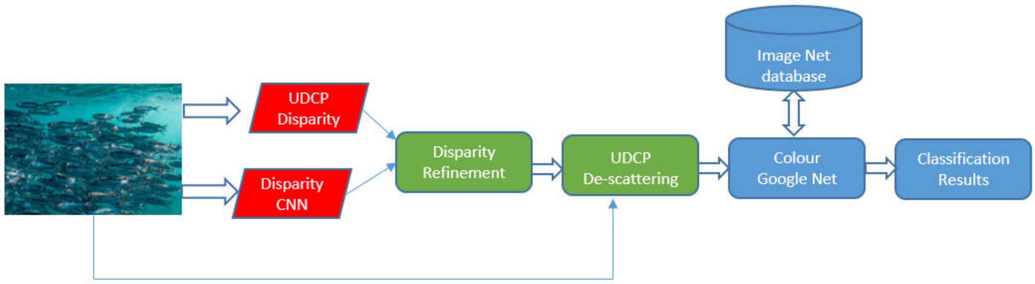


Figure 3. De-Conventional Image Layer

European Journal of Molecular & Clinical Medicine

ISSN 2515-8260 Volume 07, Issue 11, 2020



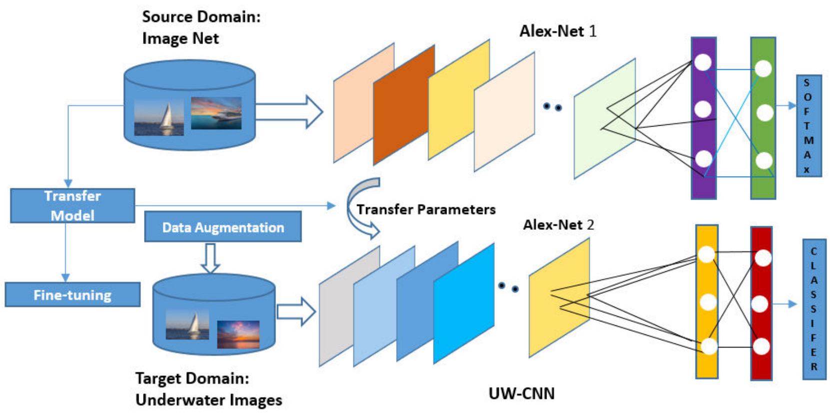


Figure 4. Proposed Framework with CNN, AlexNet method with the source and target domain

3.4. Feature Extraction

3.4.1. Transfer learning and fine-tuning techniques

The object recognition by transfer learning in CNN as attained a significant improvement where the pre-trained process has learned the features before which are helpful for the recognition task. Transfer learning along with fine-tuning has been a significant method in object recognition and it has been applied in various areas [34]. The DA is used for supervising the fine-tuning of the parameters in the training process of the target domain. This model is derived and named as the UW_CNN.

3.4.2. Deep convolutional network variants

Szegedy et al (2015) have questioned that the learning better for networks with deeper layers but the results of the ResNet101, ResNet1001 has shown better results. The disadvantages are raised here on the growing number of parameters and the reduction of the coverage speed was not ignored.

The other proposed model such as the GoogLeNet, ResNet, and VGG-16 is the alternative of the AlexNet. A large portion of trainable parameters in deep convolutional networks are induced by the fully-connected layers. But on CNN where the fully and de convolutional operations were proposed by eliminating the fully connected layers.

(a) Fully Convolutional Network (FCN)

