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Managing marine environmental pollution using Artificial Intelligence

Nitin Agarwala*

National Maritime Foundation, New Delhi, India

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Abstract

The marine environment has deteriorated to the extent that it has begun to impact human health and the planet itself. The primary causes of this deterioration are an increasing population, the Industrial Revolution, and the increased use of fossil fuels. While the damage done to the environment cannot be undone, the impact can be lessened with a better understanding of the ocean and with monitoring future pollution using technology. Such an effort will help achieve sustainability, as laid out by the Sustainable Development Goals 2030 of the United Nations. Though efforts have been made to monitor the ocean for pollutants, both physically and remotely, interpreting the data collected is a humungous task due to the high volume of data. In reply, technology again provides a solution. One such technology, namely 'Artificial Intelligence' ('AI'), can be used to understand and monitor marine pollution, and is the topic of discussion in this article. In doing so, the article will discuss the emerging opportunities and risks associated with the use of AI in managing marine environmental pollution through sustainability. To strengthen the argument, use-cases of AI in the marine environment and their scalability are discussed. However, these cases are considered merely a stimulus for a better and a larger variety of solutions to follow in the ever-evolving domain of AI.

1. Introduction

The Industrial Revolution brought about prosperity to humans. Along with prosperity, it also brought about environmental degradation, due to industrial pollution and an unprecedented increase in the population rate. While the increasing population created a stress on the available resources, the industrial pollution led to the deterioration of the air we breathe, the water we drink, and the food we eat. These, in return, affected both the land and the oceans, to the extent that it has manifested in changes to the climate of the Earth, caused the loss of a number of habitats, and created some entirely new norms that have overall increased the chances of destruction of the planet itself. Since the impact of these changes on human health is continuously increasing, it has become imperative to monitor pollution, be it in the air, the water, or the soil, so as to lessen the impact and to encourage sustainable development. It is only by such monitoring that the environmental deterioration can be stemmed and the availability of the resources for future generations be ensured.

Today, new technologies are emerging at a rapid pace, on a near-daily basis. The use of such emerging technologies is being adopted extensively in the fields of speech recognition, language translation, genetic engineering, quantum computing, virtual reality, automation, machine vision,

*Corresponding author: National Maritime Foundation, New Delhi, India
E-mail address: nitindu@yahoo.com

and navigation, to manage various risks. These technologies are, in return, completely transforming the way we work and think. Of the various emerging technologies, one technological tool that can provide a solution to the environmental concerns is Artificial Intelligence (AI), duly supported by Machine Learning (ML). While AI would help create the machine, ML would provide the platform to make predictions and decisions using historical data on which the AI can be developed. Accordingly, for the marine environment, ML can be used to understand oceans, monitor shipping, monitor ocean debris, assist ocean mining, prevent Illegal, Unregulated, and Unreported (IUU) fishing, prevent coral bleaching, or prevent the outbreak of marine diseases, based on which an application or a machine can be developed to protect the marine environment from the rampant marine pollution. Eventually, AI and ML together can help in the protection of the marine environment from pollution and the development of sustainable methods of ocean exploitation.

It is with this understanding that the article aims to provide an insight into the emerging opportunities and risks associated with the use of AI in managing marine pollution through sustainability. To strengthen the argument, use-cases of AI in managing marine pollution and their scalability will be discussed. It is important to mention that the discussed use-cases are not conclusive but provide a stimulus for a better and larger variety of solutions, since AI is evolving and becoming smarter day by day.

2. Background

The Industrial Revolution encouraged a phenomenal increase in both the per capita income and the world population. Both these increases led to increased urbanization (Kelley & Williamson, 1984) which resulted in poor living conditions, the pollution of air and water, and large quantities of waste that caused diseases and water contamination. The reforms that followed after the Black Death helped improve sanitation and living conditions (DeWitte, 2014). However, the pollution of air and water was never addressed satisfactorily, due to lack of awareness of the impact of industry on the environment. Over the years, the pollution of air and water continued to increase and grow from bad to worse (Ukaogo et al., 2020). As the world population continued to grow (Kelley & Williamson, 1984), exploitation of the oceans for food and resources became a necessity, rather than a desire, due to dwindling resources on land to support such a large population (Pimental et al., 1997). This resource exploitation, compounded by pollution from land-based activities that accounts for nearly 80 % of ocean pollution (UN, 2017), is degrading the marine environment and converting the oceans into large litter bins that have now begun to overflow. Such is the degradation that studies indicate that, by 2050, there will be more plastic in the oceans than fishes (by weight) (WEF, 2016). To add to this, the unsustainable use of fossil fuels, cement manufacture, and industries on land are causing climate change that is resulting in unwarranted changes in the oceans, such as sea-level rise, higher temperatures, and an inability to act as a natural carbon dioxide sink (Science Daily, 2018). It is no wonder that 7 of the 17 sustainable development goals of the UN are aimed at addressing environmental deterioration and the human influence on it (PwC, 2018).

Today, it is an accepted fact that the use of technology causes pollution due to excessive use of power (energy) and resources, but the same technology can also provide the means to address pollution. Some direct use technologies include laser methods, chemical methods, nanotechnology, and sensors to detect and control pollution. Technology also helps develop new sustainable materials and methods while allowing a better understanding of the environment itself. Though technology as a result of the First Industrial Revolution is considered to be the initiator of human woes, the Fourth Industrial Revolution is creating societal shifts to address this environmental deterioration that is threatening future life on Earth.

One such developmental technology of the Fourth Industrial Revolution - Artificial Intelligence (AI) - has a significant impact on every facet of our lives. The numerous possibilities of use displayed by AI, and its ever-growing capabilities, make it a tool fit to be employed to address the environmental degradation that has begun to challenge the very existence of the planet.

However, challenges, such as high cost and the need for regulatory approvals, act as barriers to their effective use. It is imperative to clarify here that AI is an all-encompassing concept that helps develop machines that can help human thinking and behavior. AI using ML and Deep Learning (DL) can be utilized to understand the complex process of the environment and sustainable trends of resource availability. This, in turn, would help nations to achieve the SDG-14 goal of conserving and using ocean resources sustainably (UN, 2015).

