MINISTERUL EDUCAȚIEI ROMÂNIA
UNIVERSITATEA DE MEDICINĂ, FARMACIE, ȘTIINȚE ȘI TEHNOLOGIE „GEORGE EMIL PALADE" DIN TÂRGU MUREȘ

sciendo

Acta Marisiensis. SeriaTechnologica
Vol. 19 (XXXVI) no. 1, 2022
ISSN 2668-4217, ISSN-L 2668-4217

10.2478/amset-2022-0006

UNDERWATER IMAGE DETECTION FOR CLEANING PURPOSES; TECHNIQUES USED FOR DETECTION BASED ON MACHINE LEARNING *

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Abstract

Serious problems are on the rise, especially in these current times. The world is facing too many environmental threats. Water pollution is one of the main issues threatening the future. In some parts of the world, the water's surface is covered by mucilage, which is dangerous for both aquatic animals and humans. This article firstly defines mucilage and highlights the reasons for its production. Afterwards to tackle water pollution, cleaning systems using image detection with the help of machine learning supervised classification algorithms are highlighted. This paper showcases the machine learning and classification used as well as the best solution for convolutional neural network and region-based convolutional neural network methods.

Key words: convolutional neural network (CNN), classification, image detection, method, region-based convolutional neural network (R-CNN), neural network (NN), water pollution.

1 Introduction

Due to significant water pollution, underwater image algorithms and methods have been invented to

prevent further damage of the marine environment. Computer vision technology and image processing are being developed and enhanced on a daily basis [1, 2]. The underwater image processing quality is always in need of better visuals and improvements. This topic is well-known globally [3]. Underwater image enhancement methods and restoration can be grouped into two categories:

- Non-physical model image enhancement;
- Physical model-based image restoration.

For underwater image enhancement, the traditional image processing methods include colour correction algorithms and contrast enhancement algorithms. The white balance method, grey world hypothesis [4] and grey edge hypothesis [5] are the typical colour correction methods. The contrast enhancement algorithms include the histogram equalisation [6] and restricted contrast histogram equalisation, which are commonly used to enhance underwater images.

The results obtained from these methods are unsatisfactory for underwater vision compared to the great results obtained by common image processing. The main reason is that the ocean environment is complex. Many unfavourable factors, such as the scattering and absorption of light by water and underwater suspended particles, severely interfere with image quality [7].

Mucilage is a sticky, viscous or gelatinous plant cell product. This substance is secreted by some plants through the action of water on the cell wall. The term is usually applied to plant gums. It is created from cactus, commonly known as water-soluble pectin-like polysaccharides. The most common ability that Cactaceae has is to retain water during unfavourable climate conditions (such as arid and hot climates) and prolong the water binding capacity of mucilage. The mucilage biosynthesis occurs in specialised cells, known as mucilage cells, and is excreted to the apoplast. This helps regulate the cellular water content during the initial phase of dehydration [8].

Mucilage is another way of expressing the well-known term 'exopolysaccharides', meaning sugar substances produced by unicell or filamentous green algae [9]. Figure 1 represents the causes and results of the mucilage problem. The yellow colour indicates the causes, and the red colour signifies the results. The causes of mucilage can be summarised as global warming, high temperature, phytoplankton increase, water pollution and water stability. As the photosynthesis of mucilage in the water steadily decreases, many affected aquatic animals will perish. Currently, the mucilage problem is becoming an increasing threat to marine life. Numerous reasons for water pollution and mucilage existence are present [10, 11]. Mucilage is mainly a chemical reaction to

