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Review

Using artificial intelligence to support marine macrolitter research: A content analysis and an online database

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ABSTRACT

Marine scientists use a variety of collection and monitoring methods to survey macrolitter in aquatic environments, aiming to assess the level of pollution and design mitigation actions. However, the large volume of collected data often makes the visual recognition and identification of macrolitter items a time-consuming and labor-intensive task, indicating the need for automated and low-cost solutions. In addition, modelling approaches are needed to identify which environmental and anthropogenic factors shape the variability of observed litter concentrations. Artificial intelligence (AI) has emerged over the last years as a promising tool to address these issues. This study provides a literature review of published research that uses AI to process macrolitter datasets derived from imagery and tabular data. The focus is on diverse topics (litter domain, dataset source, sampling system, data type, task to be resolved, region, proposed methodologies, usability) with the aim of identifying the versatile contribution of AI on this theme and providing a reference resource for marine litter scientists. To do so, we release an online database (available here), in which the user can seek publications based on several categories and tags. Current limitations, challenges and potential future directions are also discussed.

1. Introduction

Litter pollution is a growing problem, posing a pervasive threat to marine and freshwater ecosystems around the globe (Eriksen et al., 2014; Ostle et al., 2019). Marine litter has been documented in all water bodies and coastal lands, from lakes (Driedger et al., 2015; Zbyszewski et al., 2014) and the surface of the oceans (Eriksen et al., 2014), to rivers (Helinski et al., 2021), seafloor (Galgani et al., 2000; Ioakeimidis et al., 2014) beaches (Haseler et al., 2018) and dunes (Andriolo and Gonçalves, 2022). It can cause physical harm or kill marine fauna through ingestion and entanglement with more than 1400 different species found to be affected (Galgani et al., 2019). Animal species like fish, birds, and invertebrates are especially affected by micro- and meso-litter[1] made mainly of plastics (NOAA, 2014). Additionally, meso- and macro-litter[1] can degrade coastal habitats and the quality of life in coastal communities, while micro- and nano-litter[1] can pass across the seafood chain and threaten human health (Clark et al., 2022; UNEP/MAP and United, 2016).

Surveys are conducted worldwide to assess the type, size, abundance, and spatial distribution of collected marine litter items with the aim of assessing the level of pollution and designing management actions that will promote litter removal and recycling (Canals et al., 2021; Forrest et al., 2019; Kershaw et al., 2019; Madricardo et al., 2019; Pham et al., 2014). Concurrently, hydrodynamic models coupled with particle tracking models have attempted to improve our understanding of the sources, transport, and pathways of marine litter at the open sea and coastal waters (Hardesty et al., 2017; NOAA 2016; van Sebille et al., 2020).

Nowadays, scientists have at their disposal a variety of collection and monitoring methods to monitor and assess marine litter in aquatic ecosystems (Maximenko et al., 2019; Salgado-Hernanz et al., 2021). In-situ visual census surveys (e.g., beachcombing) is the most technically simplistic way to directly collect data about meso/macro-litter (GESAMP, 2019; Thiel et al., 2003) since they are visible to the naked

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[1] Macro(>25 mm)- and meso(5–25 mm)- marine litter are objects that can be monitored by visual census. Litter also enters the environment as very small particles, the so-called microlitter (300 μm - 5 mm) or nanolitter (<300 μm). These are usually derived from fragmentation of larger litter items through different processes such as photodegradation, physical degradation and hydrolysis (Fotopoulou and Karapanagioti, 2017).

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eye. Other data acquisition systems include bottom trawlers to collect seafloor macrolitter (Canals et al., 2021), manta or neuston nets to collect floating microlitter at the open sea (Adamopoulou et al., 2021; Morét-Ferguson et al., 2010), and optical devices[2] to identify macrolitter items on beaches (Escobar-Sánchez et al., 2021; Hengstmann and Fischer, 2020; Lo et al., 2020; Taddia et al., 2021), dunes (Andriolo et al., 2020, 2021a) and seafloor (Fakiris et al., 2022; Madricardo et al., 2019). Accordingly, optical devices and satellite sensors are used to monitor floating macrolitter (Garcia-Garin et al., 2020a,b; Mukonza and Chiang, 2022; Topouzelis et al., 2021), while echosounder systems have also been used for monitoring underwater litter (Broere et al., 2021).

However, the recognition and assessment of macrolitter pollution are confronted with the need for processing big volume of data to characterize litter items, a process that is time-consuming, subjective, and labor-intensive. Standard methods of macrolitter assessment are based on manual image screening and marking processes performed by trained scientists (Andriolo et al., 2021b; Andriolo and Gonçalves, 2022; Garcia-Garin et al., 2021; Merlino et al., 2021; Papachristopoulou et al., 2020). Additionally, aerial- and satellite-based remote sensing methodologies have also been proposed for detecting beached and floating macrolitter (Andriolo et al., 2021a; Cocking et al., 2022; Kataoka et al., 2012; Kataoka and Nihei, 2020; Themistocleous et al., 2020; Wang et al., 2015). Developing methods that will promote automated and rapid solutions for macrolitter identification has been recognized as a worthy goal (Canals et al., 2021; Garcia-Garin et al., 2021). Additionally, identifying key environmental and anthropogenic factors driving marine macrolitter accumulation is also a valuable task that needs efficient modelling approaches (Kaandorp et al., 2022).

Artificial Intelligence (AI) is a branch of computer science and engineering that attempts to create machines that behave as intelligent as humans (Goodfellow et al., 2015). The two subfields of AI, machine learning (ML) and deep learning (DL), have revolutionized a wide range of real-world applications by automating processes related to tabular data, images, video, speech, audio, and text (Alpaydın, 2014; Deng and Liu, 2018; Gao et al., 2020; LeCun et al., 2015).

In recent years, AI has gained attention in marine litter research by providing automatic visual recognition and identification both of macrolitter/plastics (Gnann et al., 2022; Karakuş, 2022; Mukonza and Chiang, 2022; Salgado-Hernanz et al., 2021; Topouzelis et al., 2021) and micro-litter/plastics (Lin et al., 2022; Mukonza and Chiang, 2022). In this paper, we provide a literature review of published research that uses AI to process marine litter datasets, with a special focus on macrolitter imagery and tabular data. Collected papers were tagged and analyzed under diverse aspects in order to identify the versatile contribution of AI on this theme, as well highlight current limitations, challenges and future directions. Finally, the surveyed papers were organized into an online database from which researchers could seek publications based on several categories and tags. The database is operational; new publications will be uploaded regularly, providing a convenient way for non-computer scientists to keep track of the latest AI-marine litter advancements.

Compared to the AI-macrolitter reviews, we extended the literature search to all macrolitter domains (beached, dune, floating, seafloor), multiple observing/sampling systems, and different dataset sources (in-situ, publicly available, experimental, synthetic). We also focused on technical aspects of the adopted AI methodologies (architectures, predictive accuracy, task to be resolved, and usability).

2. Literature search and selection criteria

We surveyed the literature for AI applications in marine macrolitter research, using widely used databases for archiving scientific articles, namely Wiley Online Library, IEEE, Elsevier/ScienceDirect, Scopus, and Web of Science. The keywords used as search criteria are shown in Table 1. After reviewing the content of the resulting articles to ensure their relevance to our research topic, we ended up with 80 articles, covering the period from 2004 to October 2022. We excluded sources that did not have a digital object identifier (DOI), did not implement an AI workflow (see Section 3), did not include clearly defined data sources, and non-English papers. The list of collected articles can be found in Table 2.

Table 1
Keywords used as search criteria for collecting the literature.

		AI Random Forest
Marine litter	AND	Machine Learning SVM
Marine debris		Deep Learning Classification
Marine (macro)plastics		CNN Detection
		Neural networks

3. General AI workflow applied in marine macrolitter research

A generic AI workflow, as applied to a marine macrolitter dataset for the various data types and tasks, is shown in Fig. 1. The litter dataset is first retrieved; this data can be images, orthomosaics/orthophotos,[3] or tabular.[4] Second, the AI task to be resolved is defined. The main tasks found in the collected papers are classification, object detection, instance segmentation, semantic segmentation, quantification (through segmentation), and regression. More details about the scope of these AI tasks can be found in the Appendix; a visual overview of the tasks is also shown in Fig. 2. Third, a preprocessing of the dataset is essential to prepare the data so that AI algorithms can parse it. Common works during the data preprocessing step include image labeling[5]; bounding box annotation[6]; cleaning of tabular data[7]; feature extraction from images[8]; extraction of orthophotos from orthomosaic images; segmentation of orthophotos into tiles; and the enhancement of image quality.[9] Fourth, one or more (for comparison reasons) algorithms are selected to resolve the defined task. The architectures found in the collected papers were convolutional neural network (CNN), object detection architecture (OD), feed forward neural network (FFNN), machine learning algorithm (MLA), encoder-decoder architecture (EDA), instance segmentation

[2] Drones, Autonomous Underwater Vehicles (AUVs), Remotely Operated Vehicles (ROVs), Unmanned Aerial Systems (UAS), vessel-mounted or land-based cameras, sonars, and satellites.

[3] Orthophotos are image data composed of dozens, hundreds, or thousands of smaller overlapping images, typically captured with a drone or UAV. These images are "stitched together" with specialized photogrammetry software, resulting in an orthomosaic image.

[4] Tabular data includes numeric and categorical values structured into rows, each of which contains column information of interest. Tabular data include measurements of litter abundance/density and environmental/anthropogenic variables such as waves, currents, wind speed, tides, beach exposure, marine traffic density, etc. (Kaandorp et al., 2022; Martin et al., 2021).

[5] The process of annotating the type of litter in an image, e.g., bottle. Annotated images are used for training and evaluating classification and detection tasks.

[6] The process of annotating the type of litter in an image, e.g., bottle. Annotated images are used for training and evaluating classification and detection tasks.

[7] Data cleaning includes several potential tasks such as removal of duplicate observations, correct errors and missing data, handle outliers.

[8] Features are extracted from images with several methods such as waveform data (Ge et al., 2016), RGB and NIR bands (Cortesi et al., 2022), spectral indices (Biermann et al., 2020; Jamali and Mahdianpari, 2021; Mikeli et al., 2022; Lavender, 2022; Sannigraphi et al., 2022; Sasaki et al., 2022) and other feature descriptors such as histogram of gradient, grey level co-occurrence matrix (GLCM) Gabor, histogram, normalization of bands, point sampling (Ramdani et al., 2022; Savastano et al., 2021; Sasaki et al., 2022; Taggio et al., 2022).

[9] Enhancement of image quality includes noise removal, and atmospheric, radiometric and sun glint corrections (Aleem et al., 2022; Basu et al., 2021; Booth et al., 2022; Lavender, 2022; Sannigraphi et al., 2022; Savastano et al., 2021).

Table 2
List of surveyed scientific articles (n = 80) under the scope of this review. Details about the included content categories and tags can be found in Section 4.

References	Sampling system	Dataset type	Litter domain	Usability	Dataset source	Task	Architecture
Acuña-Ruz et al. (2018)	Satellite (Sentinel-2 or WorldView-3)	Image	Beached/Dune	Litter assessment	In-situ	Classification, Quantification	MLA
Aleem et al. (2022)	Sonar	Sonar image	Floating, Seafloor	PPA	Public	Classification, Detection	OD
Andriolo et al. (2022)	UAV/UAS	Orthomosaic/ Orthophoto, Image	Floating, Beached/Dune	PPA	In-situ	Classification	MLA
Armitage et al. (2022)	Camera	Image	Floating	PPA	Experimental	Classification, Detection	OD
Bajaj et al. (2021)	AUV/ROV	Image	Seafloor	PPA	Public	Detection	OD
Bak et al. (2019)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	PPA	In-situ	Semantic segmentation	Sem-Seg
Balas et al. (2004)	Visual census	Image	Beached/Dune	PPA	In-situ	Regression	FFNN
Balas et al. (2006)	Visual census	Tabular	Beached/Dune	PPA	In-situ	Regression	FFNN
Basu et al. (2021)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	Experimental	Classification, Semantic segmentation	MLA, Clustering
Biermann et al. (2020)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Classification	MLA
Booth et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	Litter assessment	Experimental	Classification, Semantic segmentation	MLA, Sem-Seg
Chang et al. (2020)	Camera	Image	Beached/Dune	PPA	In-situ	Classification	CNN
Chin et al. (2022)		Image	Seafloor	PPA	Public	Classification, Detection	OD
Córdova et al. (2022)	Camera	Image	Floating, Beached/Dune	PPA	Public	Detection	OD
Cortesi et al. (2022)	Camera	Image	Floating, Beached/Dune	PPA	In-situ	Classification, Semantic segmentation	MLA
Cortesi et al. (2022)	UAV/UAS	Image	Floating	PPA	In-situ	Classification, Semantic segmentation	MLA
de Vries et al. (2021)	UAV/UAS, Camera	Image	Floating	Litter assessment	In-situ	Classification, Quantification	OD
Deng et al. (2021)	AUV/ROV	Image	Seafloor	PPA	Public	Classification, Detection	OD
Duarte et al. (2020)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	PPA	In-situ	Classification	CNN
Fallati et al. (2019)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	PPA	In-situ	Classification, Detection	CNN
Fossum (2022)	AUV/ROV	Image	Seafloor	PPA	In-situ	Classification, Detection	OD
Franceschini et al. (2019)	Bottom trawlers	Tabular	Seafloor	Exploratory	In-situ	Regression	FFNN
Freitas et al. (2021)	UAV/UAS	Image	Beached/Dune	PPA	Experimental	Classification, Detection	MLA
Fulton et al. (2018)	AUV/ROV	Image	Seafloor	PPA	Public	Classification, Detection	OD
Garcia-Garin et al. (2021)	UAV/UAS	Image	Floating	Litter assessment	Experimental	Classification	CNN
Ge et al. (2016)	Camera	Image	Beached/Dune	PPA	Experimental	Classification, Semantic segmentation	MLA
Gómez et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Detection	OD
Gonçalves et al. (2020a)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	Litter assessment	In-situ	Detection, Quantification	MLA
Gonçalves et al. (2020b)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	Litter assessment	In-situ	Detection, Quantification	MLA, CNN
Gonçalves et al. (2020c)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	Litter assessment	In-situ	Classification, Semantic segmentation	MLA
Hidaka et al. (2022)	Camera	Image	Beached/Dune	PPA	In-situ	Classification, Detection, Semantic segmentation	Sem-Seg
Hong et al. (2020a)	AUV/ROV	Image	Floating, Seafloor	PPA	Public	Classification	EDA
Hong et al. (2020b)	AUV/ROV	Image	Seafloor	PPA	Public	Classification, Detection, Instance segmentation	OD, Ins-Seg
Jakovljevic et al. (2020)	UAV/UAS	Orthomosaic/ Orthophoto	Floating	PPA	Experimental	Classification, Semantic segmentation	Sem-Seg
Jamali and Mahdianpari (2021)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	Experimental	Classification, Semantic segmentation	MLA
Kaandorp et al. (2022)	Visual census	Tabular	Beached/Dune	Exploratory	In-situ	Regression	MLA
Kako et al. (2020)	UAV/UAS	Image	Beached/Dune	Litter assessment	Experimental	Semantic segmentation, Quantification	FFNN
Kankane and Kang (2021)	Camera	Image	Beached/Dune	PPA	In-situ	Semantic segmentation	OD
Kikaki et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Classification, Semantic segmentation	MLA, Sem-Seg
Kylili et al. (2019)	Camera	Image	Floating	PPA	Public	Classification	CNN
Kylili et al. (2020)		Image	Floating	PPA	Public	Classification	CNN
Kylili et al. (2021)		Image	Beached/Dune	PPA	Public	Classification, Detection	OD
Lavender (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Classification, Semantic segmentation	MLA, FFNN
Lin et al. (2021)	Camera	Image	Floating	PPA	Synthetic	Detection	OD
Maharjan et al. (2022)	UAV/UAS	Image	Floating	PPA	In-situ	Classification, Detection	OD