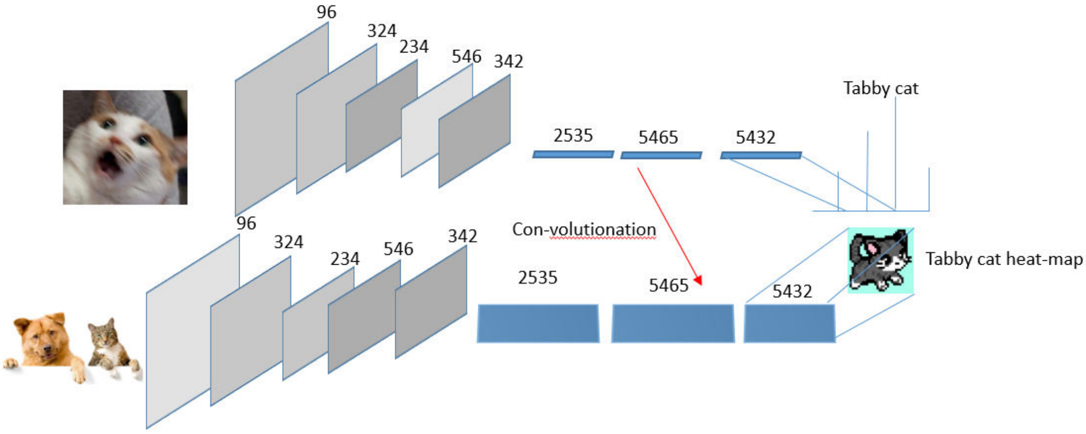


Figure 5. The FCN Structure

The FCN method in the semantic segmentation task in the full manner which helps in solving the problem of the pixel-wise labelling [37]. In the FCN where the framework was composed of the convolutional layers and a classifier. In this, the fully-connected layers are transferred into the convolutional layers. The fully connected layer is similar to that of the ConvNet. It shows that computing is complex that the ConvNet [38]. The FCN is not affected by the fix-size input images.

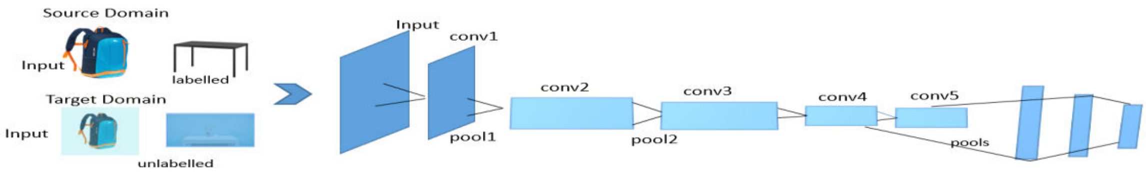
The FCN rapidly reduces the free parameters which have been applied in the aerial image semantic labelling and the large-scale remote sensing [39]. Anyhow the FCN method was not used in object recognition. The fully-connected layers of the FCN are arranged in 3 dimensions according to the width, the height, and the depth and used for the target recognition of SAR (SAR-ATR) [40].

A left regulation was used in fully-connected layers and added to the higher convolution layers & image segmentation in the up-sampling stage of the FCN [41]. To solve the dimension disaster and low accuracy, ED-Net was developed for underwater object recognition. Instead of full connection, the deconvolution kernel with a matched feature map was used [42]. Underwater images or videos are transformed into deep features by 2 convolution layers, and then the deconvolution layers are used as decoders for refining the images or videos [43]. The DA and transfer learning were employed for solving the data starvation problem. The ED-Net attained a higher accuracy than that of the UW-CNN method [44]. A RED-Net includes the ED-Net into the residual network. The RED-Net is made of the symmetric link of convolutional and de-convolutional layers where the convolutional layers act as feature extractors which preserve the components of objects by removing the corruptions in the image. De-convolutional layers are used for recovering the image contact details. The skip connections between convolutional and corresponding deconvolutional layers were built to back-propagate the signal to bottom layers directly [45]. In this context, the comprehensive image information was conveyed to the top layers, thereby benefiting in recovering the original images.

4. Experiments

4.1. Datasets descriptions

The dataset from Amazon was used as the original in-air man-made object dataset. The dataset contains images of man-made objects downloaded from amazon.com. the images are categorized into many groups, each group contains nearly 36 to 100 images. The past researchers have used objects with a regular shape and size but in these irregular shapes captured from various views have been used through the Amazon dataset. This research is contributed to 3 experiments. For this, the obtained images are divided into 2 parts. Both the part contains an image from Amazon dataset on the concept of underwater image.



During the 1st experiment, the training and the testing data were taken from the underwater imaging system, where they had the same turbidity values. The image for the experiment was generated from the 2 parts of images. In experiment 2 a set-up for the valuation of the AlexNet where the images for training and testing are provided from the same image source. This was made to test the performance of the Alexnet where the training process contains the labeled in-air images from the source and un-labeled underwater image from the target domain from the 1st part. The testing process contains underwater images from part2. The same procedure was followed in setting-up the 3rd experiment. It is used for the validation of the performance of the framework with transfer and traditional learning of the CNN model. The stimulated underwater images used in the above 3 experiments are from the in-air images which followed certain procedures.