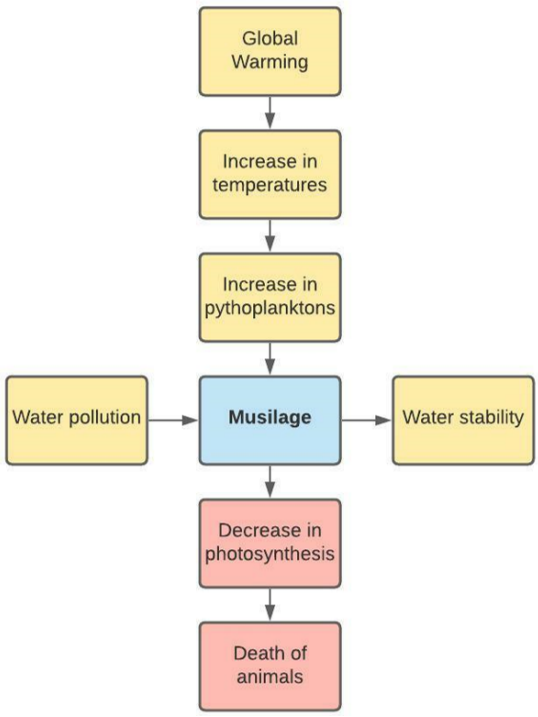

Figure 1: The process of mucilage in the environment.

increasing phytoplankton in water [12]. There are generally three causes for this phenomenon: climate change, water stability and polymer waste.

In this project, we will focus on polymer waste by collecting plastics from the water's surface and subsurface. The technology frequently used is through computer vision such as image detection with machine learning background. To understand the working principle of the project, image classification technique and the relevant algorithm are further explained. The Integrated Marine Observing System (IMOS) collects millions of underwater images every year, especially around Australia. However, only a very small number (around 5%) undergo analysis by marine experts. The National Oceanic and Atmospheric Administration also predicted that this percentage will further decrease from 5% to 1-2%. This is extremely risky for global aquatic life. Machine learning technology provides the potential opportunity of detecting underwater objects and images.

The remained of manuscript is as following: the second section of this paper presents the general approach to solve this problem, along with recent research and machine learning details on fish classification. The third section highlights the concepts of machine learning classification, and the fourth section explains image classification. The fifth section further discusses machine learning classification for plankton, while the sixth is for corals and the seventh for seagrass. The eighth section summarises plastic and microplastic, concluding with the research purposes.

2 Machine Learning Concept and Method

In the field of marine biology, deep neural network is extensively used to classify underwater living things. Underwater image detection methods are always related to the object being detected. Here, the focus is mostly on plankton, fish, coral and seagrass. Unmanned surface vehicles have been designed for learning purposes and for collecting plastics. Such vehicles have three common parts: the software system used, image classification and detection. The following sections will provide further and brief description.

The general concepts of machine learning and classification algorithms are mentioned to further explain image detection. Machine learning can be briefly defined as programming the computer to teach and learn tasks on its own and it is very related to artificial intelligence [13]. The main purpose of this technology is to allow machines to perform tasks without any human assistance. Automatic system designs are a big trend which many have attempted to accomplish.

2.1 Classification Neural Networks

Classification can be defined as the concept of grouping data to pre-defined patterns. It can be easily understood by utilising both patterns and processes of a given dataset to train and conduct supervised learning. Supervised learning splits into two branches: regression and classification.

The difference between the two is continuous/discrete sampling. Their usage varies depending on the problem. To classify a given data, it is beneficial to firstly mention a few terminologies of the fundamental concepts, such as "Classifiers", "Classification Model", "Feature" and "Labels". The classifier is an algorithm that maps the input to a specific class and the classification model predicts the class for inputs. The feature is a property that is measured, and labels are the categorised data points.

The methods of classification can be expressed in two fundamental steps. The first is using a dataset gathered from a large randomly selected population to group new patterns correctly. The error rate of each case can be measured. The semination mainly depends on the statistical pattern recognition. For this purpose, leaving-one-out resampling technique is used [14, 15].

2.2 Machine Learning for Fish Detection

Several attempts for detecting the images of fish have been accomplished from 2015 onwards. To successfully detect fish underwater, Spampinato et al. used the moving average algorithm. Ravanbakhsh et al. employed the Haar Classification to integrate face recognition and image processing [16]. Although both methods were very good solutions at the time, they possessed a major drawback: the limited ability to process large amounts of underwater images. The architecture of fish recognition and detection is illustrated in Fig. 2.