(continued on next page)

Table 2 (*continued*)

References	Sampling system	Dataset type	Litter domain	Usability	Dataset source	Task	Architecture
Majchrowska et al. (2022)		Image	Floating, Seafloor	PPA	Public	Classification, Detection	OD
Mallick et al. (2021)		Sonar image		PPA	Public	Classification	CNN
Martin et al. (2021)		Image	Seafloor	PPA	Public	Classification	CNN
Martin et al. (2018)	UAV/UAS	Image	Beached/Dune	PPA	In-situ	Classification	MLA
Martin et al. (2021)	UAV/UAS	Image, Tabular	Beached/Dune	PPA, Exploratory	In-situ	Detection, Regression	OD
Mifdal et al. (2021)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Semantic segmentation	CNN, Sem-Seg, MLA
Mikeli et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ	Classification, Semantic segmentation	MLA, Sem-Seg
Moorton et al. (2022)		Image	Seafloor	PPA	Synthetic	Classification	CNN
Moshtaghi and Knaeps (2021)	UAV/UAS	Image	Floating	PPA	Experimental	Detection	OD
Musić et al. (2020)		Image	Floating, Seafloor	PPA	Synthetic	Classification, Detection	OD
Nazerdeylami et al. (2021)	Camera	Image	Beached/Dune	PPA	In-situ, Public	Classification, Detection	OD
Panwar et al. (2020)		Image	Floating	PPA	Public	Classification, Detection	OD
Papakonstantinou et al. (2021)	UAV/UAS	Image	Beached/Dune	Litter assessment	In-situ	Classification, Quantification	CNN
Pinto et al. (2021)	UAV/UAS	Orthomosaic/ Orthophoto	Beached/Dune	Litter assessment	In-situ	Classification	FFNN
Politikos et al. (2021)	AUV/ROV	Image	Seafloor	PPA	In-situ	Classification, Detection, Instance segmentation	OD
Priyadarshini et al. (2022)		Tabular	Beached/Dune	PPA	Public	Classification	MLA
Ramdani et al. (2022)	UAV/UAS	Image	Floating	PPA	In-situ	Classification, Semantic segmentation	MLA, FFNN
Sánchez-Ferrer et al. (2022)		Image	Floating, Seafloor	PPA	Public	Classification, Semantic segmentation	OD
Sannigraphi et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	In-situ, Experimental	Classification, Semantic segmentation	MLA
Sasaki et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Beached/Dune	Litter assessment	In-situ	Classification, Semantic segmentation	MLA, FFNN
Savastano et al. (2021)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	Experimental	Classification, Semantic segmentation	MLA
Schulz and Matthies (2014)	Visual census	Tabular	Beached/Dune	Exploratory	In-situ	Regression	FFNN
Song et al. (2021)	Camera	Image	Beached/Dune	PPA	In-situ	Classification, Detection, Quantification	OD
Taggio et al. (2022)	Satellite (Sentinel-2 or WorldView-3)	Image	Floating	PPA	Experimental	Classification, Semantic segmentation	MLA, Clustering
Takaya et al. (2022)	UAV/UAS	Image	Beached/Dune	PPA	In-situ	Classification, Detection	OD
Tata et al. (2021)	Camera	Image	Floating, Seafloor	PPA	Public	Detection	OD
Teng et al. (2022)		Image	Beached/Dune	PPA	Public	Classification, Detection	OD
Tharani et al. (2020)	Camera	Image	Floating	PPA	Public	Detection	OD
Valdenegro-Toro (2016)	Sonar	Sonar image	Floating	PPA	Public	Classification, Detection	OD
van Lieshout et al. (2020)	Camera	Image	Floating	Litter assessment	In-situ	Classification, Detection, Quantification	OD
Veerasingam et al. (2022)	Camera	Image	Beached/Dune	PPA	In-situ	Detection	OD
Watanabe et al. (2019)	UAV/UAS	Image	Floating, Beached/Dune	PPA	In-situ	Detection	OD
Wolf et al. (2020)	UAV/UAS	Image	Floating, Beached/Dune	PPA	In-situ	Classification, Quantification	MLA, CNN
Xue et al. (2021a)		Image	Seafloor	PPA	Public	Classification	CNN
Xue et al. (2021a)		Image	Seafloor	PPA	Public	Classification, Detection	OD

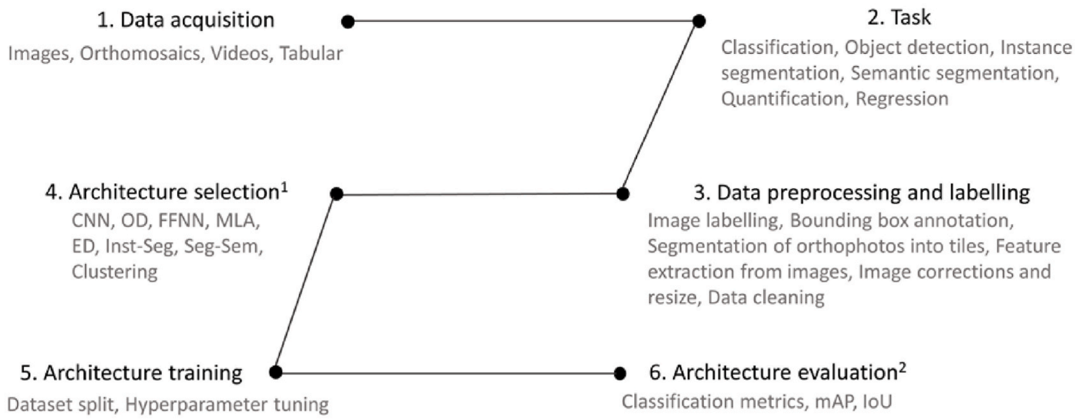
architecture (Inst-Seg), semantic segmentation architecture (Seg-Sem), and clustering. More details about the AI architectures can be found in the Appendix. Fifth, the dataset is split into the train and validation subsets, which are being used to train the AI algorithm(s) through hyperparameter tuning[10]. In the sixth step, an unknown to the training process dataset, called a test set (also created during the dataset split), is used to evaluate the predictive performance of the trained algorithm using the task-based evaluation metrics (Fig. 2). More details about the evaluation metrics can be found in the Appendix.

[10] Hyperparameters are parameters that control the structure of an algorithm (e.g., number of hidden layers or nodes) and how an algorithm gains experience (e.g., learning rate) during the training phase. They are set before training and fine-tuned with the aim of maximizing the learning process of the network. Fine-tuning is a critical step in any AI pipeline that results in a trained and validated algorithm that can then be used to make predictions.

4. Content analysis

A content analysis was conducted to review the collected literature. Content analysis explores the existence and frequency of words, concepts, or themes in a text that are related to a question of interest (Elo and Kyngäs, 2008; Krippendorff, 1980). Content analysis is more than a counting process; it aims to identify intentions, states, beliefs, trends, patterns, biases, and limitations in order to increase our knowledge and

2022; Sasaki et al., 2022; Taggio et al., 2022).



[1] Convolutional neural network (CNN), object detection architecture (OD), feed forward neural network (FFNN), machine learning algorithm (MLA), endoder-decoder architecture (ED), instance segmentation architecture (Inst-Seg), semantic segmentation architecture (Seg-Sem) and Clustering.
[2] Classification metrics: accuracy, recall, precision, F1-score; Object detection/segmentation metrics: mean Average Precision (mAP), Intersection Over Union (IoU).

Fig. 1. Generic view of AI workflow, as applied to a marine litter dataset for common data types and tasks.

understanding of specific phenomena (Downe-Wamboldt, 1992; Krippendorff, 1980). To implement a content analysis, text is coded into content categories and topics so that the researcher can look for similarities, differences, and relationships among them.

To compile the content information of the collected publications, an excel sheet was designed with the list of papers on the rows, and the following content categories on the columns: "Litter domain", "Dataset source", "Sampling system", "Data type", "Task", "Region", "Architecture", and "Usability" (Table 3). Within each content category, specific tags were defined to further associate related content in the documents.

Marine macrolitter items are mainly deposited on three landscapes: beaches/dunes, on the sea surface, and at the sea bottom. The "Litter domain" category was, therefore, represented by three tags, namely, *Beached/Dune, Floating*, and *Seafloor.*

The marine litter data used in the surveyed documents were provided from four main sources: publicly available datasets, in-situ surveys, experimental data, and synthetic data. Several open-source datasets with (marine)litter images have been created with the aim of being processed with ML/DL techniques; the most known public datasets in the literature are: Trash-ICRA19 (Fulton et al., 2019), TrashCan 1.0 (Hong et al., 2020), PlastOPol (Córdova et al., 2022), DeepPlastic (Tata, 2021), TACO (Proença and Simões, 2020), Forward-Looking sonar marine debris dataset,[11] Deep-Sea Debris Database (JAMSTEC, 2018), and the Marine Debris Tracker.[12] Additionally, web-scraping of litter images has been used as an alternative data source (e.g., Musić et al., 2020; Kylili et al., 2019). All these datasets include a wide variety of both landscape and marine litter images, generated from indoor and outdoor scenes, with multiple litter categories of different size and material (e.g., glass, paper, cardboard, plastic, metal, tiles, cups, cans, nets, wood). Contrary, in-situ litter surveys are conducted by marine research institutes in specific regions, following protocols, sampling systems and methodologies that meet their scientific goals. In some studies, marine litter was artificially deposited by researchers on the sea surface (e.g., Armitage et al., 2022; Booth et al., 2022; Jamali and Mahdianpari, 2021; Moshtaghi and Knaeps, 2021; Savastano et al., 2021; Taggio et al., 2022; Topouzelis et al., 2019) or beach (Kako et al., 2020) and experiments were designed to detect marine macrolitter with AI methods, while some authors created synthetic images for their analysis, by superimposing marine natural background images on litter items (e.g., Lin et al., 2021; Moorton et al., 2022). These different sources of datasets were classified into the "Dataset source" category through the four tags: *Public*, *In-situ, Experimental* and *Synthetic*.

The collection of litter data can take place with various monitoring systems, depending on the type of litter. Underwater and seafloor litter imagery are being collected mainly with *UAV (Underwater Autonomous Vehicles)* and *ROV (Remotely Operated Vehicles)* and *Sonar*, and seafloor litter items with bottom trawlers. Floating and beached litter images are being collected through in-situ visual census, *UAS (Unmanned Aerial Systems)*, *UAV (Unmanned Autonomous Vehicles)*, *Satellite (Sentinel-2 or WorldView-3)*, and *Camera*. These systems were used as tags in the "Sampling system" category, as *UAV/UAS, AUV/ROV, Satellite (Sentinel-2 or WorldView-3), Sonar, Visual census, Camera,* and *Bottom trawlers* (Table 3).

Four tags were used to classify the type of marine macrolitter data used in the collected papers through the "Data type" category, corresponding to *Image, Orthomosaic/Orthophoto, Sonar image,* and *Tabular* (Table 3).

The main tasks identified in the collected publications were grouped into the "Task" category through eight tags, that is: *Classification, Detection, Instance Segmentation, Semantic Segmentation, Quantification*, and *Regression* (Table 3; Appendix).

The sites of the studies that used in-situ litter surveys were assigned into "Region" category in coordinates (*Longitude, Latitude*) to depict their geographic distribution (Table 3).

Seven tags were chosen to group the different ML/DL architectures adopted in the collected papers through the "Architecture" category, that is: *CNN, OD, FFNN, MLA, EDA, Ins-Seg* and *Seg-Sem* and *Clustering* (Table 3; Appendix).

Finally, we classified the usability of the reviewed studies in the "Usability" category, based on three tags: *PPA* (Predictive Performance of the Architecture(s) for papers that primarily focused on technical aspects by evaluating how good were the adopted ML/DL algorithms to automatically recognize macrolitter items on imagery; *Litter assessment* for studies that went beyond the predictive performance of the algorithms, attempting to serve as tools that will automatically assess the abundance (items per surface of cube area) or density (kg per surface area) of litter from *in-situ* surveys; and *Exploratory* for studies that explored the influence of environmental and anthropogenic variables on

[11] https://github.com/mvaldenegro/marine-debris-fls-datasets/releases/.
[12] https://www.debristracker.org/.

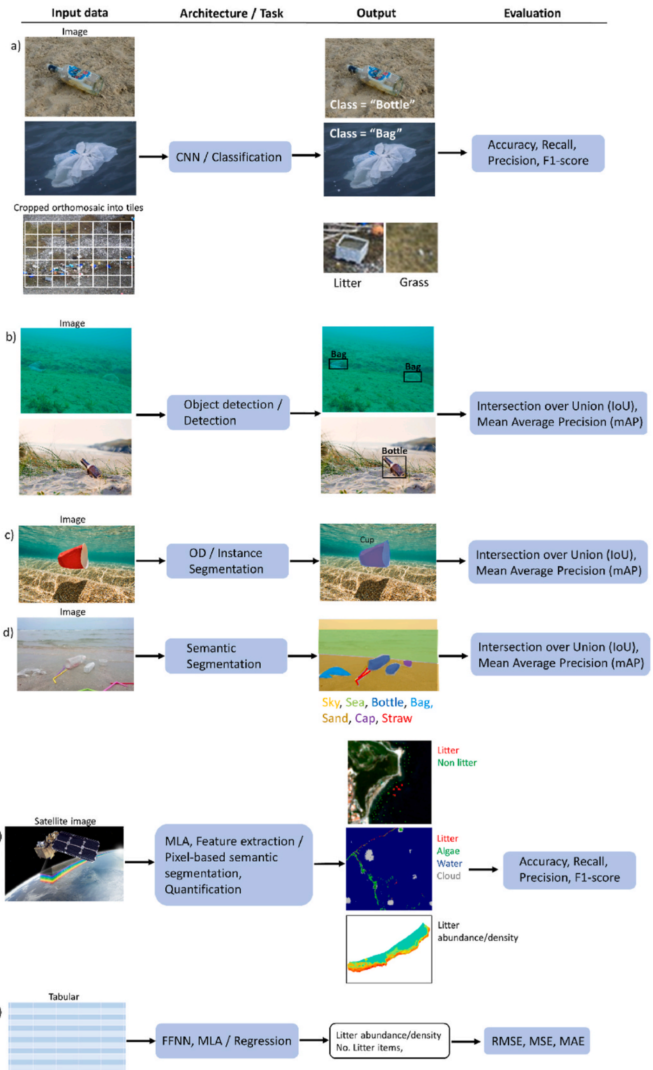


Fig. 2. Examples of tasks, as applied to marine macrolitter imagery and tabular data, with illustrations of the corresponding techniques and evaluation metrics. More details about the tasks and the evaluation metrics can be found in the Appendix.

the distribution and abundance of collected macrolitter (Table 3).

We note that multiple tags were possible within one paper for the categories "Litter domain", "Task", "Architecture" and "Region".

5. Online database

An online database with the collected papers was created. In particular, the database includes an interactive table from which the user can seek papers based on the adopted content categories and tags, as well as auxiliary bibliometric information such as title, year, author, and DOI link. The database is operational and new publications will be uploaded regularly, aiming to become a resource for marine scientists that want to follow the state-of-the-art progress of AI on the theme. The database was built with the Streamlit Python library (https://streamlit.io/), and it's available here.