Figure 6. The proposed framework with Labelled and Unlabelled images

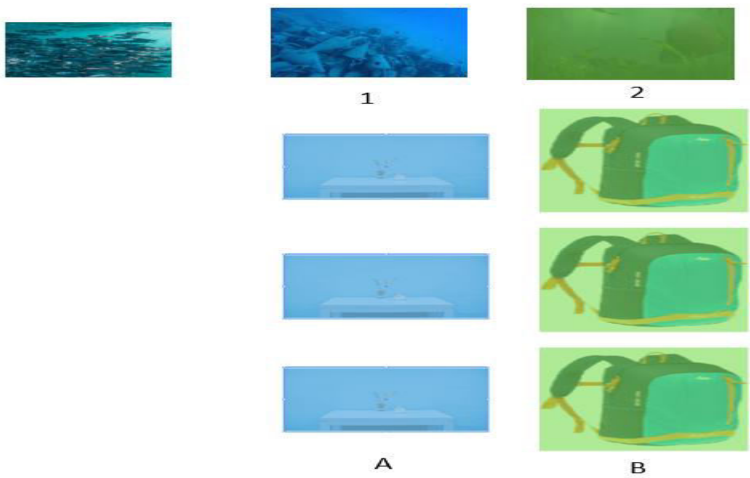


Figure 7. Underwater optical datasets

4.2. Implementation details

In our proposed implementation, the basic server settings are a 56 Intel(R)Xeon(R) CPU E5-2683 V3@ 2.00GHz, with 64G RAM and an NVIDIA GeForce 1080 GPU. All the images fed into the neural network are resized to the same size of 227×227 pixels. The proposed network is pre-trained on ImageNet [46,47], and then fine-tuned with our own data.

4.3. Experimental results

The experiment result of the 3 experiments has been compared to attain the result with various turbidities and reference settings. The AlexNet obtained 55.7% which is the highest value in the 1st experiment when compared to all the 3. It is because in the 1st experiment both the testing and training processes have the same underwater image. But in the 2nd and 3rd where the images from the different systems were used in the testing and training process, by which the performance of the AlexNet decreased rapidly. The AlexNet performance is the 2nd experiment was 17.33 percent. And in the 3rd experiment, it was 38.50 percent. It is understood that the proposed framework has the capability of transferring knowledge from the source to the target domain, which is from in-air to underwater images. For more detail, the calculation was made from 31 categories of the dataset in A1 for all the 3 experiments. This showed a good performance in experiment 1 and the poor performance was found in the 2nd experiment. The 3rd performance showed the worst performance than experiment 1.

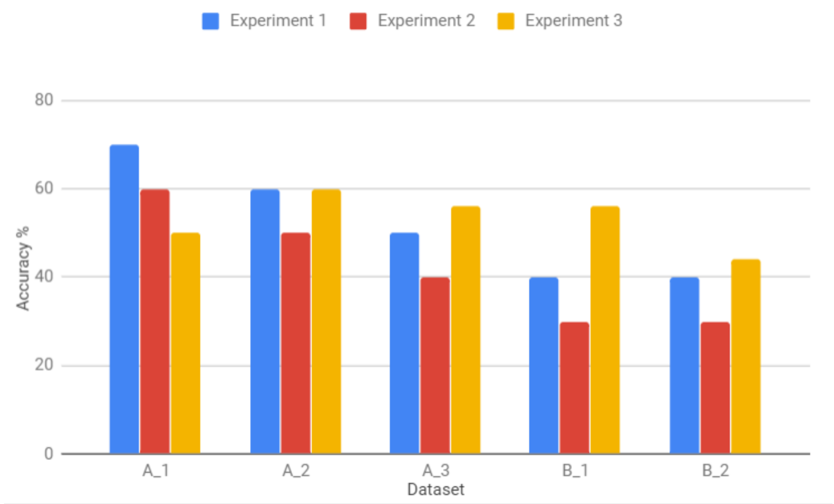


Figure 8. The Evaluation of 3 experiments.

5. Conclusion

This research was based on the framework of recognizing of the underwater man-made objects from the optical images. It works on the assumption that the labelled in-air images of man-made objects can be attained easily. With the CNN model of transfer learning, this model can parallelly obtain from the features of the representative as well as the robust across the different imaging systems. This helps us to avoid expressing and explaining the underwater images for the model. The result/ conclusion obtained from the study shows that the image recognizing performance of the presented algorithm shows that this framework can be taken as the successful basic step in the deep learning tool of optical image analysis in the underwater based system.