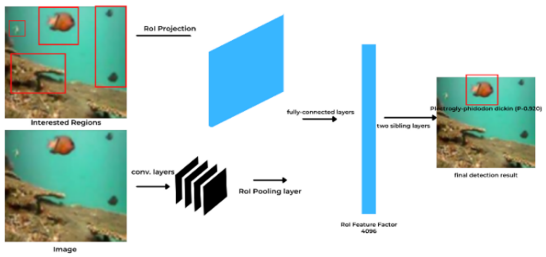

Figure 2: Architecture of fish recognition and detection.

Table 1 illustrates how the separation of fish, plankton and corals is performed. Each of them has a category. The database has certain images that explain which type of image detection is applied for each category. The features used include specific information regarding image processing and the database. In the classifier category, it can be easily seen how all results are summated. Table 2 displays 6 different types of categories and method accuracy.

The method that presents the highest chance of accuracy is the VLFeat Dense SIFT with an accuracy of 98.58%. However, all methods have proven to be useful. As can be seen, the percentage ranges between 80% to 90%, which is a very high chance of accuracy [24].

3 Results and discussions

Image classification labels images to pre-defined patterns. When a machine, such as an autonomous car for instance, sees any object using a camera system, it should be able to understand the images, such as vehicles, road lines, pedestrians, animals, etc. Fig. 3 further explains the fundamental image classification.

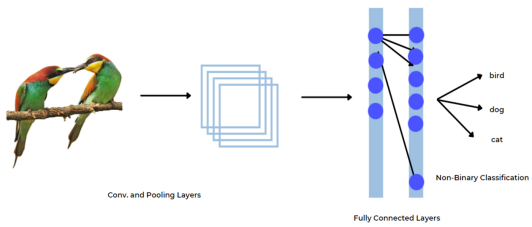

Figure 3: A general description of image Classification.

Another example would be cancer detection, where machine learning and image classification

Table 1: Underwater image Detection

Target Group	Ref.	Type of Image Dataset	Feature used	Classifier
Fish	[17]	RGB photos and videos from LideCLIEF Fish Task of ImageCLIEF	RGB-colorspace	Fast RCNN
	[18]	Marine Biodiversity Exploitation and Conservation Dataset	Motion from previous sliding window	Sostmax Classifier with neural network
Planktons	[17]	Grey scale image provided by National Data Science Bowl	Shapes and rotational symmetry	ConvNNet inspired by OxfordNet
	[19]	Grey scale image provided by National Data Science Bowl	Inception module for multiscale architecture	Deep CNN inspired by GoogleNet
	[20]	Woods Hole Oceanographic Institution (WHOI-Plankton) Dataset	Transfer learning to reduce class imbalance	CIFAR 10 CNN
Corals	[21]	ZooScane System Dataset	Data Augmentation to increase dataset	ZooPlanktoNet inspired by AlexNet and VGGNet
	[22]	Video skills of coral reef transects from the Great Barrier Reef	LBP pattern for texture and Normalised Chromaticity Coordinates histogram for colour	Linear Discriminant Analysis followed by a three layer back propagation NN
	[23]	Mocrea Labelled Corals and Herict-Watt University Atlantic Deep Sea Digital Dataset	Colour, shape and texture feature descriptions	Supervised CNNs
	[21]	Mocrea Labelled Coral (MLC) Dataset	Terton and colour based hand-crafted features Spatial Pyramid Pooling (SPP)	VGGNet

Table 2: The comparison accuracy of fish recognition [17]

Method	**Accuracy (%)**
LDA+SVM	80.14
Raw pixel SVM	82.92
Raw pixel Softmax	87.56
Raw pixel Nearest Neighbour	89.79
VLFeat Dense SIFT	98.58
Deep-CNN	98.57

techniques are also used in this field. This process can be summarised as binary, which the given x-ray image detects whether or not cancer is present [25].

3.1 Image Classification with R-CNN and YOLO

Image classification is a vast field that consists of various solutions. One such solution is region-based Convolutional Neural Network (R-CNN). Neural networks and neural computing are relatively recent developments in the information sciences; an outgrowth of artificial intelligence research of the 1950s and 1960s. Neural networks are named as such because they exhibit certain analogies, at least superficially, to the way in which arrays of neurons probably function in biological learning and memory [26].