In order to ensure sustainability and a healthy ocean, issues of pollution, habitat, species, climate change impact, and biodiversity, as seen in **Figure 1**, need to be addressed. It is with this understanding that the discussion in this article is limited to these issues alone.

Before we discuss the use of AI to address these issues, we need to understand the technological development that has happened over the years in the field of managing marine pollution, and how AI has become a mainstay of the methods that could be used to address this problem.

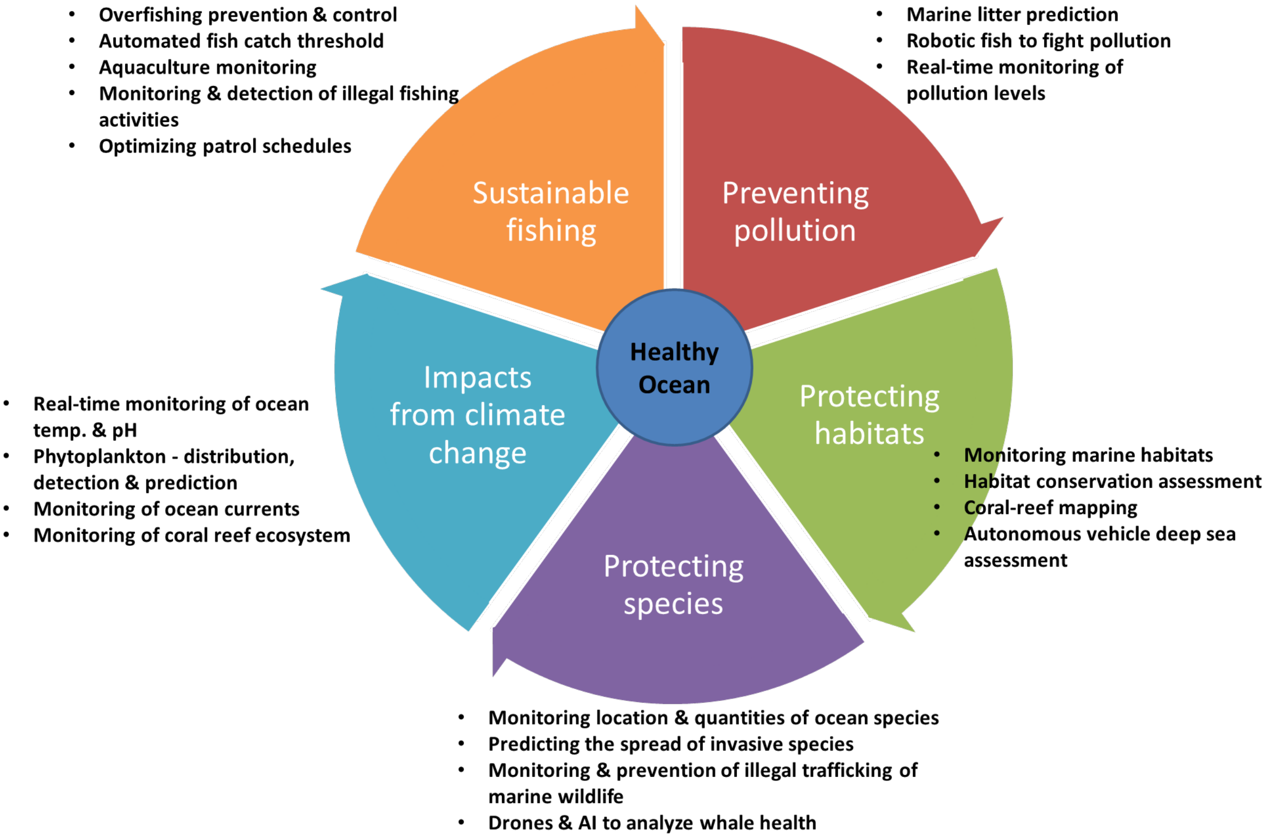

Figure 1 Requirements of a healthy ocean (Source: adapted from PwC, 2018).

Evolution of detection methods

When the negotiations of the third United Nations Conference on the Law of the Sea (UNCLOS III) were conducted, marine pollution control was a minor topic (Boehmer-Christiansen, 1982). This was primarily because no clear scientific definition of 'marine pollution control' could be established by the Joint Group of Experts on the Scientific Aspects of Marine Pollution (GESAMP). Since little reliable data on input pollutants, and even less knowledge on their impact on nature and humans, were available, it was difficult to define a control standard. However, general principles, guidelines, and criteria for the assessment of the health of the environment were put forth, which were more relevant at the regional level than at the global level and led to various regional studies† with regard to marine pollution. Since no clear definition of control was possible, the focus remained primarily on *monitoring and data collection* for the effect of analysis and decision-making.

In order to monitor the ocean over a large scale, the most obvious method to use is to see the ocean from the sky. Hence, airplanes were first used to monitor the ocean, but they could be used only when the weather was good. Furthermore, airplanes could not provide dedicated, consistent, and continuous data feeds for one region over prolonged periods of time. To overcome this, satellites began to be used in 1972 for terrestrial monitoring, and then in the late 1970s for marine spaces (Clark, 1993). This brought to the fore 'remote sensing technology' to detect, track, assess damage from, and monitor marine-based pollution (Loughland & Saji, 2008). With the development of numerous sensors of varying types and capabilities, which could be used on a variety of remote sensing platforms, remote sensing began to be carried out. However, different sensors have their own capabilities and limitations (Hafeez et al., 2018). The images so obtained require processing to make the sensing useful. Hence, the remote sensing community has focused on trying to improve the process of data processing (Lei et al., 2019).

Over the years, a number of physical and remote sensing systems have been developed for the monitoring of various ocean variables, such as temperature, conductivity, pH, salinity, dissolved oxygen, fluorescence due to chlorophyll, turbidity, color-dissolved organic matter (CDOM), and marine pollution. These systems include satellites, ships, ocean observatories, and marine robots, such as surface vehicles, wave-piercing vehicles, and sub-surface vehicles (Agarwala, 2020).