6. Analysis results

From 2004 to October 2022, the rate of yearly publications referring to AI and marine litter did not follow a linear pattern (Fig. 3). Before 2016, one published article per year explored the theme. Since 2016, there is an increased interest in the topic, with more than 15 papers per

Table 3
Content categories and tags used to explore the use of AI on marine macrolitter datasets. Architectures: Convolutional Neural Network (CNN), Object Detection architecture (OD), Feed Forward Neural Network (FFNN), Machine Learning Algorithms (MLA), Encoder-Decoder architecture (EDA), Instance Segmentation architecture (Inst-Seg) and Semantic Segmentation architecture (Seg-Sem) and Clustering. More details about the AI architectures can be found in the Appendix.

Content category	Tags
Litter domain	Beached/Dune, Floating, Seafloor
Dataset source	Public, In-situ, Experimental, Synthetic
Sampling system	(AUV) Autonomous Underwater Vehicles, ROV (Remotely Operated Vehicles), Visual census, UAS (Unmanned Aerial Systems), UAV (Unmanned Autonomous Vehicles), Sonar, Sentinel-2 satellite, Camera
Data type	Image, Orthomosaic/Orthophoto, Sonar image, Tabular
Task	Classification, Detection, Instance Segmentation, Semantic Segmentation, Quantification, Regression
Region	(Longitude, Latitude)
Architecture	CNN, OD, FFNN, MLA, EDA, Ins-Seg, Seg-Sem, Clustering
Usability	Predictive Performance of the Architecture(s) (PPA), Litter assessment, Exploratory

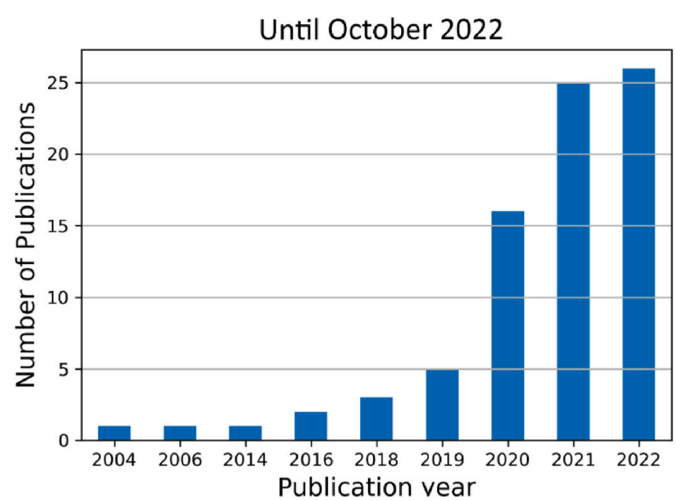


Fig. 3. Number of publications per year that implemented AI techniques on marine macrolitter datasets.

year in 2020 and 2021.26 publications were reported until October 2022 (the end of the current review), indicating a potential growth in the annual rate of publications in the years to come. The observed trend may be attributed to two main factors. First, the development of highly effective AI algorithms, in combination with the rise of computing power[13] and the release of open-source codes in distributed control systems (e.g., GitHub), allowed thousands of practitioners to apply AI in all real-world application domains. Second, the increasing interest in collecting and analyzing marine litter data in all water bodies in recent years (Andriolo et al., 2020; Canals et al., 2021; Escobar-Sánchez et al., 2021; Garcia-Garin et al., 2020a,b; Gauci et al., 2019; Merlino et al., 2020) favored the applicability of AI in this scientific field.

The geographical distribution of AI studies that used in-situ marine macrolitter datasets (without including satellite data) is shown in Fig. 4. Although marine litter has a worldwide presence, the spatial coverage of these studies was rather limited. The most studied continents were Europe and Asia, targeting mainly floating and beached litter, whereas no in-situ studies have been reported on the African and Australian

[13] The rise of graphics processing unit (GPU) technology accelerated the high demands of computational processing in AI algorithms.

continents. One study was conducted in North America, referring to floating litter. Finally, in-situ seafloor litter was studied in two publications, found in the eastern Mediterranean Sea and northern Europe. The full list of publications per country can be found in the online database.

Accordingly, nine studies combined satellite image data and AI methods to detect beached/dune (two studies) and floating (seven studies) litter (Fig. 5). These studies demonstrated greater spatial coverage compared to non-satellite data, with sampling sites located on all seven continents. This can be attributed mainly to the free access to image data provided by remote sensing satellites such as WorldView-2 or 3 and Sentinel-2 (https://earth.esa.int/eogateway; Kristollari and Karathanassi, 2020).

The number of publications per content category is shown in Fig. 6. Most studies focused on floating (42.2%) and beached/dune (37.8%) litter, and less on seafloor litter (20.0%). In-situ datasets were found in 51.2% of cases, followed by public datasets (29.3%), experimental data (15.9%) and synthetic data (3.7%). A variety of sampling systems were used to collect litter data, with UAV/UAS (34.3%), Camera (22.4%) and Satellite (Sentinel-2 or WorldView-3) (20.9%) being the most frequent. Regarding the dataset type, images (78.0%) were mostly used, followed by orthomosaics/orthophotos (11%), tabular data (7.3%), and sonar images (3.7%). Most papers had as a task the classification (44.4%) and detection (26.3%) of litter objects, and then semantic segmentation (16.5%), quantification (6.8%), regression (4.5%), and instance segmentation (1.5%). OD (35.5%) and MLA (28.0%) were the most frequent architectures used by scientists. Additionally, CNNs were used in 15.1% of cases, whereas FFNN (9.7%), Sem-Seg (7.5%), Clustering (2.2%), EDA (1.1%) and Ins-Seg (1.1%) were the less adopted architectures. Finally, the vast majority of collected papers restricted their analysis to the evaluation of the involved AI architectures (80.2%), with less providing an automatic way of litter assessment (14.8%) or an exploratory analysis (4.9%). Interested readers can seek publications based on content category on the online database.

The frequency distribution of publications at the intersection of the content categories “Litter domain” and “Dataset source” is shown in Fig. 7. Studies that used beached/dune litter were mostly based on in-situ datasets ($n = 28$), with only $n = 5$ studies using public datasets. In contrast, the processing of seafloor litter images was done mostly with public datasets ($n = 13$), with only $n = 2$ case using in-situ regional surveys. For floating litter, studies were rather balanced among public ($n = 11$), in-situ ($n = 17$) and experimental ($n = 10$) data. Readers can query publications of interest on the online database, using the filters in the columns “Litter domain” and “Dataset source”.

The frequency distribution of publications at the intersection of content categories “Litter domain” and “Task” is shown in Fig. 8. For beached/dune litter, classification ($n = 21$) and detection ($n = 14$) were the most frequent tasks, followed by semantic segmentation ($n = 8$), quantification ($n = 7$), and regression ($n = 5$) tasks. Similarly, classification ($n = 30$) and semantic segmentation ($n = 15$) were mainly conducted for floating litter and less for other tasks. Seafloor litter was mostly studied for classification ($n = 15$) and detection ($n = 12$), with two studies ($n = 2$) focusing on segmentation tasks. Readers can query publications of interest in the online database using the filters in the columns “Litter domain” and “Task”.

7. Discussion

In this study, we collected and analyzed scientific articles at the intersection of AI and marine macrolitter research. Review results showed that a variety of AI algorithms have been implemented and evaluated on macrolitter imagery and tabular data, attaining significant progress on the automatic classification, object detection, and segmentation of macrolitter objects, as well as exploring which environmental and anthropogenic variables can affect the observed litter abundance/density on the beach and seafloor. Moreover, AI has made its first steps towards supporting automated litter assessment from in-situ surveys by estimating the mass (kg/m^2) (Acuña-Ruz et al., 2018) and abundance of beached litter (at scales of items/km^2 or items/m^2 or items/m^3) (de Vries et al., 2021; Garcia-Garin et al., 2021; Gonçalves et al., 2020a,b,c; Papakonstantinou et al., 2021; Pinto et al., 2021), as well as the abundance of floating litter (items/km^2) (de Vries et al., 2021). All related papers can be seen in Table 2 (papers with the tag “Litter assessment” in the “Usability” column), as well as on the online database. Additionally, four studies have been found to process litter video footage to detect and count litter items (Armitage et al., 2022; Kylili et al., 2021; Teng et al., 2022; van Lieshout et al., 2020), indicating the potential of the automated counting of litter items in operational surveys. Finally, the extended coverage area of satellites favored the analysis of satellite-based litter imagery in extended geographic sites around the world (Fig. 5).

7.1. Performance of AI algorithms

AI algorithms generally achieved high accuracy (>70%) when they performed binary classifications of litter images, such as debris vs. water (Sannigraphi et al., 2022), plastic vs. non-plastic (Jamali and Mahdianpari, 2021), animal vs. litter (Moorton et al., 2022), the presence or absence of plastics (Armitage et al., 2022), clean vs. polluted images (Chang et al., 2020), or litter vs. water (Sannigraphi et al., 2022). Moderate-to-good performance was also achieved for the classification and detection macrolitter images both for in-situ (Cortesi et al., 2022; Gonçalves et al., 2020a; Veerasingam et al., 2022; Watanabe et al., 2019) and public (Córdova et al., 2022; Fulton et al., 2018; Hong et al., 2020a; Kylili et al., 2019; Majchrowska et al., 2022; Panwar et al., 2020; Priyadarshini et al., 2022; Tata et al., 2021) datasets. In contrast, imagery with complex natural backgrounds and small datasets tended to show moderate overall performance (Lavender, 2022; Martin et al., 2018, 2021; Politikos et al., 2021).

AI studies with satellite imagery tended to perform pixel-based classification and detection of macrolitter items. Contrary, object-based detection methods were increasingly used in non-satellite datasets. This pattern can be partially explained by the relative size of litter items compared to the resolution of the processed images. The type and characteristics of a litter item are often barely visible (just a few pixels) in satellite images (e.g., Basu et al., 2021; Biermann et al., 2020; Kikaki et al., 2022). So, using bounding box annotation of these images (annotation for object-based predictions) didn't seem to be an efficient way to train the corresponding CNN-based semantic segmentation architectures. Instead, spectral analysis was used in several cases (e.g., Biermann et al., 2020; Booth et al., 2022; Themistocleous et al., 2020) to extract features from the images and then process them with machine learning algorithms. This was proved efficient to differentiate marine litter/plastics from other classes (e.g., sea foam, seawater, ship).

To attain the highest possible predictive scores, many studies tested different algorithms on the same dataset, showing variant performance (Chin et al., 2022; Fulton et al., 2018; Kikaki et al., 2022; Maharjan et al., 2022; Martin et al., 2021; Mifdal et al., 2021; Nazerdeylami et al., 2021; Papakonstantinou et al., 2021; Priyadarshini et al., 2022; Sasaki et al., 2022; Tata et al., 2021; Tharani et al., 2020; Wolf et al., 2020; Xue et al., 2021a, b). More recent algorithms tended to have better performance within a range of 10%–30%, without, however, allowing to conclude that there is a “winner” algorithm that should be adopted in future works. Instead, trying several algorithms remains a good practice. Additionally, the performance of the algorithms was found to be litter-specific in several studies (Martin et al., 2018; Panwar et al., 2020; Pinto et al., 2021; Politikos et al., 2021; Song et al., 2021; Valdenegro-Toro, 2016; Wolf et al., 2020; Xue et al., 2021), indicating that the properties of a litter item (e.g., type, shape, size) and its natural background can be key factors for achieving correct predictions. A general conclusion about which litter items have a better chance of being predicted correctly could not be safely extracted from the analysis. An

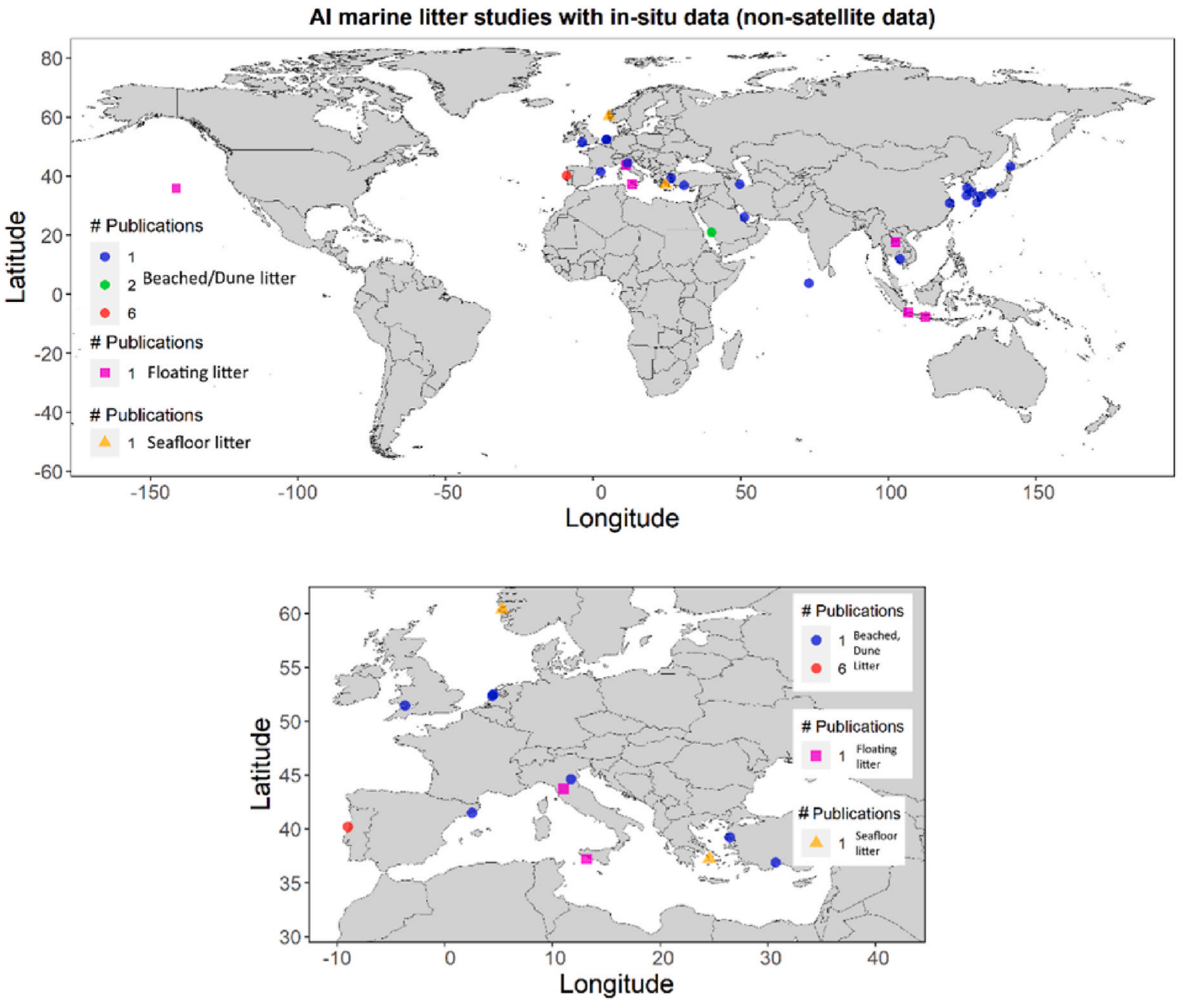


Fig. 4. World (upper) and European (lower) geographic distribution of AI studies that used regional marine macrolitter datasets collected from in-situ surveys (without including satellite data) for their analysis.