Convolutional Neural Network is used in many fields like image classification, and medical diagnosis purposes. It is a sub-class of deep learning [27]. The term comes from the convolution operator in Mathematics. Since the matrix multiplication is made by this convolution calculation, it entails faster results. The CNN structure consists of 5 different layers: the Convolutional Layer detects specification, the Non-Linearity Layer detects the nonlinearity of the system, the Pooling or Down sampling Layer decreases the weight number and controls suitability, the Flattening Layer prepares data to classical neural networks and lastly, the Fully-Connected Layer conducts standard classification of CNN. Fig. 4 represents the working layer system structure of CNN.

Regional CNN is a better approach to the Classical CNN algorithm. It firstly detects the extraction proposal of the region to 2000 candidate regions, thereby decreasing the operating time. Yet, every good solution can be enhanced to a better one. Fast R-CNN and Faster R-CNN possess different beneficial features to make image classification systems quicker.

Other algorithm solutions, such as YOLO (You Only Look Once), split the taken image to an MxM grid. For each grid, a bounding box is created. With a system of probability offset value, it runs faster than the fastest R-CNN algorithm. However, the negative aspect is that it may have difficulties when it comes to small objects. Figure 5 presents the YOLO structure.

3.2 Machine Learning for Plankton Detection and Classification

What is plankton? Plankton are marine drifters. They are organisms carried along by tides and currents. Since plankton are microorganisms, they are very difficult to detect or recognise by deep learning.

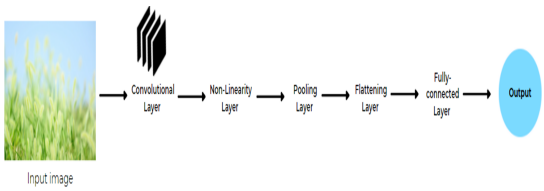

Figure 4: General view of the CNN Structure .

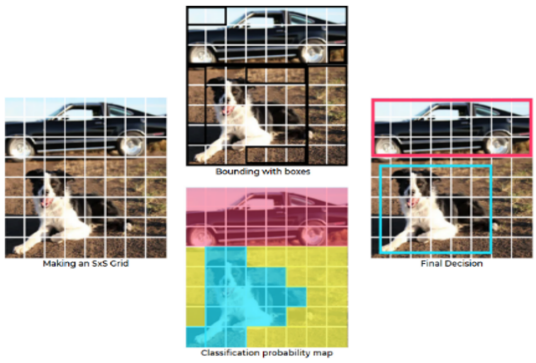

Figure 5: The general view of the YOLO Structure.

The introduction of deep convolutional network solely for the classification of zooplankton was accomplished [21]. Their dataset consists of 9460 microscopic and grey-scale zooplankton images of 13 different classes captured by the ZooScan system. They proposed a new deep learning architecture called ZooplanktoNet for zooplankton classification, which was strongly inspired by AlexNet and VGGNet. After experimenting with different convolution sizes, they concluded that ZooplanktoNet, with 11 layers, can provide the best performance thus far. To support their claim, they conducted a comparative experiment with other deep learning architectures like AlexNet, CaffeNet, VGGNet and GoogleNet. ZooplanktoNet outperformed all other architectures with an accuracy of 93.7% [21].

3.3 Machine Learning for The Classification of Coral

The colour, size, shape and texture of corals may vary according to the difference in class. The boundary differences are ambiguous and organic. Currents, algal blooms and plankton density can change the turbidity of water and light availability, affecting the image colour. These types of challenges make conventional annotation techniques (such as bounding boxes, image labels and full segmentation) inappropriate. Local Binary Pattern (LBP) for texture and Normalised Chromaticity Coordinate (NCC) for colour have been used. They employed a three-layer back propagated neural network for classification purposes. However, Beijbom et al. first addressed automated annotation on a large scale for coral reef survey images by introducing the Moorea Labelled Corals (MLC) dataset [28]. They proposed a method based on colour and texture descriptors over multiple scales which outperformed traditional methods of texture classification.