The possibility of developing these increasing variables and the increasing number of monitoring methods was due to the development of software and the computational power of computers. This development allowed the data collected to increase by many magnitudes and, within no time, ocean sensing entered the big-data era, as seen in **Figure 2**. At the same time, to handle this increasing data, 'Machine Learning' was developing, as seen in its development timeline in **Figure 3**. Today, to effectively use big-data, ML (that uses algorithms to parse data, learn from that data, and make decisions based on the learning) and its evolution of DL (using programmable neural networks (NN)) have become a necessity.

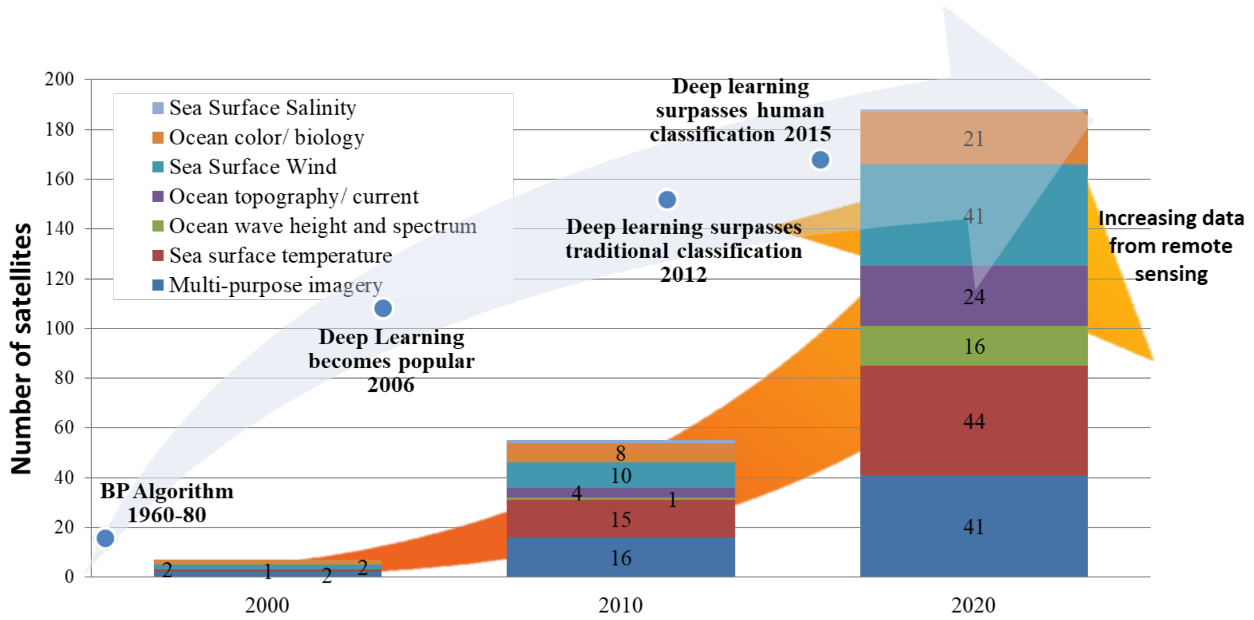

Figure 2 Ocean remote sensing entering the big-data era (Source: adapted from Li et al., 2020).

† Such as those under the UNEP in the Baltic Sea, the North Sea and the NE Atlantic, the Mediterranean, the Red Sea, the Persian Gulf, the waters of the Caribbean, the sea off West Africa and the West Coast of South America, and East Asian waters.

Before 1943	Various statistical methods developed and refined.
1943	First mathematical model (Walter Pitts & Warren Mcullock)
1950	The prediction of Machine language (Alan Turing)
1951	First Artificial Neural Network (ANN) built (Marvin Minsky Dean Edmond)
1952	First Machine Language (ML) programme (Arthur Samuel)
1957	Setting a foundation for Deep Neural Network (DNN) (Frank Rosenblast)
1959	Discovery of simple cells complex cells as inspiration for many ANN (David Hubel & Toren Weisel)
1960	Control theory (Henry J Kelley), Back Propagation (BP) model developed to train Neural Network (NN)
1962	BP with Chain rule (Stuart Dreyfus)
1965	First working DLN (Alexey Ivakhnenko & VG Lapa) as Modern Deep Learning (DL). Gave birth to the multi-layered NN
1967	The Nearest Neighbour algorithm given (for classification & regression ML) (Thomas Cover Peter E Hart)
1969	Fall of Perceptrons encouraging an AI winter
1974-80	First AI winter begins
1970	BP is computer coded
1971	NN goes Deep
1979-80	ANN learns to recognise visual patterns (Kunihiko Fukushima) and creation of Neocognitron, an ANN
1982	Prog. Learns to pronounce English words (Terry Sejnowski call NETtalk
1986	Improvements in shape recognition and word prediction (David Rumelhart, Jeoffrey Hinton & Ronald J Williams), Implementation of BP in NN
1986	Restricted Boltzmann Machine (RBM) (Paul Smolensky)
1987-93	Second AI Winter
1989	Universal Approximators Theorem (George Cybenko)
1989	Q-learning (Christopher Watkins)
1989	CNN using BP allowing machines read handwritten digits (Yann LeCunn)
1990	Boosting algorithm (Robert Schapire & Yoav Frennd)
1991	Vanishing Gradient Problem identified (Sepp Hochreiter)
1993	A very Deep Learning task solved (Jurgen Schmidhuber)
1995	Support Vectors Machine (SVM) refined (Corinna Cortes Vladimir Vapnik)
1995	Random decision forest algorithm introduced (Tin Kam Ho)
1997	Long Short-Term Memory (LSTM) network proposed (Jurgen Schmidhuber & Sepp Rochreiter)
1998	Gradient based learning (Yann LeCun), A stochastic Gradient descent algorithm and BP used
2000	DL used for te first time (Igor Frizenberg)
2006	Deep Belief Network (Geoffrey Hilton et al.)
2008	GPU revolution begins. Training of DNN with PU to bring practicality in learning
2009	Launch of ImageNet (Fei-Fei Li) a large free database of labelled image
2011	Creation of AlexNet (Alex Krizhevsky) A Convolutional Neural Network (CNN). Kicked off use of CNN in DL
2011	Vanishing Gradient addressed by using the ReLU activation function. DNN training now possible by this along with GPU.
2014	DeepFace (social media DL system) Uses NN to identify faces with 97.35% accuracy
2014	Generative Adversarial Neural Networks (GANN). Help tackle unsupervised learning
2016	Powerful ML products (Face to Face comparisons, Waymo – Autonomous cars etc.)