REFERENCES

1. Y. Lee, J. Choi, N. Y. Ko, and H. T. Choi, "Probability-based recognition framework for underwater landmarks using sonar images.," Sensors, vol. 17, no. 9, 2017.
2. Natlia Hurts Vilarnau, "Forward-looking sonar mosaicing for underwater environments," Universitat De Girona, 2014.
3. Xiaoou Tang and W. Kenneth Stewart, "Optical and sonar image classification: Wavelet packet transform vs fourier transform," Computer Vision & Image Understanding, vol. 79, no. 1, pp. 25–46, 2000.
4. Jules S. Jaffe, "Underwater optical imaging: The past, the present, and the prospects," IEEE
Journal of Oceanic Engineering, vol. 40, no. 3, pp. 683–700, 2015.
5. Yoav Y Schechner and Nir Karpel, "Recovery of underwater visibility and structure by polarization analysis," IEEE Journal of Oceanic Engineering, vol. 30, no. 3, pp. 570–587, 2006.
6. Yujie Li, Huimin Lu, Jianru Li, Xin Li, Yun Li, and Seiichi Serikawa, "Underwater image de-scattering and classification by deep neural network," Computers & Electrical Engineering, vol. 54, pp. 68–77, 2016.
7. K. Srividhya and M. M. Ramya, "Accurate object recognition in the underwater images using learning algorithms and texture features," Multimedia Tools & Applications, pp. 1–17, 2017.
8. Huimin Lu, Yujie Li, Yudong Zhang, Min Chen, Seiichi Serikawa, and Hyoungseop Kim, "Underwater optical image processing: a comprehensive review," Mobile Networks & Applications, pp. 1–8, 2017.
9. Pooria Pakrooh, Louis L. Scharf, and Mahmood R. Azimi-Sadjadi, "Underwater target classification using a pose-invariant matched manifold classifier," in IEEE International Workshop on Machine Learning for Signal Processing, 2016, pp. 1–5.
10. Isabelle Quidu and Luc Jaulin, "Color-based underwater object recognition using water light attenuation," Intelligent Service Robotics, vol. 5, no. 2, pp. 109–118, 2012.
11. Stphane Bazeille, Isabelle Quidu, and Luc Jaulin, "Identification of underwater man-made object using a colour criterion," 2007.
12. Hou, "Underwater man-made object recognition on the basis of color and shape features," Journal of Coastal Research, vol. 32, no. 5, pp. 1135–1141, 2016.
13. Syed Safdar Hussain and Syed Sajjad Haider Zaidi, "Underwater man-made object prediction using line detection technique," in International Conference on Electronics, Computers and Artificial Intelligence, 2015, pp. 1–6.
14. Adriana Olmos and Emanuele Trucco, "Detecting manmade objects in unconstrained subsea videos," in British Machine Vision Conference, 2002, pp. 517–526.
15. G. E. Hinton, S Osindero, and Y. W. Teh, "A fast learning algorithm for deep belief nets," Neural Computation, vol. 18, no. 7, pp. 1527, 2006.

16. P Sermanet, S Chintala, and Y Lecun, “Convolutional neural networks applied to house numbers digit classification,” in International Conference on Pattern Recognition, 2012, pp. 3288–3291.
17. Schettini, Raimondo, and Silvia Corchs. "Underwater image processing: state of the art of restoration and image enhancement methods." *EURASIP Journal on Advances in Signal Processing* 2010 (2010): 1-14.
18. Zhiyuan Chen and Bing Liu, “Lifelong machine learning,” vol. 10, no. 3, pp. 1–145, 2016.
19. Kaiming He, Jian Sun, and Xiaoou Tang, “Single image haze removal using dark channel prior,” in Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, 2009, pp. 1956–1963.
20. R. M. H. Nguyen, S. J. Kim, and M. S. Brown, Illuminant Aware Gamut-Based Color Transfer, The Eurographs Association & John Wiley & Sons, Ltd., 2014.
21. Yoav Y. Schechner and Nir Karpel, “Clear underwater vision,” in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, 2004, pp. I–536–I– 543 Vol.1.
22. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, “Imagenet classification with deep convolutional neural networks,” in International Conference on Neural Information Processing Systems, 2012, pp. 1097– 1105.
23. Sinno Jialin Pan and Qiang Yang, “A survey on transfer learning,” IEEE Transactions on Knowledge & Data Engineering, vol. 22, no. 10, pp. 1345–1359, 2010.
24. Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell, “Adapting visual category models to new domains,” in European Conference on Computer Vision, 2010, pp. 213–226.
25. Zhen Dong, Yuwei Wu, Mingtao Pei, and Yunde Jia, “Vehicle type classification using a semisupervised convolutional neural network,” IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 4, pp. 2247– 2256, 2015.
26. Yu, Xian, et al. "Man-Made Object Recognition from Underwater Optical Images Using Deep Learning and Transfer Learning." *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2018.
27. Bazeille, Stéphane, Isabelle Quidu, and Luc Jaulin. "Color-based underwater object recognition using water light attenuation." *Intelligent service robotics* 5.2 (2012): 109-118.
28. Barat, Christian, and Ronald Phlypo. "A fully automated method to detect and segment a manufactured object in an underwater color image." *EURASIP Journal on Advances in Signal Processing* 2010 (2010): 1-10.
29. Cheng, Binbin, Wenwu Wang, and Yao Chen. "A man-made object detection for underwater TV." *MIPPR 2017: Remote Sensing Image Processing, Geographic Information Systems, and Other Applications*. Vol. 10611. International Society for Optics and Photonics, 2018.