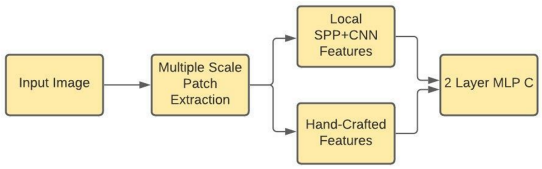

Figure 6: Block diagram for combined computer numerical control (CNC) architecture for coral classification.

3.4 Deep Learning for Seagrass Detection

For the stabilisation of sediment, sequestration of carbon and provision of food and habitat for enormous oceanic animals, seagrass is extremely vital [23]. To enhance the understanding of temporal and spatial patterns in species composition, reproductive phenology, the abundance of seagrass and the influence of commercialisation and human interaction, it is very important to monitor seagrass in more areas. Presently, a conventional digital imagery approach approved by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Health Safety and Environment Policies (HSE), Australia, take approximately 60×80 cm images using a digital camera every three seconds. The camera is normally kept attached to a frame towed behind a boat travelling at 1.5-3 knots, ensuring that the images are spaced approximately 2-3 meters apart. These images are then analysed using the Photo Grid or Transcent Measure (®SeaGIS) software. A regular grid of 20 dots is superimposed (Fig. 7) and a human operator identifies the presence and species of seagrass. It typically takes a technician several hours to process image data for a single transect of 50 m and with 25-50 images. Since most surveys must cover hundreds of metres of seabed, it can take up to several days to conduct the analysis [19].

Different technicians may also vary in their ability to detect seagrass within images. Deep learning approaches can increase efficiency and simultaneously remove observer bias from the analysis. However, to the best of our knowledge, no approach that applies deep learning to digital images for seagrass detection exists. Therefore, there is a great opportunity to use deep neural network to examine, detect and classify various seagrass species within seabed. This matter will be the focus of our future work.

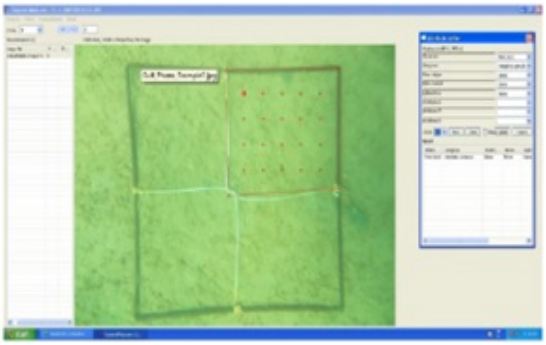

Figure 7: Transcent measure software environment.

```python
import cv2
import numpy as np

rsm= cv2.imread("new.jpeg")

#Taking photo saving it
segment=rsm[200:500,600:700]
cv2.imwrite("newsegment.jpeg", segment)
segment[:,:,0]=50
segment[:,:,1]=40
#cv2.imshow("renklenmisKesit",kesit)

#Choosing a segment and stick into another
rsm= cv2.imread("new.jpeg")
segment=rsm[200:500,600:700]
rsm[0:300,0:100]=segment
cv2.imshow("StickedPic",rsm)


cv2.waitKey(0)
cv2.destroyAllWindows()
```

Figure 8: Python OpenCV implementation of image reading, dividing and pre-processing.

3.5 Plastics and Microplastics

Plastics are polymer wastes. With wind and solar power, they have the tendency to erode into little particles called microplastics. Their sizes can become less than 5 mm, making them small enough for fish to eat. This directly affects the marine ecosystem and indirectly affects human health. These polymer waste have different densities within the ocean, floating in various underwater segments. These microplastics are causing major plastic pollution, spreading far and wide throughout oceans. They are hazardous whether floating on the water's surface or underneath throughout the ocean floor.

3.6 Plastic Detection for Cleaning Purposes

Water pollution is a serious problem. The increasing amounts of microplastics and large polymer waste are damaging the marine ecosystem. Research from marine faculty members have stated that the amount of microplastics in the water will eventually become more than the number of fishes in their natural habitat. To control this dilemma, robotic systems are currently in the design phase. These types of USV systems have a hierarchical structure with perception, decision and execution layers.