Figure 3 Development timeline of Machine Learning (Source: Author).

Like the word specifies, teaching a machine to predict or understand a pattern is what is called 'Machine Learning'. Accordingly, the data collected from various sources are utilized to train the machine to detect, predict, and analyze a target. It is important to understand that the data collected from sensors in the sky are usually in the forms of light signals. Since near-infrared light is absorbed differently by water and pollutants, the difference in light absorption can assist in the detection of floating objects on the sea surface. Using this varying light absorption, the machine is taught to identify objects such as plastics, oil, algae, seaweeds, seafoam, driftwood, etc., on the sea water surface (Biermann et al., 2020).

However, ML can neither extract locally generated signatures that are present in a small percentage of the remote sensing image, nor can it extract long-time series data. This thus necessitates the need for new data mining algorithms that would eventually support developing new DL approaches (Li et al., 2020).

While surface pollutants can use satellites for data, submerged pollutants require marine robots, such as Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vessels (ROVs), to collect and provide the requisite data for ML (Watanabe et al., 2019; Fulton et al., 2018).

In order to discuss the possibility of managing marine environmental pollution using ML from the data collected and, hence, AI, we take the support of some use-cases to discuss the emerging opportunities and risks associated with the use of AI in the marine environment and their possible scalability for greater results. It is pertinent to highlight that the use-cases are merely stimulants for a better understanding of a large variety of solutions that are possible using AI.

3. Use-cases

In order to appreciate the use of AI for the protection of the marine environment through sustainability, let us look at some use-cases that have been developed. One notices that, for each concern area, there are multiple use-cases, showing the versatility of AI to address the problems in numerous ways. For ease of understanding, these use-cases have been organized under concern areas. It is essential to mention that the cases discussed here are not complete, but only provide a flavor of how AI can contribute to marine environment protection.

3.1 Oil spills

Oil spill can happen both naturally and due to human efforts. Those occurring naturally are of low magnitude and account for a mere 10 % of the total cases. On the other hand, those due to human efforts may be either intentional (to cheaply dispose of oil residues in the tanks of ships) or due to disaster at sea (Zhang et al., 2019). Since the resulting oil spills are dynamic in nature, due to their movement with the ocean waves, it is essential that both remote and fixed sensors are utilized in order to monitor them. Of these, fixed sensors, such as side-looking airborne radar (SLAR), laser fluorosensors (LF), and ultraviolet and thermal infrared video cameras, are effective only when the area of an oil spill is known (Zeng & Wang, 2020). Hence, the use of fixed sensors to monitor oil spills is limited as, in most cases, due to their dynamic nature, the areas are not known and, by the time they are identified, they have already spread over large areas.

In order to identify oils spills remotely, so as to be one step ahead in addressing them effectively, Synthetic Aperture Radar (SAR) is considered to be the most reliable, and has been used effectively (Li & Zhang, 2014; Garcia-Pineda et al., 2017). SAR measures sea surface roughness which, for oil-covered regions, is damped due to the surface tension of oil film. Sometimes, the presence of seaweeds also displays such reduced surface roughness (Xu et al., 2020). Hence, in order to correctly identify oil spills, human intervention is required to assist the radar to identify the difference in surface roughness due to oil and natural elements. With the development of AI, this differentiation between the surface roughness of a wave with and without the presence of oil is possible with greater ease. Since SAR is satellite-based, monitoring of remote areas can also be undertaken without human intervention. This approach assists in detecting oil spills quickly and in ensuring the protection of both human and marine life. Such systems can also help prevent illegal dumping that cause ocean pollution.

One such example currently being used is the Canadian Environmental Hazards Detection System (CEHDS). It uses image processing from two satellites, RADARSAT (a Canadian remote sensing Earth observation satellite) and ERS-1 (European Remote-Sensing Satellite-1), and the 1-NN (1-nearest-neighbour) rule with SHRINK, as the learning algorithms. The system allows the retraining of the system if more data are available (Kubat et al., 1998).

3.2 Plastic/ debris monitoring and removal

It is natural for pollutants to move from land to the oceans, as both environments are interconnected. It is no wonder that whatever happens on the land has a direct impact on what happens in the ocean. It is because of this that pollution from land is seen to be the major contributor of ocean pollution, with the pollutant debris consisting primarily of plastic. These pollutants are either dumped knowingly or are washed/ blown into the ocean. The result is damage to the marine environment and to the health of marine organisms. The plastic items found here vary in size and take many years to decompose. Numerous varieties of this plastic debris do not float on the surface and are lost to the depths of the ocean. Such debris collects in large patches called ocean gyres. The largest of these gyres is the Great Pacific Garbage Patch (GPGP) that is known to spread over 1.6 million square kilometers (617,763 square miles). The magnitude of this problem is so phenomenal that it is essential to address ocean pollution suitably. Accordingly, two broad methods that aim at the removal of existing marine debris, and create deterrence through monitoring and identifying the source, are being progressed. Both these processes use AI extensively to be autonomous and real-time.

3.2.1 Mapping marine debris

Debris in the ocean is made up of various types of pollutants, and has been found to primarily consist of plastics and microplastics (both by direct infusion and breakdown of larger plastics). In order to identify the location of the debris, the ocean needs to be mapped. The basic principle used in this process is to first identify the ocean space where the debris is predominantly observed, using images of ocean color with and without debris. In order to predict the nature of the debris, numerous images and videos of the ocean surface with the debris are collected using satellites and drones. In addition to these images, those taken by local people can also be uploaded for use. These images are then used to tag the items in the floating debris by teams of scientists, researchers, volunteers, and data analysts. These tagged images (see **Figures 4** and **5**) become the learning data for a machine. Using suitable algorithms, the AI differentiates between ocean debris from marine biota and animals.