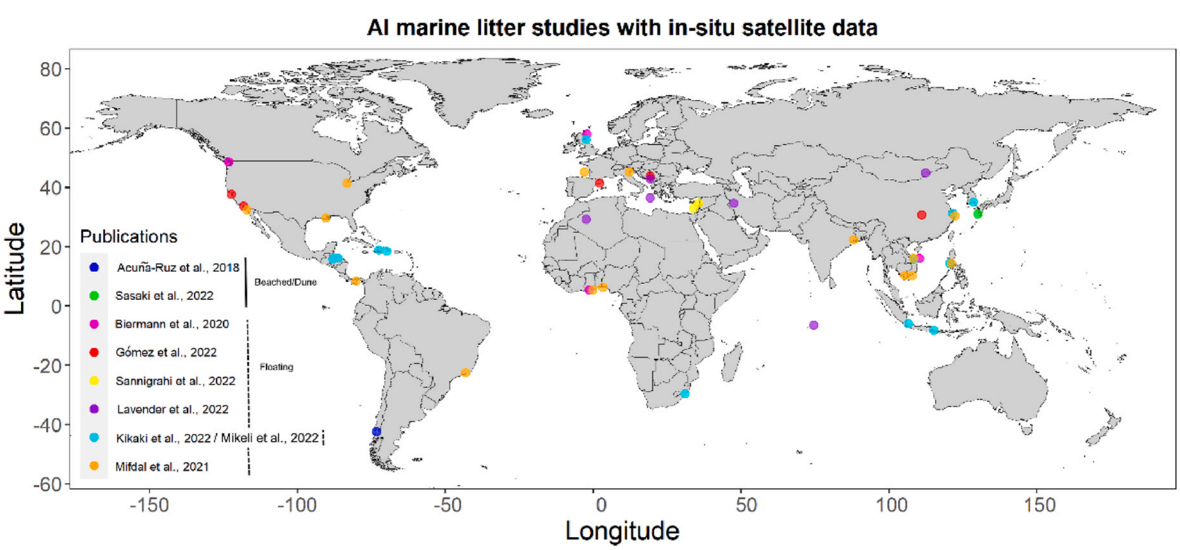


Fig. 5. World geographic distribution of AI marine macrolitter studies that used in-situ satellite image data for their analysis.

overview of the performance of the algorithms in each collected document, as computed from the evaluation metrics can be found on the online dataset (column: "Predictability").

Exploratory studies have mainly used MLA and FFNN to predict floating and beached litter abundance/density using a diverse list of predictors, such as depth, slope, distance from cities and rivers, waves,

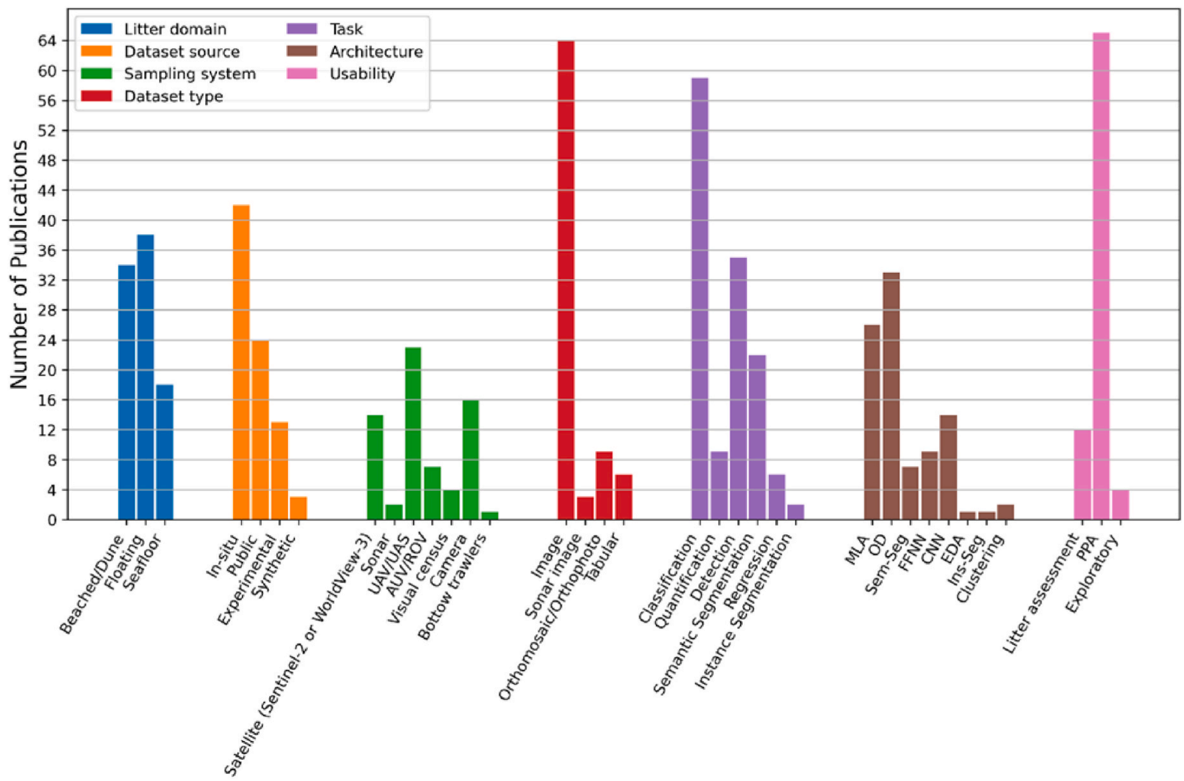


Fig. 6. Number of publications per content category. We note that multiple tags were possible within a reviewed document for the content categories: "Litter domain, "Sampling system", "Task", "Architecture" and "Usability". This implies that the frequency numbers of these categories can sum over the total number of surveyed documents (n = 80).

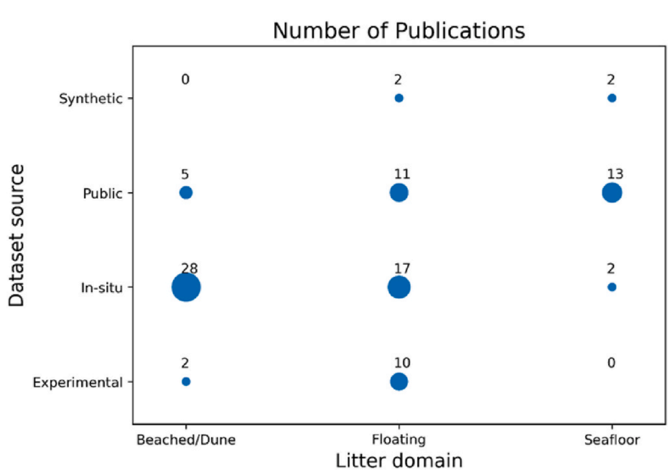


Fig. 7. Frequency distribution of publications at the intersection of "Litter domain" and "Dataset source" content categories.

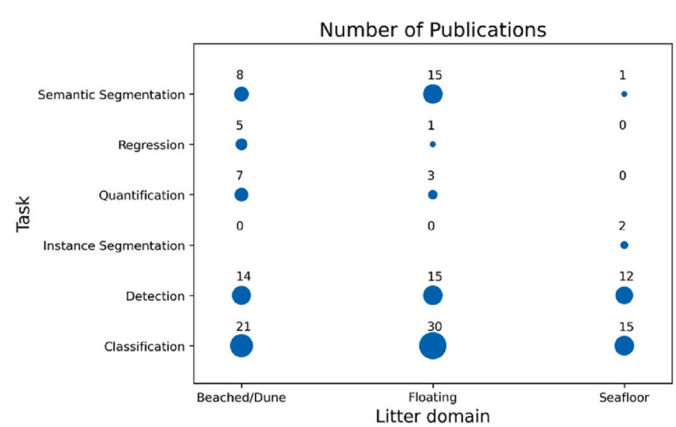


Fig. 8. Frequency distribution of publications at the intersection of "Litter domain" and "Task" content categories.

tides, currents, wind speed, vegetation coverage, isolation, beach exposure, and marine traffic density (Franceschini et al., 2019; Kaandorp et al., 2022; Martin et al., 2021). Schulz and Matthies (2014) selected season, tangled nets, strapping bands, and crisp and sweet packaging, as input variables to explain beached litter abundance for several source categories (plastic, fishing, shipping, and tourism). Their success (observed vs. predicted litter quantity) was variable, ranging from good ($R^2 > 0.5$: Franceschini et al., 2019; Pearson correlation >0.6: Kaandorp et al., 2022) to moderate ($R^2 = 0.23$: Martin et al., 2021; $R^2 <$ 0.4: Schulz and Matthies, 2014), likely implying that some critical explanatory variables have not been considered. Given that the in-situ collection of macrolitter items on the beaches and seafloor is a main source of data in monitoring programs (UNEP, 2021; Canals et al., 2021), we believe that this kind of studies should be further developed in the future.

7.2. Limitations

The present review also identified several limitations. Data collection and assessment are at the core of marine litter monitoring. Promoting the automatic assessment of marine litter should the goal of an AI application on this domain. Nevertheless, limited progress has been achieved in this direction. The majority of publications (80.2%) focused either on fine-tuning and evaluating the performance of existing algorithms on their imagery or on modifying these architectures with new branches, in an attempt to get better results (Table 2, papers with the tag

“PPA” in the “Usability” column). AI-macrolitter assessment was limited to three studies for floating litter (de Vries et al., 2021; Garcia-Garin et al., 2021; van Lieshout et al., 2020), whereas it was more active for beached litter (Table 2, tag “Litter assessment” in the “Usability” column). This can be attributed to the fact that the acquisition of beached litter data is a relatively low-cost process with aerial surveying from land. In contrast, the collection of floating and seafloor litter data requires the use of research vessels in the open sea, implying high operational costs.

29.3% of the reviewed documents used publicly available imagery for their analysis (Table 2; papers with the tag “Public” in the “Data source” column). Although public datasets have the benefit of resolving the problem of expensive data collection and image labeling, they don’t have a practical usability in litter assessment, since in several datasets litter items were collected in controlled setups, i.e., with only one instance of litter per image or taken in indoor scenarios. However, this is rare in real-world marine environments. So, the added value of these studies lies mainly in testing the predictive capabilities of the algorithms. This pattern indicates a discrepancy; while there is an increasing number of scientists who seek to advance AI in marine litter research, the limited availability of real datasets hinders this potential, which in turn confines the geographic extension of real-world AI litter applications, especially for non-satellite data. Interestingly, some authors overcame the lack of data by conducting experimental releases of macrolitter in specific areas (15.9% of articles; Table 2, tag “Experimental” in the “Dataset source” column), but, again, this didn’t contribute to the automatic litter assessment.

7.3. Challenges

Review analysis illustrated the diverse challenges that authors encountered during the implementation of AI algorithms. Litter imagery often contains small or/and imbalanced (low number of samples for some litter classes) datasets (Booth et al., 2022; Córdova et al., 2022; Duarte et al., 2020; Gómez et al., 2022; Politikos et al., 2021; Song et al., 2021). This may affect the training process of the algorithms, often leading to overfitting,[14] which in turn may imply poor performance on new, unseen data. To partially resolve this issue, data augmentation techniques are commonly adopted to artificially increase the size of training data (Aleem et al., 2022; de Vries et al., 2021; Politikos et al., 2021; Tata et al., 2021; Teng et al., 2022) to prevent overfitting. Duarte et al. (2020) conducted oversampling to increase the minority class (litter) to match the same amount of no litter samples, and Nazerdeylami et al. (2021) merged in-situ with public datasets to increase the performance of adopted algorithms. In parallel, the need for collecting bigger training samples to attain better classification and detection results has been highlighted (Basu et al., 2021; van Lieshout et al., 2020; Papakonstantinou et al., 2021).

Litter identification in real-world marine environments constitutes a very challenging task for AI algorithms. The automated recognition of beached/dune litter may be affected by complex natural backgrounds such as vegetation, the presence of natural wood litter and seashells among litter items (Andriolo et al., 2022; Gonçalves et al., 2020a; Nazerdeylami et al., 2021; Song et al., 2021). On the seafloor, litter items are often degraded, semi-buried or may be found within seagrass or among rocks to such an extent that they are hardly distinguishable even by human observers, or they are (Fulton et al., 2019; Politikos et al., 2021). In addition, litter objects may have huge intraclass variability (same type but different shape, e.g., bag) and interclass similarity (e.g., cloth and plastic segment), and this may affect predictability (Xue et al., 2021a, b). In satellite images, high cloud coverage or false annotations by experts in complex cases (e.g., ship vs. wake) can infer mispredictions of floating items (Mifdal et al., 2021; Kikaki et al., 2022). Moreover, the spatial resolution of the satellite images has specific specifications (e.g., Sentinel-2 image is equal to10 m). Although smaller plastic targets can be discriminated and identified under specific conditions (e.g., 3 m × 10 m in Themistocleous et al., 2020), satellite data can be mainly used for the detection/monitoring of large-size litter (Jamali and Mahdianpari, 2021). False predictions may also occur when litter items have similar spectral signatures and where low concentrations compared to the background signal (Lavender, 2022).

The collection of good quality images of litter is also critical for a successful task. For instance, the distance between a sampling system and an object may affect the correct classification of both beached/dune (Ge et al., 2016; Gonçalves et al., 2020a) and floating (Cortesi et al., 2022; Watanabe et al., 2019) litter, since with higher altitudes, it may be difficult to identify objects due to various water surface conditions, beached landscapes or color and size of targets. Jakovljevic et al. (2020; floating litter) and Hidaka et al. (2022); beached/dune litter) noted that the decreased spatial resolution of an image compared to the detectable litter size may affect accuracy in model predictions. Similarly, Armitage et al. (2022) underlined that the object detection of floating litter items can be affected when they have a low pixel percentage within an image, suggesting cropping the image to smaller ones. A good orientation is also needed for a camera to take a clear picture of the seafloor marine litter and avoid a loss in model (Chin et al., 2022). Furthermore, aerial surveys should be conducted in favorable weather conditions, such as calm wind, absence of fog, mist, and rain and weak sunlight reflections (Andriolo and Gonçalves, 2022; Fallati et al., 2019; Garcia-Garin et al., 2021; Takaya et al., 2022) to collect good quality data.

The advancements, current limitations and challenges identified from the use of AI in marine macrolitter research are summarized in Table 4.

7.4. Future directions

AI has a tremendous toolkit that could be potentially used in the future for marine macrolitter research. For instance, Vision Transformers (ViTs) have emerged as an alternative to CNNs that are the most widely used networks in image recognition tasks (Dosovitskiy et al., 2021). ViTs extract patches from images and feed them into a transformer encoder to obtain a global representation, which will finally be used for classification. Additionally, unsupervised deep learning techniques, such as SCAN (Van Gansbeke et al., 2020) and DeepDPM (Ronen et al., 2022), have been proposed for automatically grouping images into semantically meaningful clusters when image labels are absent. As CNNs require thousands of annotated images to be trained before generalizing their learning to unseen scenarios, unsupervised learning could eliminate the time needed for image labeling and, hence, significantly speed up the classification process. Basu et al. (2021) and Taggio et al. (2022), used both classification and common unsupervised algorithms referring to clustering (K-Means and Fuzzy C-Means) to identify plastic litter from satellite images. Although clustering methods achieved lower performance compared to classification, these studies constitute a starting point towards this direction.

A common and effective strategy to overcome the limited size of training data is transfer learning, where knowledge gained from one task is used on a new problem of interest (Pan and Yang, 2010). The idea is to reuse a previously learned network that has been pre-trained on a very large dataset (e.g., ImageNet[15]) to improve prediction in the new task, even if the dataset is small. For instance, transfer learning showed significantly better classification performance on test images of marine litter (Martin et al., 2021). Furthermore, the geographical transferability

[14] Overfitting happens when a model learns too closely the details and the noise of the training set to the extent that it cannot generalize enough to make good predictions on new, unseen data.