Plastic detection can be accomplished by initially understanding the place of the object through double vision technology, making segmentation and then finding a path for collecting waste. After setting up the software, the machine will be able to swim on the water's surface and catch floating polymer wastes with the use of mechanical components integrated with electronic parts. To design such systems, powerful GPU cards and integrated systems should be developed. Implementation can be accomplished using Python libraries, such as OpenCV and TensorFlow. A code example for image reading, pre-processing and dividing a picture for given constraints is displayed in Fig. 8.

4 Conclusion

This paper discussed the recent approaches for detecting and classifying various underwater marine objects using the deep learning technique. Approaches are categorised according to detection targets. The employed features and deep learning architectures have been summarised. It was necessary to highlight all approaches of marine data analysis in a single paper so that it becomes easy to focus on the possibilities of future works based on the deep neural network method. It was discovered that endeavours have been made for coral detection and classification using the deep learning method, however, no work has been accomplished for the case of seagrass which is equally vital for a balanced oceanic ecosystem. The effectiveness, accuracy and robustness of any detection and classification algorithm can be significantly increased if both colour and texture-based features are combined. Accumulation of hand-crafted features and neural network may provide better results for seagrass detection and classification. Therefore, there is an opportunity to develop an efficient and effective deep learning approach for underwater seagrass imagery, which will be the focus of our future work.

References

[1] K. Wang, L. Shen, Y. Lin, M. Li, and Q. Zhao, "Joint iterative color correction and dehazing for underwater image enhancement," *IEEE Robotics and Automation Letters*, vol. 6, no. 3, pp. 5121–5128, 2021.

[2] N. Panchi, E. Kim, and A. Bhattacharyya, "Supplementing remote sensing of ice: Deep learning-based image segmentation system for automatic detection and localization of sea-ice formations from close-range optical images," *IEEE Sensors Journal*, vol. 21, no. 16, pp. 18 004–18 019, 2021.

[3] B. Song, K. Li, Y. Zong, J. Zhu, W. Zheng, J. Shi, and L. Zhao, "Recognizing spontaneous micro-expression using a three-stream convolutional neural network," *IEEE Access*, vol. 7, pp. 184 537–184 551, 2019.

[4] E. Lam, "Combining gray world and retinex theory for automatic white balance in digital photography," in *Proceedings of the Ninth International Symposium on Consumer Electronics, 2005. (ISCE 2005).*, 2005, pp. 134–139.

[5] G. Buchsbaum, "A spatial processor model for object colour perception," *Journal of the Franklin Institute*, vol. 310, no. 1, pp. 1–26, 1980. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0016003280900587

[6] J. van de Weijer, T. Gevers, and A. Gijsenij, "Edge-based color constancy," *IEEE Transactions on Image Processing*, vol. 16, no. 9, pp. 2207–2214, 2007.

[7] C.-C. Wang and H. Samani, "Object detection using transfer learning for underwater robot," in *2020 International Conference on Advanced Robotics and Intelligent Systems (ARIS)*, 2020, pp. 1–4.

[8] E.N.Transeau, "General botany," *Discovery Publishing House*, 1994.

[9] M. J. M. Christenhusz, "The kew plant glossary, an illustrated dictionary of plant terms," *Botanical Journal of the Linnean Society*, vol. 164, no. 4, pp. 440–441, 2010. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1095-8339.2010.01099.x

[10] R. Dorothy, J. R M, J. Rathish, S. Prabha, S. Rajendran, and S. Joseph, "Image enhancement by histogram equalization," *International Journal of Nano Corrosion Science and Engineering*, vol. 2, pp. 21–30, 09 2015.

[11] T. T. Türkistanlı, C. Sevgili Ve, and Ö. Arslan, "Bibliometric analysis of the literature on marine mucilage," in *Avrupa Bilim ve Teknoloji Dergisi, sayı. 28, ss. 947-958*, Kas.

[12] G. F. C. Campos, S. M. Mastelini, G. J. Aguiar, R. G. Mantovani, L. F. d. Melo, and S. Barbon, "Machine learning hyperparameter selection for contrast limited adaptive histogram equalization," *EURASIP Journal on Image and Video Processing*, vol. 2019, no. 1, p. 59, May 2019. [Online]. Available: https://doi.org/10.1186/s13640-019-0445-4

[13] G. Vasile, A. Girard, G. d'Urso, E. de Oliveira, F. Hieramente, and O. Philippe, "Active acoustic signature extraction by machine learning data analysis for underwater fish counters," in *Global Oceans 2020: Singapore – U.S. Gulf Coast*, 2020, pp. 1–4.