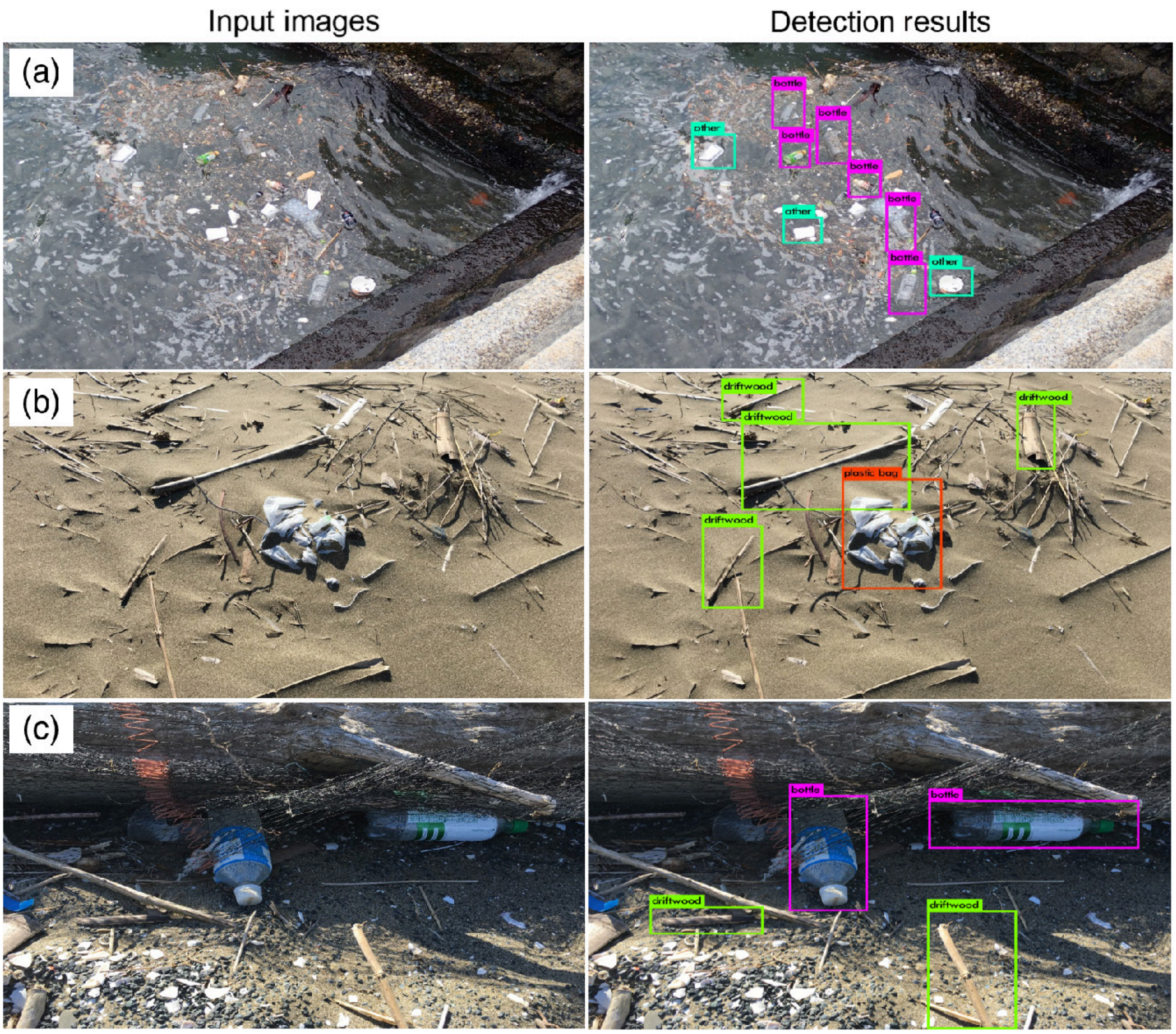

Figure 4 ML model for marine debris (Source: Watanabe et al., 2019).

Figure 5 ML model for marine debris (Source: Choney, 2020).

This project started in the UK and is now going global and has the potential to be scalable. The technology can also be used to monitor both the seafloor and the sea surface (Harris, 2018). On the same lines, various other applications have been developed. These include the Marine Debris Tracker (by NOAA), MarineLitterWatch (by the European Environment Agency), CleanSwell (by the Ocean Conservancy) and Coastbuster (by the Ocean Networks, Canada).

While large particles can invariably be mapped using this technique, plastics of smaller size and microplastics (less than 5 mm in length) need to be treated differently. For mapping *plastics*, AI systems use the European Space Agency's (ESA) satellites (Macaulay, 2020). By studying the 'spectral signatures' produced by the debris, the nature and the extent of the debris can be defined. The algorithm was trained by the researchers from Plymouth Marine Laboratory in the UK. When run, the algorithm is able to differentiate between plastics and natural materials with 86 % accuracy. The technique is currently being refined for turbid and coastal waters. Similarly, for mapping *microplastics*, plankton nets have been used. However, these nets cannot collect microplastics of sizes of less than 0.3 mm. Since there is an increasing awareness of the harmful influence of smaller-sized microplastics, a new device using AI is being developed by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) and private companies in Japan (Japan News, 2018). This device will automatically measure the amount, type of waste, and influence on the ecosystem using a high-resolution camera. Based on ML, AI will then analyze the seawater and identify the microplastics. The device is expected to be ready by 2022.

Once the mapping has been done, accurate open-source maps are created for people to use and apprise themselves of the magnitude of the problem and the areas most affected. This creates both, an awareness and a deterrence for individuals and organizations to ensure that debris dumping does not happen through the actions of either themselves or others.

3.2.2 Removal of garbage

In order to remove existing garbage, two approaches have been experimented with. The first involves the removal of garbage from the ocean itself, while the second looks at collecting garbage at the source itself, i.e., from the rivers.

The first is an autonomous floating garbage truck powered by AI that aims to remove existing garbage from ocean gyres. Using an innovative design that has been iterated and refined since 2012, a Dutch company, the Ocean Cleanup, has launched an ocean cleaning system, as seen in **Figure 6**. The cleaning system uses algorithms that help identify the optimal deployment location of the removal system. Once this is done, the system roams in the gyre autonomously to collect the garbage. The health and functioning of the collector are monitored using real-time telemetry. The system can be scaled up in size and quantity, with the aim of cleaning up to 90 % of plastic debris from the ocean (Meyer, 2019).