[15] A large dataset, which contains 1.2 million training images from 1000 classes (https://www.image-net.org/).

Table 4
Overview of advancements, current limitations, challenges, and future directions identified from the use of AI in marine macrolitter research.

Advancements
• Automated classification, object detection, and segmentation of marine macrolitter imagery with AI is feasible. • AI has made its first steps towards supporting automated litter assessment from in-situ surveys. • Very good performance of AI algorithms on binary (polluted vs. non polluted) classification of images. • Good performance of AI algorithms on classifying and detecting beached/dune, floating and seafloor litter for several case studies. • Machine learning algorithms achieved, although with variant performance, to identify the impact of environmental and anthropogenic variables on shaping macrolitter abundance/density on the beach and seafloor. • AI has the tools to process video footage for litter monitoring. • Extended geographic coverage of AI applications with in-situ satellite data.
Limitations
• Moderate-to-good performance of AI algorithms on detecting beached/dune, floating and seafloor litter for small size and complex datasets. • Limited geographic distribution of AI applications with in-situ, non-satellite data. • Limited use of AI to support litter assessment goals. • Complex natural backgrounds (e.g., grass, rocks), complex properties of litter items (e.g., type, shape, size) and conditions of data acquisition (e.g., image resolution, weather, flight altitude of optical devices) may deceive the performance of AI algorithms. • Small or imbalanced datasets may deceive the performance of AI algorithms. • The resolution of satellite-based images (10 m × 10 m) limits the detection to large macrolitter items.
Challenges
• Handling of small and imbalanced datasets. • Improve classification and detection of macrolitter found in complex environments and those having interclass similarity (e.g., cloth and bag) or intraclass variability (e.g., a bag and a portion of the bag can have different shape). • Acquisition of good quality data.
Future directions
• Collection of bigger and more balanced datasets. • Promote geographic transferability of AI-marine litter studies. • Explore the use of alternative, state-of-the-art AI architectures. • Closer collaboration between computer scientists and marine scientists to design a vision plan.

of a trained algorithm from one location to another is important since it is time-consuming and costly to generate location training litter data (Duarte et al., 2020). The studies of Maharjan et al. (2022), Papakonstantinou et al. (2021), and Topouzelis et al. (2021) have contributed to the transferability of their methods to new and unknown macrolitter imagery. Further initiatives to compile in-situ datasets from different regions, retrain state-of-the-art algorithms in the resulting big datasets, and test them in different sites can potentially broaden the applicability of AI-marine litter studies and improve their performance.

7.5. Policies, management, and governance

In terms of management, public policy, and governance support, the potential of AI is significant. Global initiatives are numerous and include the marine Litter platforms from G7 and G20 (Chen, 2015; Vince and Hardesty, 2018; UNEP, 2021), regional action plans of the regional seas conventions associated with UNEP, coordinated by the Global Partnership on Marine Litter (GPML), and in Europe, the Marine Strategy Framework Directive, which includes a monitoring program and a mitigation action plan. Monitoring plans are all based on the collection of standardized and harmonized data, according to similar protocols, with some indicators under development, based on imagery, especially for floating objects or on the bottom. This is how EMODnet Chemistry has collected marine litter data since 2016, including data in a large, consolidated infrastructure guarantees metadata completeness, adopting different strategies for the management of the diverse litter data types, exploiting the advantages deriving from the application of the FAIR (Findability, Accessibility, Interoperability, and Reusability) principles in marine litter data stewardship (Partescano et al., 2021).

More recently, an international negotiation has been initiated in order to establish, in 2024, a legally binding convention to limit plastic pollution[16] (Wang, 2023), with GPML to organize, in parallel, various communities of practices in a UN digital platform,[17] in order to support the integration and harmonizing data and databases, promoting new approaches to support global monitoring, including new indicators based on imagery (satellites, video) to support evaluations of both trends in mounts of litter, and the efficiency of reduction measures.

In fine, the programs of the ocean decade and the EU horizon Europe Mission "Restore our Oceans and Waters", are aimed at launching an ocean twin, in order to manage both data and analyzing tools. It will include a component dedicated to the marine litter; something that cannot be dissociated from the current and future developments of artificial intelligence, as it is the essence of the development of digital tools.

7.6. AI micro-litter/plastic research

AI has been used in laboratory microlitter research as well for detecting and counting collected micro-plastics/fibres and determining their size and chemical nature. As it was out of our scope to make a review of these studies, we mention a few examples for illustration purposes. Lorenzo-Navarro et al. (2021) used a neural network to automatically count and classify microplastics (1–5 mm) into three different shape categories (fragments, pellets, and lines) using pictures taken with a digital camera and a mobile phone. Deep learning architectures were applied in scanning electron microscopy images for semantic segmentation of micro-plastics/fibres in the range of 50 μm-1mm (Shi et al., 2022). In addition, microscope holographic images were processed with machine learning methods for identifying microplastics inside heterogeneous pretreated water samples (Bianco et al., 2020). Massarelli et al. (2021) developed a computer vision and machine learning system to automatically count and classify microplastics in four morphology (fragment, pellet, line, fibre) and size (<500 μm, 500–1000 μm, 1000–2000 μm, and 2000–5000 μm) categories. Other studies combined machine learning with Fourier-transform infrared spectroscopy (FTIR) spectra to distinguish different polymer types in the examined microplastic samples (Hufnagl et al., 2022; Kedzierski et al., 2019). Further microplastics segmentation analysis based on various deep learning models was reported in Park et al. (2022).

8. Conclusions

This review illustrated the developments that have been made in the domain of macrolitter monitoring and assessment using AI methodologies. Results showcased that AI has achieved significant progress over the last few years to provide automatic and scalable solutions for detecting and classifying macrolitter in all marine landscapes. Concurrently, the wide use of AI algorithms on various case studies helped us to acquire significant knowledge about their capabilities and limitations in such complex and peculiar imagery. Further progress is needed, however, to shift from technical implications of the tested algorithms, mainly presented in the collected literature, towards methodologies that will meet the needs of the marine litter research community for the automated assessment of litter distribution and quantities. Additionally, promoting the collection of big litter data from realistic environments and the transferability of gained knowledge from one location to another will further support this goal. Finally, initiatives that will bring closer

[16] https://www.un.org/en/delegate/nations-sign-end-global-scourge-plastic-pollution.
[17] https://wedocs.unep.org/handle/20.500.11822/37070.

computer scientists and marine scientists to design a vision plan how AI will contribute on this theme more effectively in the future is a crucial step.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix

In this Appendix, we provide a brief overview of key ML/DL concepts and methods with a special focus on those that have been adopted in marine litter research and found in the collected literature. Interested readers should consult introductory texts (Chollet, 2017; Harrison, 2019) to deepen their understanding.

Machine learning algorithms

ML is a subfield of AI that includes a large set of algorithms and heuristics that computer systems use to find complex patterns in data without explicit programming (Alpaydın, 2014). In ML, the two most common approaches, applied to real-world datasets, are supervised and unsupervised learning.[18] Supervised learning requires a labeled dataset and training of the algorithm system to gain experience; the algorithm is then used to make predictions on a new dataset. The most common supervised tasks are classification and regression. Classification aims to assign data to specific classes. For example, in the case of predicting if a transaction is a fraud or not based on several numeric and categorical data (e.g., card number, product value, device used for the transaction, e-mail of the purchaser), the algorithm system would be provided with many transactions that have already been labeled as either being fraud or not. At first the algorithm Is trained and validated with the labeled transactions and then tested with new unlabeled ones. Regression aims to predict a numeric value of interest, called target variable (e.g., temperature, age, salary, price, etc.) based on a list of dependent variables that are considered as potential drivers of the target variable. To do so, a training set is used to train a regressor and the test set is used to evaluate the performance of the trained model. In unsupervised learning, the algorithm system is provided with unlabeled data to find structures on its own. The most common unsupervised tasks are clustering (grouping of data items into clusters based on their similarities or differences), dimensionality reduction (filtering of non-important variables in a given dataset), association rule mining (finding of meaningful relationships between variables in a given dataset), outlier/anomaly detection (detection of data items that deviate from a dataset's normal behavior) and density estimation (estimation of a continuous density field from discretely sampled data items) (Han et al., 2011). ML algorithms can generally handle all types of data, namely tabular, images, videos, or documents (Sarker, 2021).

Neural networks

DL is a subdomain of ML that uses deep neural networks to imitate human learning and inference to analyze data on a large scale. DL functions by mimicking the neural connections made in the human brain (Goodfellow et al., 2015). A feedforward neural network (FFNN) is the simplest type of neural network. FFNN learns the relationship between independent variables that serve as inputs to the network, and dependent variables that serve as outputs of the network (Fig. A1). For example, if we would like to predict whether it will rain tomorrow based on humidity, temperature and wind speed, the inputs to the network would be the values of these three variables and the output would be if we would have rain or not. FFNNs are made up of several layers of interconnected nodes, each of which improves the network's predictability. These interconnections are not all equal. Instead, each connection may have a different strength, quantified by learnable parameters, called *weights*. Weights are updated during the training phase of the network according to a cost function that minimizes the differences between the network outputs and the known 'true' outputs. Final weights encode the overall knowledge of the network and are used to make predictions of unseen data points. FFNN is generally suited for supervised learning with large numerical datasets, though it is less effective with image data since it cannot consider the spatial dependencies of features in an image, while it cannot be used with sequential data (time series, text) because it has no memory of the input it receives and hence it's unable to predict what's coming next. This brings us to the more advanced classes of neural networks that will be discussed in the following subsections.

Image classification

Image classification is the task of identifying what an image represents, say, a bottle, a bag, a cup, or a can (Fig. 2a). Image classification was one of the first areas in which DL made a major contribution to computer vision.[19] Convolutional Neural Networks (CNNs) are the most representative networks designed for image classification (Chen et al., 2021). The main components of a CNN are the convolutional layer, the pooling layer, the nonlinear activation layer, and the fully connected layer. First, an image is fed into a CNN through the input layer. Then, it is processed through a stack of alternately arranged convolutional, pooling, and activation layers, and finally it is classified by fully connected layers (Fig. A1). Contrary to

[18] Other approaches are semi-supervised learning and reinforcement learning (Sarker, 2021).
[19] Computer vision is a field of artificial intelligence that trains computers to interpret and understand the visual world.

traditional ML classification methods, from which image features are extracted manually, CNNs follow an end-to-end approach, in which only the image is an input, while the whole learning process is carried out in the network to identify simple shapes (edges, lines, etc.) in the first layers, to more sophisticated patterns in the next layers, and classes of objects in the final layers. What makes CNNs popular is their efficiency in capturing the spatial interaction between adjacent pixels in an image and determining which features (e.g., the neck of a bottle) are most important in differentiating one litter from another. Over the last years, researchers have come up with several, well-established CNN architectures, for instance, AlexNet (Krizhevsky et al., 2012), VGGNet (Simonyan and Zisserman, 2014) and Inception (Szegedy et al., 2014). For more details about CNNs, the reader is referred to the recent review paper by Chen et al. (2021).

Other CNN-based architectures that can be used, among others, for image classification are encoder-decoder networks (Badrinarayanan et al., 2017; Hong et al., 2019). An encoder-decoder architecture consists of a pair of two connected networks (e.g., feed forward neural networks, CNNs): an encoder model and a decoder model. For computer vision tasks, the encoder is used to learn a compressed representation of the input image (also called latent space) in such a way that the decoder can reconstruct the original image as closely as possible to the original (Fig. A1). Once the encoder-decoder is trained and validated, the decoder is discarded, and the encoder is used for the classification task.

Object detection

Object detection is a computer vision task that involves both classifying and localizing objects within an image (Fig. 2b). More specifically, object detection aims to determine whether there are any objects from given categories (e.g., bag, bottle, paper, can, cup, etc.) and, if present, to return the spatial location of each object, wrapped by a bounding box (Liu et al., 2019).

Object detection has been approached by two main types, namely two-stage and one-stage detectors. Two-stage detectors use a sliding window to generate candidate object region proposals in an image during the first stage, and then classify and localize them during the second stage. The core architecture of these detectors includes an agnostic region proposal module coupled with a CNN to convert detection into classification and localization problems. Single-stage detectors skip the region proposal stage step and classify and localize semantic objects in a single shot, using a dense sampling of possible locations of various scales and aspect ratios (Elgendy, 2020). In the literature, an extended list of object detection architectures can be found both for two-stage detectors (e.g., R–CNN [Girshick et al., 2014]) and one-stage detectors (e.g., SSD [Liu et al., 2016], YOLO [Redmon et al., 2016], EfficientDet [Tan et al., 2020]). The different algorithms attempt to add or modify branches in their architecture to extract efficient features from the images that will improve their detection capability. For more details on object detection networks, the reader is referred to the recent review papers by Liu et al. (2019) and Zaidi et al. (2021).

Instance segmentation

Instance segmentation is a further extension of object detection, creating a pixel-wise mask for object(s) found in an image (Fig. 2c). Contrary to object detection, which returns bounding boxes that are always rectangular and hence cannot determine the shape of objects, instance segmentation can provide more quantitative information about the object(s), estimating their surface area or perimeter. In these networks, an instance mask branch is usually added in parallel to the classification and bounding parts of object detection architectures. Well-known deep learning architectures that have been developed to resolve this topic are, among others, Mask R–CNN (He et al., 2017), PANet (Liu et al., 2018), and YOLACT (Bolya et al., 2019). For more details about instance segmentation and the aforementioned networks, the reader is referred to the recent review by Hafiz and Bhat (2020).

Semantic segmentation

Object-based semantic segmentation is also a significant topic in computer vision, where the goal is to assign a class label to each pixel in the image (Fig. 2d). This task is commonly referred to as “dense prediction”. Semantic segmentation is useful in several tasks, as for example in autonomous driving to locate frontal objects (roads, vehicles, pavements, humans) (Kaymak and Uçar, 2019) and medical image diagnostics (Liu et al., 2021). A variety of deep learning architectures (e.g., fully convolutional networks encoder-decoder models, attention-based models, recurrent neural network-based models, dilated convolutional models) have been proposed in the literature to resolve this task. Indicatively, well-known architectures designed for semantic segmentation are ReSeg (Visin et al., 2016), SegNet (Badrinarayanan et al., 2017), and DeepLab (Chen et al., 2017). For more details on the semantic segmentation architectures, the reader is referred to the recent review papers by Minaee et al. (2020) and Mo et al. (2022).