30. Kumar, Nitin, et al. "Saliency Subtraction Inspired Automated Event Detection in Underwater Environments." *Cognitive Computation* 12.1 (2020): 115-127.
31. Rekik, Farah, Walid Ayedi, and Mohammed Jallouli. "Evaluation of an object detection system in the submarine environment." (2017).
32. Kannan, Srividhya. "Intelligent object recognition in underwater images using evolutionary-based Gaussian mixture model and shape matching." *Signal, Image and Video Processing* (2020): 1-9.
33. Ancuti, Codruta O., et al. "Color balance and fusion for underwater image enhancement." *IEEE Transactions on image processing* 27.1 (2017): 379-393.
34. Marcos, Ma Shiela Angeli C., Maricor N. Soriano, and Caesar A. Saloma. "Classification of coral reef images from underwater video using neural networks." *Optics express* 13.22 (2005): 8766-8771.
35. Chen, Chaoqi, et al. "Weakly-Supervised Man-Made Object Recognition in Underwater Optimal Image Through Deep Domain Adaptation." *International Conference on Neural Information Processing*. Springer, Cham, 2018.
36. Jia, Liu, et al. "Obstacle detection method for underwater mine emergency rescue AUV." *2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST)*. IEEE, 2017.
37. Dang, Fengying, Sanjida Nasreen, and Feitian Zhang. "Background Flow Sensing for Autonomous Underwater Vehicles Using Model Reduction with Dynamic Mode Decomposition." *2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, 2020.
38. Alfalou, Ayman, and Christian Brosseau. "Recent advances in optical image processing." *Progress in optics*. Vol. 60. Elsevier, 2015. 119-262.
39. Qiao, Xi, et al. "An automatic active contour method for sea cucumber segmentation in natural underwater environments." *Computers and Electronics in Agriculture* 135 (2017): 134-142.
40. Chen, Zhe, et al. "Visual-adaptation-mechanism based underwater object extraction." *Optics & Laser Technology* 56 (2014): 119-130.
41. Feng, Hui, et al. "Underwater salient object detection jointly using improved spectral residual and Fuzzy c-Means." *Journal of Intelligent & Fuzzy Systems* 37.1 (2019): 329-339.
42. Han, Fenglei, et al. "Marine Organism Detection and Classification from Underwater Vision Based on the Deep CNN Method." *Mathematical Problems in Engineering* 2020 (2020).
43. Bindhu, A., K. Lakshmipriya, and O. Uma Maheswari. "Classification based on underwater degradation using neural network." *Journal of Ambient Intelligence and Humanized Computing* (2020): 1-8.
44. Leonard, Isabelle, A. Arnold-Bos, and Ayman Alfalou. "Interest of correlation-based automatic target recognition in underwater optical images: theoretical justification and

first results." *Ocean Sensing and Monitoring II*. Vol. 7678. International Society for Optics and Photonics, 2010.

45. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A 2015 Going deeper with convolutions, In Proc. Of IEEE Conf Comput Vis Pattern Recognit, pp.1–12
46. Nicholas C-B, Anush M, and Eustice RM (2010) Initial results in underwater single image dehazing, In Proc. of IEEE OCEANS, pp. 1–8
47. Lu, Huimin, et al. "FDCNet: filtering deep convolutional network for marine organism classification." *Multimedia tools and applications* 77.17 (2018): 21847-21860.

Bibliography:

C. Annadurai is the Associate Professor in the Department of ECE at SSN College of Engineering, Kalavakkam, and Chennai, India. He received B.E degree and M.E degree in 1991 and 2002, respectively, from Bharathiar University, Coimbatore India, and Ph.D from Anna University, Chennai, India in 2016. He is Life time member of ISTE and IEI. His research interests include several aspects of wireless communications such as MIMO, Cooperative communication, Machine Learning, Deep learning and Embedded Design.

Nelson Iruthayanathan received the B.E., M.E., and Ph.D. degrees from the University of Madras, Chennai, India, in 1995, College of Engineering, Guindy and Anna University, Chennai in 1995, 1998 and 2018 respectively. His research field includes MIMO, multi-carrier communications in underwater communication and applications of machine learning algorithms.