Some other debris collection projects that use AI are the robot Wilson, the Sea-neT project, the Jellyfishbot robot from IADYS, and drones from the Plastic Tide Project.

The second method of *removing* the debris in water bodies is more versatile, as it has been used by various innovators over the years. Various technologies have been developed and successfully utilized to collect and remove marine debris from the source itself. These include the Bubble Barrier,[‡] Mr Trash Wheel,[§] The Manta,[**] the Floating Boom,[††] and the Interceptor. Of these, only the Interceptor is known to use AI. 'The Interceptor' is a catamaran that has a conveyor belt as seen in **Figure 7**. This conveyor belt sieves the water of the river as it flows. The sieved debris is collected within the Interceptor and disposed off using a barge, or when in harbor. The Interceptor is scalable and uses renewable energy for its operations. It is being used successfully on

[‡] *See*, https://thegreatbubblebarrier.com/en/
[§] *See*, https://www.mrtrashwheel.com/
[**] *See*, https://www.theseacleaners.org/en
[††] *See*, https://www.claim-h2020project.eu/technologies/

the Klang River in Malaysia, Jakarta in Indonesia, Santo Domingo in the Dominican Republic, and in the Mekong Delta in Vietnam.

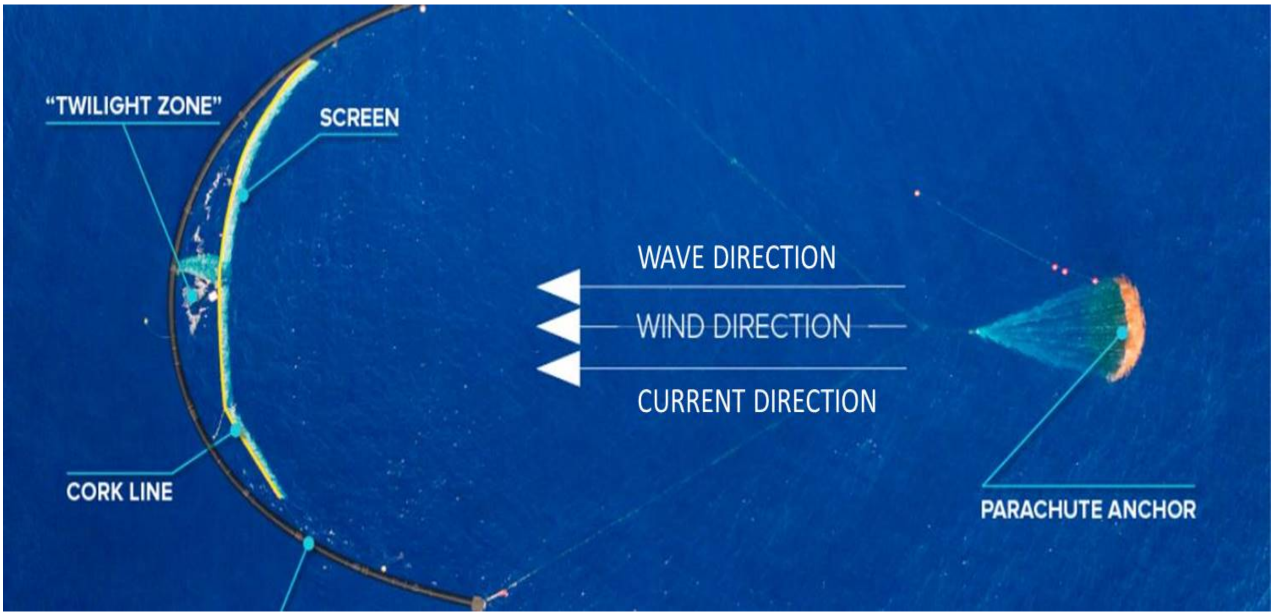

Figure 6 Ocean garbage collector (Source: The Ocean Cleanup).