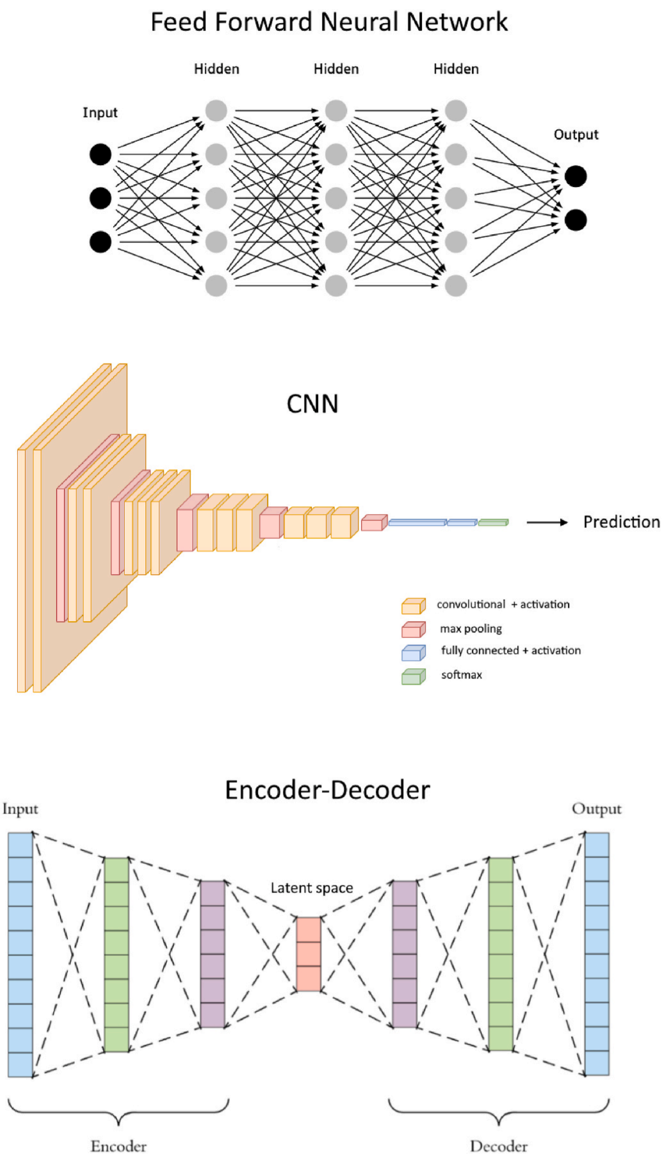

Fig. A1. Schematic diagram of Feed Forward Neural Network, Convolutional Neural Network (CNN) and Encoder-Decoder architecture.

Evaluating the performance of a ML-DL algorithm is essential for measuring its predictive accuracy. For instance, a computer system should be efficient to distinguish between categories, e.g., bottle and. Bag. For (image) classification tasks, the most common evaluation metrics are accuracy, recall, precision, and F1-score (Fig. 2). For evaluating a segmentation task, the two common metrics are: mean Average Precision (mAP) and Intersection Over Union (IoU) (Fig. 2). The closer all these metrics are to one, the better and more accurate the performance of that model. Finally, regression tasks are commonly evaluated through the metrics of Mean Square Error (MSE), Mean absolute Error (MAE), Root Mean Square Error (RMSE) and R^2. A short description of the evaluation metrics along with their formulas are shown in Table A1.

Table A1
Metrics for evaluating the performance of AI algorithms.

Metric (Task)	Description	Formula
Accuracy (Acc) (Classification)	Fraction of correct classifications out of the total number of classifications.	$Acc = \frac{TP + TN}{TP + FP + TN + FN}$, TP: True positives TN: True negatives FP: False positives FN: False negatives
Precision (P) (Classification)	Fraction of true positive classifications over the sum of true positive and false positive classifications.	$P = \frac{TP}{TP + FP}$, TP: True positives FP: False positives
RecallI) (Classification)	Fraction of true positive classifications over the sum of true positive and false negative classifications.	

(continued on next page)

Table A1 (*continued*)

Metric (Task)	Description	Formula
		$R = \frac{TP}{TP+FN}$, TP: True positives FN: False negatives
F1 score (F) (Classification)	F1 score is a unified metric, computed as the harmonic mean of precision and recall.	$F = 2\frac{P*R}{P+R}$, P: precision, R: recall
mAP (Object detection, Segmentation)	mAP (mean Average Precision) shows how well the predicted box matches the ground truth (localization), and whether the class label is correctly predicted (classification).	$mAP = \sum_{i=1}^{N} AP_i$,
	AP (Average precision) value is the mean value of the precision value under different recalls	$AP = \int_0^1 P(R)dR$, P: precision, R: recall and N: the total number of data instances
IoU (Object detection, Segmentation)	IoU (Intersection Over Union) measures the percent overlap between the correct region (ground truth) and the classified region (algorithm output). IoU ranges between 0 and 1, with 0 signifying no overlap and 1 signifying a perfect overlap.	$IoU = \frac{\text{Area of Overlap}}{Area\ of\ Union}$
MSE, MAE RMSE, R2 (Regression)	Mean Squared Error (MSE), Mean absolute Error (MAE) and Root Mean Square Error (RMSE) represent various ways to measure the error difference between ground truth observations ($\hat{y}_i$) and predictions (y_i). Coefficient of determination (R^2) is a number between 0 and 1 that measures how well a statistical model predicts an outcome. R^2 closer to 1 imply a better prediction.	$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$ $MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert y_i - \hat{y}_i\rvert^2$ $\text{RMSE} = \sqrt{MSE}$ $R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$ N: total number of observations $\bar{y}$: average value of predictions N: total number of data instances

References

Acuna Ruz, T., et al., 2018. Anthropogenic marine debris over beaches: spectral characterization for remote sensing applications. Remote Sens. Environ. 217, 309–322. https://doi.org/10.1016/j.rse.2018.08.008.

Adamopoulou, A., et al., 2021. Distribution patterns of floating microplastics in open and coastal waters of the eastern Mediterranean Sea (Ionian, Aegean, and Levantine seas). Front. Mar. Sci. 8, 699000 https://doi.org/10.3389/fmars.2021.699000.

Aleem, A., Tehsin, S., Kausar, S., Jameel, A., 2022. Target classification of marine debris using deep learning. Intell. Autom. Soft Comput. 32, 73–85. https://doi.org/10.32604/iasc.2022.021583.

Alpaydın, E., 2014. Introduction to Machine Learning. MIT Press, p. 640.

Andriolo, U., et al., 2022. Beached and floating litter surveys by unmanned aerial vehicles: operational analogies and differences. Remote Sens 14, 1336. https://doi.org/10.3390/rs14061336.

Andriolo, U., Goncalves, G.G., 2022. Is coastal erosion a source of marine litter pollution? Evidence of coastal dunes being a reservoir of plastics. Mar. Pollut. Bull. 174, 113307 https://doi.org/10.1016/j.marpolbul.2021.113307.

Andriolo, U., Goncalves, G., Sobral, P., Fontan Bouzas, A., Bessa, F., 2020. Beach-dune morphodynamics and marine macro-litter abundance: an integrated approach with Unmanned Aerial System. Sci. Total Environ. 749, 141474 https://doi.org/10.1016/j.scitotenv.2020.141474.

Andriolo, U., Goncalves, G., Sobral, P., Bessa, F., 2021a. Spatial and size distribution of macro-litter on coastal dunes from drone images: a case study on the Atlantic coast. Mar. Pollut. Bull. 169, 112490 https://doi.org/10.1016/j.marpolbul.2021.112490.

Andriolo, U., et al., 2021b. Drones for litter mapping: an inter-operator concordance test in marking beached items on aerial images. Mar. Pollut. Bull. 69, 112542 https://doi.org/10.1016/j.marpolbul.2021.112542.

Armitage, S., Awty-Carroll, K., Clewley, D., Martinez-Vicente, V., 2022. Detection and classification of floating plastic litter using a vessel-mounted video camera and deep learning. Rem. Sens. 14, 3425. https://doi.org/10.3390/rs14143425, 2022.

Badrinarayanan, V., Kendall, A., Cipolla, R., 2017. Segnet: a deep convolutional encoder-decoder architecture for image segmentation. IEEE Trans. Pattern Anal. Mach. Intell. 39 (12), 2481–2495. https://doi.org/10.1109/TPAMI.2016.2644615.

Bajaj, R., et al., 2021. Sea debris detection using deep learning: diving deep into the sea. IEEE Int. Conf. Intell. Comput. Power Comm. Tech. (GUCON) 1–6. https://doi.org/10.1109/GUCON50781.2021.9573722.

Bak, S.H., et al., 2019. Detection and monitoring of beach litter using UAV image and deep neural network. Int. Arch. Photogr. Remote Sens. Spat. Inf. Sci. XLII-3/W8, 55–58. https://doi.org/10.5194/isprs-archives-XLII-3-W8-55-2019.

Balas, C.E., Ergın, A., Williams, A.T, Koc, L., 2004. Marine litter prediction by artificial intelligence. Mar. Pollut. Bull. 48, 449–457. https://doi.org/10.1016/j.marpolbul.2003.08.020.

Balas, C.E., Williams, A.T., Ergin, A., Koç, M.L., 2006. Litter categorization of beaches in Wales, UK by multi-layer neural networks. J. Coast. Res. JCR SI 39, 1516–1520. http://www.jstor.org/stable/25743008.

Basu, B., Sannigrahi, S., Basu, A.S., Pilla, F., 2021. Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral Sentinel-2 remote sensing imagery. Rem. Sens. 13, 1598. https://doi.org/10.3390/rs13081598.

Bianco, V., et al., 2020. Microplastic identification via holographic imaging and machine learning. Adv. Intell. Syst. 2, 1900153 https://doi.org/10.1002/aisy.201900153.

Biermann, L., Clewley, D., Martinez-Vicente, V., Topouzelis, K., 2020. Finding plastic patches in coastal waters using optical satellite data. Sci. Rep. 10, 5364. https://doi.org/10.1038/s41598-020-62298-z.

Bolya, D., Zhou, C., Xiao, F., Lee, Y.J., 2019. YOLACT: real-time instance segmentation. SAVE Proc. IEEE Comput. Soc. Conf. Comput. Vis. 9157–9166. https://doi.org/10.1109/ICCV.2019.00925.

Booth, H., Ma, W., Karakus, O., 2022. High-precision density mapping of marine debris and floating plastics via satellite imagery. arXiv preprint. https://doi.org/10.48550/arXiv.2210.05468.

Broere, S., van Emmerik, T., Gonzalez Fernandez, D., Luxemburg, W., de Schipper, M., Cozar, A., van de Giesen, N., 2021. Towards underwater aterseriza monitoring using echo sounding. Front. Earth Sci. 9, 628704 https://doi.org/10.3389/feart.2021.628704.

Canals, M., et al., 2021. The quest for seafloor macrolitter: a critical review of background knowledge, current methods and future prospects. Environ. Res. Lett. 16, 023001 https://doi.org/10.1088/1748-9326/abc6d4.

Chang, M., Xing, Y.Y., Zhang, Q.Y., Han, S.J., Kim, M., 2020. A CNN image classification analysis for "Clean-Coast Detector" as tourism service distribution. J. Distrib. Sci. 18, 15–26. https://doi.org/10.15722/jds.18.1.202001.15.

Chen, C.L., 2015. Regulation and management of marine litter. In: Bergman, M., M., Gutow, L., Klages, M. (Eds.), Marine Anthropogenic Litter. Springer, pp. 395–428. https://doi.org/10.1007/978-3-319-16510-3.

Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L., 2017. Deeplab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected Crfs. https://doi.org/10.48550/arXiv.1606.00915 arXiv preprint.

Chen, L., et al., 2021. Review of image classification algorithms based on convolutional neural networks. Rem. Sens. 13 (22), 4712. https://doi.org/10.3390/rs13224712.

Chin, C.S., Neo, A.B.H., See, S., 2022. Visual marine debris detection using Yolov5s for autonomous underwater vehicle. IEEE/ACIS 22nd Int. Conf. Comput. Inf. 20–24. https://doi.org/10.1109/ICIS54925.2022.9882484.

Chollet, F., 2017. Deep Learning with Python. Manning Publications, p. 384.

Clark, N.J., Khan, R., Mitrano, D.M., Boyle, D., Thompson, R., 2022. Demonstrating the translocation of nanoplastics across the fish intestine using palladium-doped polystyrene in a salmon gut-sac. Environ. Int. 159, 06994 https://doi.org/10.1016/j.envint.2021.106994.

Cocking, J., Narayanaswamy, B.E., Waluda, C.M., Williamson, B.J., 2022. Aerial detection of beached marine plastic using a novel, hyperspectral short-wave infrared (SWIR) camera. ICES J. Mar. Sci. 79 (3), 648–660. https://doi.org/10.1093/icesjms/fsac006.

Córdova, M., et al., 2022. Litter detection with deep learning: a comparative study. Sensors 22 (2), 548. https://doi.org/10.3390/s22020548.