[14] A. Łysiak and M. Szmajda, "Empirical comparison of the feature evaluation methods based on statistical measures," *IEEE Access*, vol. 9, pp. 27 868–27 883, 2021.

[15] A. K. Malik, M. Ganaie, M. Tanveer, and P. Suganthan, "A novel ensemble method of rvfl for classification problem," in *2021 International Joint Conference on Neural Networks (IJCNN)*, 2021, pp. 1–8.

[16] M. Ravanbakhsh, M. Nabi, E. Sangineto, L. Marcenaro, C. Regazzoni, and N. Sebe, "Abnormal event detection in videos using generative adversarial nets," 09 2017.

[17] X. Li, M. Shang, H. Qin, and L. Chen, "Fast accurate fish detection and recognition of underwater images with fast r-cnn," in *OCEANS 2015 - MTS/IEEE Washington*, 2015, pp. 1–5.

[18] "Rete neurale convoluzionale," http://nl.mathworks.com/discovery/convolutional-neural-network-matlab.html..html, accessed: 2022-02-27.

[19] M. Vanderklift, D. Bearham, M. Haywood, H. Lozano-Montes, R. Mccallum, J. McLaughlin, K. Mcmahon, N. Mortimer, and P. Lavery, "Natural dynamics: understanding natural dynamics of seagrasses in north-western australia wamsi dredging science node report," 10 2016.

[20] A. Mahmood, M. Bennamoun, S. An, F. Sohel, F. Boussaid, R. Hovey, G. Kendrick, and R. Fisher, "Coral classification with hybrid feature representations," in *2016 IEEE International Conference on Image Processing (ICIP)*. United States: Institute of Electrical and Electronics Engineers (IEEE), Sep. 2016, pp. 519–523, 2016 IEEE International Conference on Image Processing, ICIP 2016 ; Conference date: 25-09-2016 Through 28-09-2016. [Online]. Available: https://www2.securecms.com/ICIP2016/Default.asp

[21] J. Dai, R. Wang, H. Zheng, G. Ji, and X. Qiao, "Zooplanktonet: Deep convolutional network for zooplankton classification," in *OCEANS 2016 - Shanghai*, 2016, pp. 1–6.

[22] "R-cnn, fast r-cnn, faster r-cnn, yolo - object detection algorithms," http://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e, accessed: 2022-02-27.

[23] P. Lavery, K. Mcmahon, J. Weyers, M. Boyce, and C. Oldham, "Release of dissolved organic carbon from seagrass wrack and its implications for trophic connectivity," *Marine Ecology Progress Series*, vol. 494, pp. 121–133, 12 2013.

[24] M. Moniruzzaman, S. Islam, M. Bennamoun, and P. Lavery, "Deep learning on underwater marine object detection: A survey," 11 2017, pp. 150–160.

[25] S. Iqbal, G. F. Siddiqui, A. Rehman, L. Hussain, T. Saba, U. Tariq, and A. A. Abbasi, "Prostate cancer detection using deep learning and traditional techniques," *IEEE Access*, vol. 9, pp. 27 085–27 100, 2021.

[26] A. M. Santilli, A. Jamzad, A. Sedghi, M. Kaufmann, S. Merchant, J. Engel, K. Logan, J. Wallis, N. Janssen, S. Varmak, G. Fichtinger, J. F. Rudan, and P. Mousavi, "Self-supervised learning for detection of breast cancer in surgical margins with limited data," in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, 2021, pp. 980–984.

[27] L. Kouhalvandi, L. Matekovits, and I. Peter, "Deep learning and its benefits in prediction of patients through medical images," in *2021 IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*, 2021, pp. 139–142.

[28] O. Beijbom, P. Edmunds, D. Kline, B. Mitchell, and D. Kriegman, "Automated annotation of coral reef survey images," 06 2012, pp. 1170–1177.