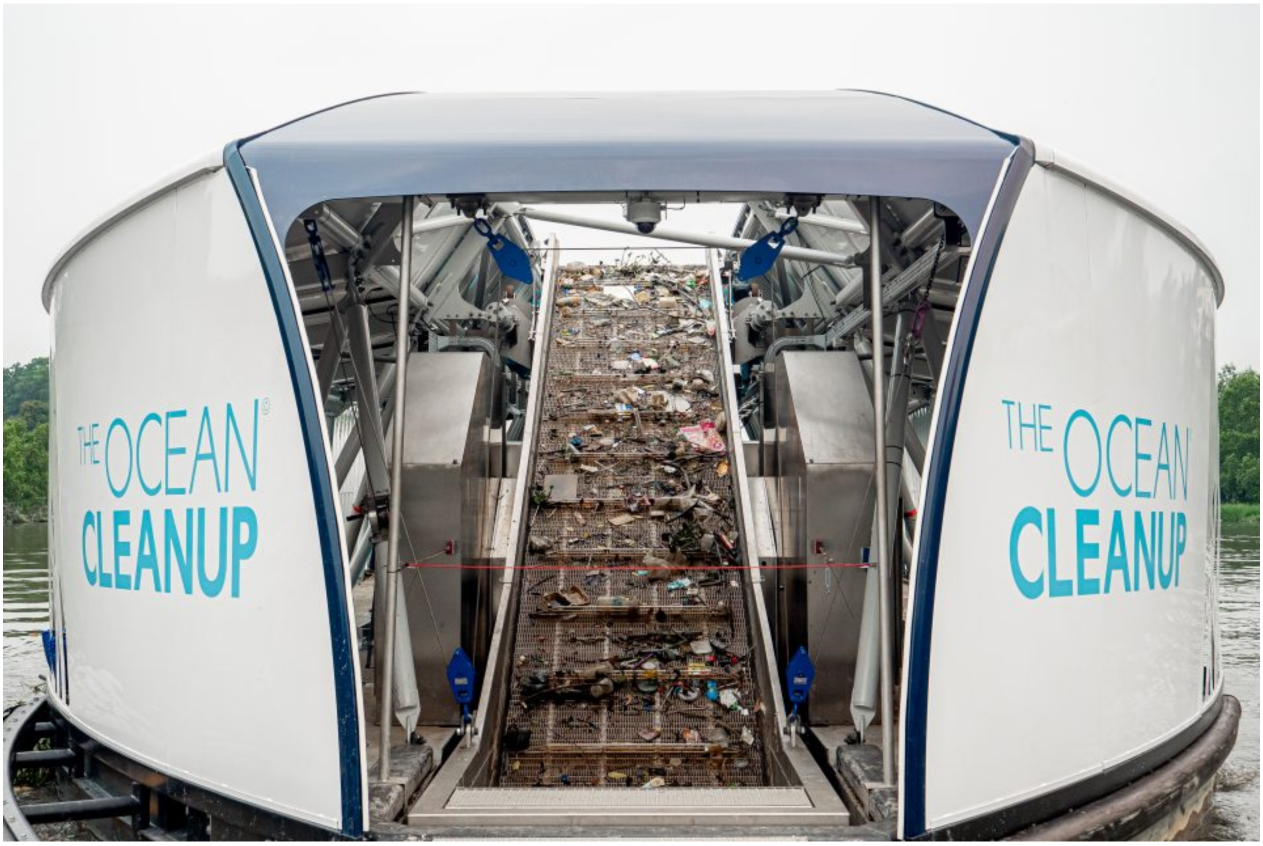

Figure 7 Interceptor- a river garbage collector (Source: The Ocean Cleanup)[‡‡].

[‡‡] *See*, https://theoceancleanup.com/rivers/

3.3 Monitoring marine life

AI, using ML and NN, has made amazing strides in recognizing human faces. Extending this model, scientists can now identify individual patterns on whale fins, flukes, and whale sharks. This allows monitoring of the species of a region using videos and photographs, so as to cause minimal disturbance to the biodiversity, with images archived for future research (Costello, 2020). Some of the examples available and used for marine life mapping and identification are iNaturalist[§§] (data available on the Global Biodiversity Information Facility), Ecotaxa[***] and www.PIC[†††] (to identify plankton), Linne Lens[‡‡‡] (to identify multiple marine animals in real-time using a smart-phone application), FathomNet,[§§§] Video and Image Analytics for Marine Environments (VIAME),[****] Squidle+,[††††] and Bio-Image Semantic Query User Environment (BISQUE)[‡‡‡‡] (for marine image storage, mapping and annotation), biome.com[§§§§] (for environmental image analysis for species identification in Japan), and WildTrack[*****] (to monitor endangered species and their threats using images of footprints) (Costello, 2020).

3.4 Monitoring coral health

Scientists have noted that, even if we stop the use of fossil fuel completely, we will still lose 90 % of the ocean's corals by 2050 (Burke et al., 2011; Heron et al., 2017). These corals form the life system of the ocean and, without them life in the ocean may not exist. It is, hence, essential that we protect, and even attempt to reseed, them. Accordingly, a number of efforts have been made to understand and map corals, so as to control their degradation. Those using AI include CoralNet[†††††], which is an AI resource to analyze coral and rocky reefs using benthic images. Using deep neural networks, both automated and semi-automated, annotation of images is possible. It is an open-source application that serves as a data repository and a collaboration platform. Similarly, Intel, Accenture, and the Sulubaaï Environmental Foundation (of the Philippines) have partnered to analyze and protect coral reefs (EU Commission, n.d) through their program CORail. The data collection is done using AI-driven video analytics, cameras fitted in the ocean, and continuous and non-invasive monitoring. Such automated data collection helps save costs and the time of researchers and divers in collecting information on coral reefs and other marine habitats. Subsequently, this information is provided to researchers to determine strategies to protect these marine ecosystems (UNEP, n.d). The technique is being expanded to study the migration patterns of tropical fishes. Other projects include those such as the Allen Coral Atlas project, the Shell Ocean Discovery XPrize, and the LarvalBot, to reseed endangered reefs.

3.5 Underwater mapping

One of the key roles of the ocean is 'climate regulation'. In order to understand how this happens, and to understand the resources available within the ocean (food, minerals, energy, etc.), we need a better understanding of the ocean and the seafloor. Today, various properties of the ocean are measured through remote sensing (using drones, satellites, probes, mapping vehicles, etc.). Despite this, less than 10 % of the seafloor has been mapped meaningfully, while depths greater than 4,000 m remain out of reach. Mapping and analysis of the entire seabed is needed to

[§§] *See*, https://www.inaturalist.org/
[***] *See*, https://ecotaxa.obs-vlfr.fr/
[†††] *See*, https://bv.fapesp.br/en/auxilios/104881/world-wide-web-of-plankton-image-curation-wwwpic/
[‡‡‡] *See*, https://lens.linne.ai/en/
[§§§] *See*, https://www.mbari.org/fathomnet/
[****] *See*, https://www.viametoolkit.org/
[††††] *See*, https://squidle.org/
[‡‡‡‡] *See*, https://bioimage.ucsb.edu/bisque
[§§§§] *See*, https://biome.co.jp/about/
[*****] *See*, https://wildtrack.org/
[†††††] *See*, https://coralnet.ucsd.edu/

understand phenomena such as ocean circulation, seabed geomorphology, benthic processes, the impact of human activities on these phenomena, and the effects of climate change on the oceans. These efforts require automation and advanced technology, such as AI, to process the data collected, for better and faster understanding and to enable the sustainability of human activities in fragile environments and ecosystems. Accordingly, some AI-based projects have been developed. Of these, Project Natick is the world's first deployed underwater datacenter that uses AI (through training) to monitor the impact of the datacenter on the surrounding environment, by studying the changing marine animals around the datacenter. This process is considered scalable, is possible to automate, and can be used for monitoring environmental impacts in various environmental settings (Zhu, 2018). Another project aims to improve underwater mapping for more accurate surveying and mapping of the seafloor using an AI algorithm, with the data collected using sonar (Just, 2020). This procedure can help determine the best location for positioning monitoring stations for collecting comprehensive seafloor data (Ponce de Leon, 2019). To help address knowledge gaps, applications like SINAY[‡‡‡‡‡] and Data360[§§§§§] have been developed. These AI-based applications first aggregate data from various sources, ranging from Internet of Things (IoT) sensors to ocean acoustics, and then apply ML to facilitate real-time decision-making and to educate society about marine environmental damage.