Cortesi, I., Masiero, A., Tucci, G., Topouzelis, K., 2022. UAV-based river plastic detection with a multispectral camera. Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. 43, 855–861. https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-855-2022.
de Vries, R., Egger, M., Mani, T., Lebreton, L., 2021. Quantifying floating plastic debris at sea using vessel-based optical data and artificial intelligence. Rem. Sens. 13, 3401. https://doi.org/10.3390/rs13173401.
Deng, H., et al., 2021. An embeddable algorithm for automatic garbage detection based on complex marine environment. Sensors 21, 6391. https://doi.org/10.3390/s21196391.
Deng, Li, Liu, Y., 2018. Deep Learning in Natural Language Processing. Springer, p. 329.
Dosovitskiy, A., et al., 2021. An image is worth 16x16 words: transformers for image recognition at scale. arXiv preprint. https://doi.org/10.48550/arXiv.2010.11929.
Downe-Wamboldt, B., 1992. Content analysis: method, applications, and issues. Health Care Women Int. 13 (3), 313–321. https://doi.org/10.1080/07399339209516006.
Driedger, A.G.J., et al., 2015. Plastic debris in the Laurentian Great Lakes: a review. J. Great Lakes Res. 41 (1), 9–19. https://doi.org/10.1016/j.jglr.2014.12.020.
Duarte, D., Andriolo, U., Goncalves, G., 2020. Addressing the class imbalance problem in the automatic image classification of coastal litter from orthophotos derived from UAS imagery. ISPRS Ann. Photogramm. Rem. Sens. Spat. Inf. Sci. 3–2020, 439–445. https://doi.org/10.5194/isprs-annals-V-3-2020-439-2020.
Elgendy, M., 2020. Deep Learning for Vision Systems. Manning Publications, p. 480.
Elo, S., Kyngas, H., 2008. The qualitative content analysis process. J. Adv. Nurs. 2 (1), 107–115. https://doi.org/10.1111/j.1365-2648.2007.04569.x.
Eriksen, M., et al., 2014. Plastic pollution in the world's oceans: more than 5 trillion plastic pieces weighing over 250,000 tons afloat at sea. PLoS One 9 (12), e111913. https://doi.org/10.1371/journal.pone.0111913.
Escobar Sanchez, G., Haseler, M., Oppelt, N., Schernewski, G., 2021. Efficiency of aerial drones for macrolitter monitoring on Baltic Sea beaches. Front. Environ. Sci. 8, 560237 https://doi.org/10.3389/fenvs.2020.560237.
Fakiris, E., et al., 2022. Insights into seafloor litter spatiotemporal dynamics in urbanized shallow Mediterranean bays. An optimized monitoring protocol using towed underwater cameras. J. Environ. Manag. 308, 114647 https://doi.org/10.1016/j.jenvman.2022.114647.
Fallati, L., et al., 2019. Anthropogenic marine debris assessment with unmanned aerial vehicle imagery and deep learning: a case study along the beaches of the Republic of Maldives. Sci. Total Environ. 693, 133581 https://doi.org/10.1016/j.scitotenv.2019.133581.
Forrest, A., et al., 2019. Eliminating plastic pollution: how a voluntary contribution from industry will drive the circular plastics economy. Front. Mar. Sci. 6, 627. https://doi.org/10.3389/fmars.2019.00627.
Fossum, T.O., 2022. Underwater autonomous mapping and characterization of marine debris in urban water bodies. arXiv preprint.. https://doi.org/10.48550/arXiv.2208.00802.
Fotopoulou, K.N., Karapanagioti, H.K., 2017. Degradation of various plastics in the environment. In: The Handbook of Environmental Chemistry. Springer, Berlin, Heidelberg, pp. 1–22.
Franceschini, S., et al., 2019. Rummaging through the bin: modelling marine litter distribution using Artificial Neural Networks. Mar. Pollut. Bull. 149, 110580 https://doi.org/10.1016/j.marpolbul.2019.110580.
Freitas, S., Silva, H., Silva, E., 2021. Remote hyperspectral imaging acquisition and characterization for marine litter detection. Remote Sens. 13, 2536. https://doi.org/10.3390/rs13132536.
Fulton, M., Hong, J., Islam, M.J., Sattar, J., 2018. Robotic detection of marine litter using deep visual detection models. arXiv preprint. https://arxiv.org/abs/1804.01079.
Fulton, M., Hong, J., Islam, M.J., Sattar, J., 2019. Robotic detection of marine litter using deep visual detection models. arXiv preprint. https://arxiv.org/abs/1804.01079.
Galgani, F., et al., 2000. Litter on the sea floor along European coasts. Mar. Pollut. Bull. 40, 516–527. https://doi.org/10.1016/S0025-326X(99)00234-9.
Galgani, L., et al., 2019. Editorial: impacts of marine litter. Front. Mar. Sci. 6, 208. https://doi.org/10.3389/fmars.2019.00208.
Gao, J., Li, P., Chen, Z., Zhang, J., 2020. A survey on deep learning for multimodal data fusion. Neural Comput. 32 (5), 829–864. https://doi.org/10.1162/neco_a_01273.
Garcia-Garin, O., et al., 2020a. Who's better at spotting? A comparison between aerial photography and observer-based methods to monitor floating marine litter and marine mega-fauna. Environ. Pollut. 258, 113680 https://doi.org/10.1016/j.envpol.2019.113680.
Garcia-Garin, O., et al., 2020b. Floating marine macro-litter in the North Western Mediterranean Sea: results from a combined monitoring approach. Mar. Pollut. Bull. 159, 111467 https://doi.org/10.1016/j.marpolbul.2020.111467.
Garcia-Garin, O., et al., 2021. Automatic detection and quantification of floating marine macro-litter in aerial images: introducing a novel deep learning approach connected to a web application in R. Environ. Pollut. 273, 116490 https://doi.org/10.1016/j.envpol.2021.116490.
Gauci, A., Deidun, A., Montebello, J., Abela, J., Galgani, F., 2019. Automating the characterization of beach microplastics through the application of image analyses. Ocean Coast Manag. 182, 104950 https://doi.org/10.1016/j.ocecoaman.2019.104950.
Ge, Z., et al., 2016. Semi-automatic recognition of marine debris on beaches. Sci. Rep. 6, 25759 https://doi.org/10.1038/srep25759.
Gesamp, 2019. Guidelines or the monitoring and assessment of plastic litter and microplastics in the ocean. In: Kershaw, P.J., Turra, A., Galgani, F. (Eds.), IMO/FAO/UNESCO-IOC/UNIDO/WMO/IAEA/UN/UNEP/UNDP/ISA Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection, 99. Rep. Stud. GESAMP No., p. 130
Girshick, R., Donahue, J., Darrell, T., Malik, J., 2014. Rich feature hierarchies for accurate object detection and semantic segmentation. arXiv preprint. https://doi.org/10.48550/arXiv.1311.2524.
Gnann, N., Baschek, B., Ternes, T.A., 2022. Close-range Remote Sensing-Based Detection and Identification of Macroplastics on Water Assisted by Artificial Intelligence: A Review. Water Res., p. 118902. https://doi.org/10.1016/j.watres.2022.118902
Gomez, A., Scandolo, L., Eismann, E., 2022. A learning approach for river debris detection. Int. J. Appl. Earth Obs. Geoinf. 107, 102682 https://doi.org/10.1016/j.jag.2022.102682.
Goncalves, G., Andriolo, U., Pinto, L., Bessa, F., 2020a. Mapping marine litter using UAS on a beach-dune system: a multidisciplinary approach. Sci. Total Environ. 706, 135742 https://doi.org/10.1016/j.scitotenv.2019.135742.
Goncalves, G., Andriolo, U., Pinto, L., Duarte, D., 2020b. Mapping marine litter with Unmanned Aerial Systems: a showcase comparison among manual image screening and machine learning techniques. Mar. Pollut. Bull. 155, 111158 https://doi.org/10.1016/j.marpolbul.2020.111158.
Goncalves, G., Andriolo, U., Goncalves, L., Sobral, P., Bessa, F., 2020c. Quantifying marine macro litter abundance on a sandy beach using unmanned aerial systems and object-oriented machine learning methods. Rem. Sens. 12, 2599. https://doi.org/10.3390/rs12162599.
Goodfellow, I.J., Bengio, Y., Courville, A., 2015. Deep Learning. MIT Press, p. 433.
Hafiz, A.M., Bhat, G.M., 2020. A Survey on Instance Segmentation: State of the Art arXiv preprint. https://arxiv.org/abs/2007.00047.
Han, J., Kamber, M., Pei, J., 2011. Data Mining: Concepts and Techniques, third ed. Springer, p. 740.
Hardesty, B.D., et al., 2017. Using numerical model simulations to improve the understanding of microplastic distribution and pathways in the marine environment. Front. Mar. Sci. 30, 1–9. https://doi.org/10.3389/fmars.2017.00030.
Harrison, M., 2019. Machine Learning Pocket Reference. O'Reilly Media, Inc.
Haseler, M., Schernewski, G., Balciunas, A., Sabaliauskaite, V., 2018. Monitoring methods for large micro- and meso-litter and applications at Baltic beaches. J. Coast Conserv. 22 (1), 27–50. https://doi.org/10.1007/s11852-017-0497-5.
He, K., Gkioxari, G., Dollar, P., Girshick, R., 2017. Mask R-CNN arXiv preprint. https://arxiv.org/abs/1703.06870.
Helinski, O.K., Poor, C., Wolfand, J.M., 2021. Ridding our rivers of plastic: a framework for plastic pollution capture device selection. Mar. Pollut. Bull. 165, 112095 https://doi.org/10.1016/j.marpolbul.2021.112095.
Hengstmann, E., Fischer, E.K., 2020. Anthropogenic litter in freshwater environments study on lake beaches evaluating marine guidelines and aerial imaging. Environ. Res. 189 https://doi.org/10.1016/j.envres.2020.109945.
Hong, J., Fulton, M., Sattar, J., 2019. A generative approach towards improved robotic detection of marine litter. arXiv preprint. https://doi.org/10.48550/arXiv.1910.04754.
Hidaka, M., et al., 2022. Pixel-level image classification for detecting beach litter using a deep learning approach. Mar. Pollut. Bull. 175, 113371 https://doi.org/10.1016/j.marpolbul.2022.113371.
Hong, J., Fulton, M., Junaed, S., 2020. TrashCan: a semantically-segmented dataset towards visual detection of marine debris. arXiv preprint. https://doi.org/10.48550/arXiv.2007.08097.
Hufnagl, B., et al., 2022. Computer-assisted analysis of microplastics in environmental samples based on μFTIR imaging in combination with machine learning. Environ. Sci. Technol. Lett. 9, 90–95. https://doi.org/10.1021/acs.estlett.1c00851.
Ioakeimidis, C., et al., 2014. A comparative study of marine litter on the seafloor of coastal areas in the Eastern Mediterranean and Black Seas. Mar. Pollut. Bull. 89 (1–2), 296–304. https://doi.org/10.1016/j.marpolbul.2014.09.044.
Jakovljevic, G., Govedarica, M., Alvarez-Taboada, F., 2020. A deep learning model for automatic plastic mapping using unmanned aerial vehicle (UAV) data. Rem. Sens. 12, 1515. https://doi.org/10.3390/rs12091515.
Jamali, A., Mahdianpari, M.A., 2021. Cloud-based framework for large-scale monitoring of ocean plastics using multi-spectral satellite imagery and generative adversarial network. Water 13, 2553. https://doi.org/10.3390/w13182553.
JAMSTEC, 2018. Deep-sea Debris Database. Japan Agency for Marine Earth Science and Technology. http://www.godac.jamstec.go.jp/catalog/dsdebris/metadataList?lang=en.
Kaandorp, M.L.A., et al., 2022. Using machine learning and beach cleanup data to explain litter quantities along the Dutch North Sea coast. Ocean Sci. 18, 269–293. https://doi.org/10.5194/os-18-269-2022.
Kako, S., Morita, S., Taneda, T., 2020. Estimation of plastic marine debris volumes on beaches using unmanned aerial vehicles and image processing based on deep learning. Mar. Pollut. Bull. 155, 111127 https://doi.org/10.1016/j.marpolbul.2020.111127.
Kankane, A., Kang, D., 2021. Detection of seashore debris with fixed camera images using computer vision and deep learning. 6th Int. Conf. Intell. Inf. Biomed. Sci. 34–38. https://doi.org/10.1109/ICIIBMS52876.2021.9651572.
Karakuş, O., 2022. Can we "sense" the call of the ocean? current advances in remote sensing computational imaging for marine debris monitoring. arXiv preprint. https://doi.org/10.48550/arXiv.2210.06090.
Kataoka, T., Nihei, Y., 2020. Quantification of floating riverine macro-debris transport using an image processing approach. Sci. Rep. 10, 2198. https://doi.org/10.1038/s41598-020-59201-1.
Kataoka, T., Hinata, H., Kako, S., 2012. A new technique for detecting colored macro plastic debris on beaches using webcam images and CIELUV. Mar. Pollut. Bull. 64 (9), 1829–1836. https://doi.org/10.1016/j.marpolbul.2012.06.006.
Kaymak, C., Ucar, A., 2019. A Brief survey and an application of semantic image segmentation for autonomous driving. In: Handbook of Deep Learning Applications, (Edits) Valentina Emilia Balas, Sanjiban Sekhar Roy. Springer, pp. 161–200.

Kedzierski, M., et al., 2019. A machine learning algorithm for high throughput identification of FTIR spectra: application on microplastics collected in the Mediterranean Sea. Chemosphere 234, 242–251. https://doi.org/10.1016/j.chemosphere.2019.05.113.

Kershaw, P., Turra, A., Galgani, F., van Franeker, J.A., 2019. Guidelines for the monitoring and assessment of plastic litter in the ocean. Rep. Stud. GESAMP No. 99, 130. https://wesr.unep.org/media/docs/marine_plastics/une_science_dvision_gesamp_reports.pdf.

Kikaki, K., et al., 2022. MARIDA: a benchmark for marine debris detection from Sentinel-2 remote sensing data. PLoS One 17 (1), e0262247. https://doi.org/10.1371/journal.pone.0262247.

Krippendorff, K., 1980. Content Analysis: an Introduction to its Methodology. Sage Publications, p. 422.

Kristollari, V., Karathanassi, V., 2020. Artificial neural networks for cloud masking of Sentinel-2 ocean images with noise and sunglint. Int. J. Rem. Sens. 41, 4102–4135. https://doi.org/10.1080/01431161.2020.1714776.

Krizhevsky, A., Sutskever, I., Hinton, G., 2012. ImageNet classification with deep convolutional neural networks. Neural Inf. Process. Syst. 25, 1–9, 1097-1105. https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf.

Kylili, K., Kyriakides, I., Artusi, A., Hadjistassou, C., 2019. Identifying floating plastic marine debris using a deep learning approach. Environ. Sci. Pollut. Res. 26, 17091–17099.

Kylili, K., Artusi, A., Hadjistassou, C., 2021. A new paradigm for estimating the prevalence of plastic litter in the marine environment. Mar. Pollut. Bull. 173, 113127. https://doi.org/10.1016/j.marpolbul.2021.113127.

Kylili, K., Hadjistassou, C., Artusi, A., 2020. An intelligent way for discerning plastics at the shorelines and the seas. Environ. Sci. Pollut. Res. 27, 42631–42643. https://doi.org/10.1007/s11356-019-05148-4.

Lavender, S., 2022. Detection of waste plastics in the environment: application of Copernicus earth observation data. Rem. Sens. 14, 4772. https://doi.org/10.3390/rs14194772.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444. https://doi.org/10.1038/nature14539.

Lin, F., Hou, T., Jin, Q., You, A., 2021. Improved YOLO based detection algorithm for floating debris in waterway. Entropy 23, 1111. https://doi.org/10.3390/e23091111.

Lin, J.-yu, Liu, H.-t., Zhang, J., 2022. Recent advances in the application of machine learning methods to improve identification of the microplastics in environment. Chemosphere 307, 136092. https://doi.org/10.1016/j.chemosphere.2022.136092.

Liu, W., et al., 2016. SSD: Single Shot MultiBox Detector. https://doi.org/10.48550/arXiv.1512.02325 arXiv preprint.

Liu, S., Qi, L., Qin, H., Shi, J., Jia, J., 2018. Path aggregation network for instance segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. CVPR), pp. 8759–8768. https://doi.org/10.48550/arXiv.1803.01534.

Liu, L., et al., 2019. Deep Learning for Generic Object Detection: A Survey arXiv preprint. https://arxiv.org/abs/1809.02165.

Liu, X., Song, L., Liu, S., Zhang, Y.A., 2021. Review of deep-learning-based medical image segmentation methods. Sustainability 13, 1224. https://doi.org/10.3390/su13031224.

Lo, H.-S., Wong, L.-C., Kwok, S.-H., Lee, Y.-K., Po, B.H.-K., Wong, C.-Y., Tam, N.F.-Y., Cheung, S.-G., 2020. Field test of beach litter assessment by commercial aerial drone. Mar. Pollut. Bull. 151, 110823 https://doi.org/10.1016/j.marpolbul.2019.110823.

Lorenzo-Navarro, J., et al., 2021. Deep learning approach for automatic microplastics counting and classification. Sci. Total Environ. 765, 142728. https://doi.org/10.1016/j.scitotenv.2020.142728.

Madricardo, F., et al., 2019. Assessing the human footprint on the sea-floor of coastal systems: the case of the Venice Lagoon. Italy. Sci. Rep. 9, 6615. https://doi.org/10.1038/s41598-019-43027-7.

Maharjan, N., Miyazaki, H., Pati, B.M., Dailey, M.N., Shrestha, S., Nakamura, T., 2022. Detection of river plastic using UAV sensor data and deep learning. Rem. Sens. 14, 3049. https://doi.org/10.3390/rs14133049.

Majchrowska, S, et al., 2022. Deep learning-based waste detection in natural and urban environments. Waste Manag. 138, 274–284. https://doi.org/10.1016/j.wasman.2021.12.001.

Mallick, A., Plöger, P., Valdenegro-Toro, M., 2021. Forward-Looking sonar patch matching: Modern CNNs, ensembling, and uncertainty. arXiv preprint.. https://doi.org/10.48550/arXiv.2108.01066.

Martin, C., et al., 2018. Use of unmanned aerial vehicles for efficient beach litter monitoring. Mar. Pollut. Bull. 131, 662–673. https://doi.org/10.1016/j.marpolbul.2018.04.045.

Martin, C., Zhang, Q., Zhai, D., Zhang, X., Duarte, C., 2021. Enabling a large-scale assessment of litter along Saudi Arabian red sea shores by combining drones and machine learning. Environ. Pollut. 277, 116730 https://doi.org/10.1016/j.envpol.2021.116730.

Massarelli, C., Campanale, C., Uricchio, V.F., 2021. A handy open-source application based on computer vision and machine learning algorithms to count and classify microplastics. Water 13, 2104. https://doi.org/10.3390/w13152104.

Maximenko, N., et al., 2019. Toward the integrated marine debris observing system. Front. Mar. Sci. 6, 447. https://doi.org/10.3389/fmars.2019.00447.

Merlino, S., Paterni, M., Berton, A., Massetti, L., 2020. Unmanned aerial vehicles for debris survey in coastal areas: long-term monitoring programme to study spatial and temporal accumulation of the dynamics of beached marine litter. Rem. Sens. 12, 1260. https://doi.org/10.3390/rs12081260, 2020.