4. Discussion

Over the years, numerous Machine Learning paradigms have evolved, such as the manifold, the semi-supervised, the active, the transfer, and the structured learning. These paradigms, and the way we look at data images, have created new methods for research and development and, in return, have provided new ways of approaching the available data (Camps-Valls, 2009). Today, using ML, though the process is not straightforward, various researchers, in an effort to provide solutions have utilized sometimes conflicting ways. The usual issues include the choice of algorithm, the availability of training data, and the selection and optimization of the process chosen, which ultimately impact the computational costs and, hence, the acceptance of the process (Maxwell et al., 2018).

The purpose of this article has not been to delve into a detailed review of the developments made in remote sensing for marine pollutants, but to provide a synthesis of how remote sensing using AI can help address issues of preserving the marine environment. It is important to realize that, even though the use of remote sensing started off late for marine areas, as against terrestrial areas, considerable progress has been made in recent years. However, since this field is a work-in-progress, and is ever-evolving, the article has aimed to provide some possible potential methods that have been experimented with, to some success. This article intends to act as merely a stimulus for a better and a large variety of solutions that can be further explored in the references cited, but not discussed explicitly, owing to their ongoing development. All in all, one need to realize that, while the use of AI in the preservation of the marine environment is an essential way ahead, its success is dependent on the support it gets from regulators and users alike. The fear of being penalized or fined immediately for polluting, as a nation or as a community, since data and analysis in real-time, is just one of the many issues that discourage the all-out utilization of this technology.

This said, given the way humans are polluting the marine space, and the retort the ocean is offering, it is time to take hard and concrete steps to preserve the marine environment, and AI is just the tool that can help in achieving this goal. To make it a viable reality, trained manpower and detailed cost-benefit analysis are considered essential to ensure wider acceptability.

It is essential to realize that, while it is simple to say that AI can be used, AI requires ML to be effective. In order to have effective analysis, the ML has to be exact and extensive, or else the results obtained would be highly inaccurate. This means that, before ML can be used, it requires

[‡‡‡‡‡] *See*, https://www.sinay.fr/
[§§§§§] *See*, http://www.data360.in/

extensive data and, since they are manually labeled, high label accuracy is essential, or else human errors during labeling will be introduced in the output results. For a more accurate model, data must not be limited to a region or condition, but be versatile, which requires worldwide collaboration. The second area of concern is in the data itself. Since ML is effective only with accurate data, and this accuracy changes with the sensor used, ML would need to be re-trained with each sensor, which is labor-intensive and, thus, expensive. Hence, there is a need to study the interoperability of ML between various sensors and conditions to make AI more versatile. The third area of concern is the number of available and developing methods used to undertake supervised ML. While the number of methods is already numerous, such as support vector machines (SVM), single decision trees (DTs), Random Forests (HoG or 4 color spaces), boosted DTs, artificial neural networks (ANN), k-nearest neighbors (k-NN), and convolutional neural networks (CNN), these are increasing with greater research, and there is a limitation in comparing them with each other (due to camera resolution, height and type of sensor, etc.) which need to be addressed.

5. The way ahead

In the article, we have seen how AI has made numerous strides in the field of marine environmental protection. Some of the use-cases discussed show promise and provide the required information about the marine environmental damage occurring due to humanity. While these use-cases focus on products that are commercially available, there are many others, as indicated in the references, which are in the developmental stages or are being proposed, such as the Integrated Marine Debris Observing System (IMDOS) (Maximenko et al., 2019). Today, with advanced technology such as AI being common-place, several companies are providing services and tools for data collection, real-time analysis, and data processing to provide actionable results for pollution response, debris collection, developing an understanding of the impact of climate change, protection, conservation, and the mapping of marine habitats (Diaz, 2020).

The development of AI has increased to such an extent that several companies, such as Google LLC, Stem Inc., Hazama Ando Corp., IBM Corp., Nnergix Environmental Protection SL, Verdigris Technologies Inc., Siemens AG, Honeywell International Inc., Raycatch, Ltd., HST Solar, and Upside Energy Ltd., are offering AI solutions for environmental protection. As the number of firms increases, the quality and quantity of the forecast will improve, to help humanity to achieve marine environmental protection in a sustainable manner. It is, however, important to note that the AI can only provide the forecast and information, while the use and commitment has to be from the humans themselves. Since we have no Planet B, if action is not taken today, the existing planet will certainly be destroyed by our own doing, leaving no future for our children. AI provides a good tool to ensure that necessary and required corrective steps are taken in time to avoid such a catastrophe.

It is important to understand that sustainability is feasible only if baseline data are available. Our efforts, hence, need to be in the direction of collecting as much data as possible, through both active and passive means. Only when the data are available can ML be employed effectively to create the required algorithms that can provide the requisite knowledge for sustainable exploitation. Such information from AI can help in enhancing decision-making and policy-making for the environment.

6. Conclusions

As the need to monitor the ocean space has caught the fancy of the scientific community, in order to understand climate change, weather, natural disasters, and ocean resources, human movement into the ocean has increased, leading to increased numbers of satellites being used for remote sensing. This increase in satellites has increased the data collected and, hence, the need to handle and analyze this huge amount of data. To handle this analysis, AI is being utilized in different ways.

AI-based techniques are considered to have an advantage where work related to the environment is concerned. This is because AI can process large amounts of data in a short time, while being able to provide conclusions which, at times, are difficult for humans to even imagine. AI also makes possible better coordination between researchers in sharing and analyzing data. These trends and variations may be missed out by humans, as small changes in the environment may go unnoticed and, with time, may cause serious changes in the environment (Rayome, 2019). Such changes would invariably be noticed and flagged by AI. Hence, the importance of AI in the marine environment protection through sustainability cannot be ignored. As AI becomes commonplace, more players in the market will allow competition to improve, thus making information cheaper and easier to access. The article has discussed some use-cases to achieve maritime environmental protection through sustainability. One realizes that Machine Learning, and now the developing Deep Learning, are providing the necessary support to undertake the analysis of the data collected by remote sensors. While some cases have been discussed, these cases cannot be considered as being able to satisfy the requirements, and they should be treated as mere stimulants for a better and a larger variety of solutions, since the field of AI is evolving and becoming smarter day by day.

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