Merlino, S., Paterni, M., Locritani, M., Andriolo, U., Goncalves, G., Massetti, L., 2021. Citizen science for marine litter detection and classification on unmanned aerial vehicle images. Water 13, 3349. https://doi.org/10.3390/w13233349, 2021.

Mifdal, J., Longepe, N., Rubwurm, M., 2021. Towards detecting floating objects on a global scale with learned spatial features using sentinel 2. ISPRS Ann. Photogram. Rem. Sens. Spat. Info. Sci. 3–2021, 285–303. https://doi.org/10.5194/isprs-annals-V-3-2021-285-2021.

Mikeli, P., Kikaki, K., Kakogeorgioy, I., Karantzalos, K., 2022. How challenging is the discrimination of floating materials on the sea surface using high resolution multispectral satellite data? Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. B3-2022 XLIII-, 151. https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-151-2022. –157.

Minaee, S., et al., 2020. Image Segmentation Using Deep Learning: A Survey arXiv preprint. https://arxiv.org/abs/2001.05566.

Mo, Y., Wu, Y., Yang, X., Liu, F., Liao, Y., 2022. Review the state-of-the-art technologies of semantic segmentation based on deep learning. Neurocomputing 493, 626–646. https://doi.org/10.1016/j.neucom.2022.01.005.

Moorton, Z., Kurt, Z., Woo, W.L., 2022. Is the use of deep learning an appropriate means to locate debris in the ocean without harming aquatic wildlife? Mar. Pollut. Bull. 181, 113853 https://doi.org/10.1016/j.marpolbul.2022.113853.

Moret Ferguson, S., et al., 2010. The size, mass, and composition of plastic debris in the Western North Atlantic Ocean. Mar. Pollut. Bull. 60 (10), 1873–1878. https://doi.org/10.1016/j.marpolbul.2010.07.020.

Moshtaghi, M., Knaeps, E., 2021. Combining spectral approaches and AI for marine litter detection and identification. Int. Geosci. Remote Sens. Symp. 1130–1133. https://doi.org/10.1109/IGARSS47720.2021.9553958.

Mukonza, S.S., Chiang, J.-L., 2022. Satellite sensors as an emerging technique for monitoring macro- and microplastics in aquatic ecosystems. Water Emerg. Contam. Nanoplastics 1, 17. https://doi.org/10.20517/wecn.2022.12.

Music, J., et al., 2020. Detecting underwater sea litter using deep neural networks: an initial study. 5th Int. Conf. Smart Sust. Tech. 1–6. https://doi.org/10.23919/SpliTech49282.2020.9243709.

Nazerdeylami, A., Majidi, B., Movaghar, A., 2021. Autonomous litter surveying and human activity monitoring for governance intelligence in coastal eco-cyber-physical systems. Ocean Coast Manag. 200, 105478 https://doi.org/10.1016/j.ocecoaman.2020.105478.

NOAA, 2014. Report on the Occurrence and Health Effects of Anthropogenic Debris Ingested by Marine Organisms. Silver Spring, MD, p. 19.

NOAA, 2016. Report on Modeling Oceanic Transport of Floating Marine Litter. Silver Spring, MD, p. 21.

Ostle, C., et al., 2019. The rise in ocean plastics evidenced from a 60-year time series. Nat. Commun. 10, 1622. https://doi.org/10.1038/s41467-019-09506-1.

Pan, S.J., Yang, Q., 2010. A survey on transfer learning. IEEE Trans. Knowl. Data Eng. 22, 1345–1359. https://doi.org/10.1109/TKDE.2009.191.

Panwar, H., et al., 2020. AquaVision: automating the detection of waste in water bodies using deep transfer learning. Case Stud. Chem. Environ. Eng. 2, 100026 https://doi.org/10.1016/j.cscee.2020.100026, 2020.

Papachristopoulou, I., Filippides, A., Fakiris, E., Papatheodorou, G., 2020. Vessel- based photographic assessment of beach litter in remote coasts. A wide scale application in Saronikos Gulf, Greece. Mar. Pollut. Bull. 150, 110684 https://doi.org/10.1016/j.marpolbul.2019.110684.

Papakonstantinou, A., Batsaris, M., Spondylidis, S., Topouzelis, K., 2021. A Citizen science unmanned aerial system data acquisition protocol and deep learning techniques for the automatic detection and mapping of marine litter concentrations in the coastal zone. Drones 5, 6. https://doi.org/10.3390/drones5010006.

Park, H-m., et al., 2022. MP-Net: deep learning-based segmentation for fluorescence microscopy images of microplastics isolated from clams. PLoS One 17 (6), e0269449. https://doi.org/10.1371/journal.pone.0269449.

Partescano, E., et al., 2021. Data quality and FAIR principles applied to marine litter data in Europe. Mar. Pollut. Bull. 173, 112965 https://doi.org/10.1016/j.marpolbul.2021.112965.

Pham, C.K., et al., 2014. Marine litter distribution and density in European Seas, from the shelves to deep basins. PLoS One 9 (4), 1831. https://doi.org/10.1371/journal.pone.0095839 e95839.

Pinto, L., Andriolo, U., Goncalves, G., 2021. Detecting stranded macro-litter categories on drone orthophoto by a multi-class neural network. Mar. Pollut. Bull. 169, 112594 https://doi.org/10.1016/j.marpolbul.2021.112594.

Politikos, D.V., Fakiris, E., Davvetas, A., Klampanos, I.A., Papatheodorou, G., 2021. Automatic detection of seafloor marine litter using towed camera images and deep learning. Mar. Pollut. Bull. 164, 111974. https://doi.org/10.1016/j.marpolbul.2021.111974.

Priyadarshini, I., Alkhayyat, A., Obaid, A.J., Sharma, R., 2022. Water pollution reduction for sustainable urban development using machine learning techniques. Cities 130, 103970. https://doi.org/10.1016/j.cities.2022.103970.

Proenca, P.F., Simoes, P., 2020. TACO: Trash Annotations in Context for Litter Detection arXiv preprint. https://arxiv.org/abs/2003.06975.

Ramdani, F., Sianturi, R.S., Furqon, M.T., Ananta, M.T., 2022. Mapping riparian zone macro litter abundance using combination of optical and thermal sensor. Sci. Rep. 12, 6081. https://doi.org/10.1038/s41598-022-09974-4.

Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You only look once: unified, realtime object detection. arXiv preprint. https://doi.org/10.48550/arXiv.1506.02640.

Ronen, M., Finder, S.E., Freifeld, O., 2022. DeepDPM: deep clustering with an unknown number of clusters. arXiv preprint. https://doi.org/10.48550/arXiv.2203.14309.

Salgado-Hernanz, P.M., et al., 2021. Assessment of marine litter through remote sensing: recent approaches and future goals. Mar. Pollut. Bull. 168, 112347 https://doi.org/10.1016/j.marpolbul.2021.112347.

Sánchez-Ferrer, A., Gallego, A.J., Valero-Mas, J.J., Calvo-Zaragoza, J., 2022. The CleanSea set: A bbenchmark corpus for underwater debris detection and recognition. In: Pinho, A.J., Georgieva, P., Teixeira, L.F., Sánchez, J.A. (Eds.), Pattern Recognition and Image Analysis. IbPRIA 2022, Lecture Notes in Computer Science, 13256. Springer, Cham. https://doi.org/10.1007/978-3-031-04881-4_49.

Sannigraphi, S., Basu, B., Basu, A.S., Pilla, F., 2022. Development of automated marine floating plastic detection system using Sentinel-2 imagery and machine learning models. Mar. Pollut. Bull. 178, 113527 https://doi.org/10.1016/j.marpolbul.2022.113527.

Sarker, I.H., 2021. Machine learning: algorithms, real-world applications and research directions. SN Comput. Sci. 2, 160. https://doi.org/10.1007/s42979-021-00592-x.

Sasaki, K., et al., 2022. Coastal marine debris detection and density mapping with very high resolution satellite imagery. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 15, 6391–6401. https://doi.org/10.1109/JSTARS.2022.3193993.

Savastano, S., Cester, I., Perpinyà, M., Romero, L., 2021. A first approach to the automatic detection of marine litter in SAR images using artificial intelligence. Int. Geosci. Remote Sens. Symp. 8704–8707. https://doi.org/10.1109/IGARSS47720.2021.9737038.

Schulz, M., Matthies, M., 2014. Artificial neural networks for modeling time series of beach litter in the southern North Sea. Mar. Environ. Res. 98, 14–20. https://doi.org/10.1016/j.marenvres.2014.03.014.

Shi, B., et al., 2022. Automatic quantification and classification of microplastics in scanning electron micrographs via deep learning. Sci. Total Environ. 825, 153903 https://doi.org/10.1016/j.scitotenv.2022.153903.

Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint. https://doi.org/10.48550/arXiv.1409.1556.

Song, K., Jung, J.-Y., Lee, S.H., Park, S., 2021. A comparative study of deep learning-based network model and conventional method to assess beach debris standing-stock. Mar. Pollut. Bull. 168, 112466 https://doi.org/10.1016/j.marpolbul.2021.112466.

Szegedy, C., et al., 2014. Going deeper with convolutions. In: Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), USA, pp. 1–9. https://doi.org/10.48550/arXiv.1409.4842.

Taddia, Y., Corbau, C., Buoninsegni, J., Simeoni, U., Pellegrinelli, A., 2021. UAV approach for detecting plastic marine debris on the beach: a case study in the Po River Delta (Italy). Drones 5, 140. https://doi.org/10.3390/drones5040140, 2021.

Taggio, N., et al., 2022. Combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data. Rem. Sens. 14, 3606. https://doi.org/10.3390/rs14153606.

Takaya, K., Shibata, A., Mizuno, Y., Ise, T., 2022. Unmanned aerial vehicles and deep learning for assessment of anthropogenic marine debris on beaches on an island in a semi-enclosed sea in Japan. Environ. Res. Commun. 4, 015003 https://doi.org/10.1088/2515-7620/ac473b.

Tan, M., Pang, R., Le, Q.V., 2020. EfficientDet: scalable and efficient object detection. arXiv preprint. https://doi.org/10.48550/arXiv.1911.09070.

Tata, G., 2021. DeepPlastic: an Open Source Image Dataset for Epipelagic Marine Plastic Detection. https://zenodo.org/record/5562940#.Y2OyH3ZByUk.

Tata, G., Royer, S.-J., Poirion, O., Lowe, J., 2021. A robotic approach towards quantifying epipelagic bound plastic using deep visual models. arXiv preprint.. https://doi.org/10.48550/arXiv.2105.01882.

Teng, C., Kylili, K., Hadjistassou, C., 2022. Deploying deep learning to estimate the abundance of marine debris from video footage. Mar. Pollut. Bull. 183, 114049 https://doi.org/10.1016/j.marpolbul.2022.114049.

Tharani, M., Amin, A.W., Maaz, M., Taj, M., 2020. Attention Neural Network for Trash Detection on Water Channels, 04639 arXiv:2007. https://arxiv.org/abs/2007.04639.

Themistocleous, K., Papoutsa, C., Michaelides, S., Hadjimitsis, D., 2020. Investigating detection of floating plastic litter from space using Sentinel-2 imagery. Rem. Sens. 12, 2648. https://doi.org/10.3390/rs12162648.

Thiel, M., et al., 2003. Floating marine debris in coastal waters of the SE-pacific (Chile). Mar. Pollut. Bull. 46, 224–231. https://doi.org/10.1016/s0025-326x(02)00365-x.

Topouzelis, K., Papakonstantinou, A., Garaba, S.P., 2019. Detection of floating plastics from satellite and unmanned aerial systems (plastic litter project 2018). Int. J. Appl. Earth Obs. Geoinformation 79, 175–183. https://doi.org/10.1016/j.jag.2019.03.011.

Topouzelis, K., Papageorgiou, D., Suaria, G., 2021. Floating marine litter detection algorithms and techniques using optical remote sensing data: a review. Mar. Pollut. Bull. 112675 https://doi.org/10.1016/j.marpolbul.2021.112675.

UNEP, 2021. From Pollution to Solution: A Global Assessment of Marine Litter and Plastic Pollution. UNEP report UNEA process, p. 148. https://wedocs.unep.org/bitstream/handle/20.500.11822/36963/POLSOL.pdf.

UNEP/MAP, 2016. In: United (Ed.), Marine Litter Assessment in the Mediterranean 2015.

Valdenegro-Toro, M., 2016. Submerged marine debris detection with autonomous underwater vehicles. In: 2016 International Conference on Robotics and Automation for Humanitarian Applications (RAHA), pp. 1–7. https://doi.org/10.1109/RAHA.2016.7931907.

Van Gansbeke, W., Vandenhende, S., Georgoulis, S., Proesmans, M., Van Gool, L., 2020. SCAN: Learning to Classify Images without Labels. https://doi.org/10.48550/arXiv.2005.12320 arXiv preprint.

van Lieshout, C., van Oeveren, K., van Emmerik, T., Postma, E., 2020. Automated river plastic monitoring using deep learning and cameras. Earth Space Sci. 7, e2019EA000960 https://doi.org/10.1029/2019EA000960.

van Sebille, et al., 2020. The physical oceanography of the transport of floating marine debris. Environ. Res. Lett. 15 (2), 023003 https://doi.org/10.1088/1748-9326/ab6d7d.

Veerasingam, S., et al., 2022. Detection and assessment of marine litter in an uninhabited island, Arabian Gulf: a case study with conventional and machine learning approaches. Sci. Total Environ. 838, 156064. https://doi.org/10.1016/j.scitotenv.2022.156064.

Vince, J., Hardesty, B., 2018. Governance solutions to the tragedy of the commons that marine plastics have become. Front. Mar. Sci. 5, 214. https://doi.org/10.3389/fmars.2018.00214.

Visin, F., et al., 2016. Reseg: a recurrent neural network-based model for semantic segmentation. arXiv preprint. https://doi.org/10.48550/arXiv.1511.07053.

Wang, S., 2022. International law-making process of combating plastic pollution: status Quo, debates and prospects. Mar. Pol. 147, 105376 https://doi.org/10.1016/j.marpol.2022.105376.

Wang, Y., et al., 2015. Aquatic debris detection using embedded camera sensors. Sensors 15, 3116–3137. https://doi.org/10.3390/s150203116.

Watanabe, J., Shao, Y., Miura, N., 2019. Underwater and airborne monitoring of marine ecosystems and debris. J. Appl. Remote Sens. 13 (4), 044509 https://doi.org/10.1117/1.JRS.13.044509.

Wolf, M., et al., 2020. Machine learning for aquatic plastic litter detection, classification and quantification (APLASTIC-Q). Environ. Res. Lett. 15, 114042 https://doi.org/10.1088/1748-9326/abbd01.

Xue, B., Huang, B., Chen, G., Li, H., Wei, W., 2021. Deep-sea debris identification using deep convolutional neural networks. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 14, 8909–8921. https://doi.org/10.1109/JSTARS.2021.3107853.

Xue, et al., 2021b. An efficient deep-sea debris detection method using deep neural networks. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 14, 12348–12360. https://doi.org/10.1109/JSTARS.2021.3130238.

Zaidi, S.S.A., et al., 2021. A survey of modern deep learning based object detection models. arXiv preprint. https://arxiv.org/abs/2104.11892.

Zbyszewski, M., Corcoran, P.L., Hockin, A., 2014. Comparison of the distribution and degradation of plastic debris along shorelines of the Great Lakes, North America. J. Great Lake. Res. 40 (2), 288–299. https://doi.org/10.1016/j.jglr.2014.02.012.