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Transformer Assisted U-Net for Marine Litter Detection on Sentinel-2 Imagery

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Abstract

The contamination of marine environments with man-made litter is a growing nation-wide concern. Satellite imagery combined with deep learning–based detection models has emerged as a robust and cost-effective solution for large-scale marine litter monitoring. In this article, we present a novel deep learning-based scheme to detect marine litter using Sentinel-2 imagery based on the Deep UNet architecture, introducing self- and cross-attention mechanisms into the decoder via transformer layers. The model leverages all Sentinel-2 bands except B10, and the NDVI and FDI indices are additionally incorporated to better guide the segmentation process. To evaluate the proposed model, we train it on the FloatingObjects dataset, a widely used benchmark for marine debris detection, and compare its performance against state-of-the-art approaches.
Keywords: Marine Litter, Plastics, Detection, Semantic Segmentation, Sentinel-2, U-Net, Transformers.

1 Introduction

Marine litter is increasingly common along coastlines, where items such as bags, food wrappings, and tin cans are frequently found. While the composition of marine litter is varied, about 80% of man-made items that end up on marine environments are made from plastic [38]. The contamination of marine ecosystems with large quantities of plastics and microplastics has escalated rapidly over recent decades [32], becoming a global environmental, health, and socioeconomic concern [42]. More than 350 million tonnes (Mt) of plastic are produced annually, of which approximately 14.5 Mt are estimated to enter the ocean [55]—a figure likely underestimated due to the challenges associated with detecting microplastics [16]. The fundamental issue with this type of contamination lies in its persistence, as the degradation process is extremely slow [1].

Because of this persistence, plastic pollution generates multiple environmental and socioeconomic impacts. First and foremost is the harm caused to marine wildlife [48, 27, 56]. From entanglement in discarded fishing nets to the ingestion of plastic debris, numerous species of seabirds, turtles, and marine mammals are adversely affected [27] in different parts of the world [48, 34]. Human health is also at risk. Exposure can occur indirectly, through the consumption of marine organisms such as fish or crustaceans that have ingested plastic residues [2], or directly, via chemical substances leaching from plastics into seawater, potentially altering water quality, temperature, and pH [18]. Economic wise, marine litter and plastic pollution entail costs of preventive measures, direct damage to equipment and commercial stocks, remediation, and indirect costs associated with inaction [33]. McIlgorm et al. [34] estimated that in 2020 marine litter caused damages of US$21.3 billion to the global marine economy, with projections rising to US$197 billion by 2030, or US$229 billion if plastic waste continues to increase proportionally with plastic production.

Marine litter contamination is distributed across beaches, the sea surface, and the seafloor, with beach litter being the easiest to detect and seafloor pollution the most challenging. Floating debris fall in between. Globally, the density of floating debris ranges from nearly 0 to over 600 items per km^2 [17]. This large variability makes the detection of small residues particularly difficult. Traditional monitoring has relied on ship-based visual surveys, which require considerable human and financial resources [46], or numerical models, which may lack the desired accuracy [52].

In recent years, the use of unmanned aerial vehicles (UAVs) and satellite imagery for detecting marine litter has also been explored. UAVs provide very high spatial resolution but scale poorly in space and time, as acquiring imagery over large regions and extended periods is not feasible. Conversely, certain satellite missions, such as Sentinel-2 (S2) [14], despite having low to medium resolution (of up to 10 m in the case of S2), offer global coverage at a high revisit frequency. Despite the fact that, at this scale, detecting small- to medium-sized floating debris is difficult, natural phenomena, such as wind, tides and ocean currents, can lead to convergence zones in which marine litter accumulates [10]. What is more, it has been observed that plastics exhibit distinctive spectral signatures in the near-infrared (NIR) and short-wave infrared (SWIR) regions [5], which can be effectively detected by spectral sensors onboard satellites such as S2 [25]. This has lead researches to develop marine litter detection schemes using satellite imagery only. While machine learning-based models have been proposed to this end [5, 47], deep learning architectures have shown the most promising results [37, 23].

In this article, we propose a deep learning–based, end-to-end semantic segmentation model for detecting marine litter using Sentinel-2 imagery. The model is built upon a Deep U-Net architecture [29] and extends our previous work [9]. It incorporates an encoder and a transformer-assisted decoder with skip connections, designed to optimize the number of learnable parameters. Our primary contribution lies in the integration of a transformer layer into the U-Net decoder, which enhances the model's ability to capture long-range dependencies. Specifically, self-attention is employed in the transformer layers at the lowest level of the U-Net, while at higher levels cross-attention is applied by leveraging information from the corresponding encoder layers to compute the attention maps. To evaluate the proposed model, we train it on the FloatingObjects dataset [37, 6], a widely used benchmark for marine debris detection, and compare its performance against state-of-the-art approaches.

The remainder of the paper is organized as follows: Section 2 provides a comprehensive review of recent work concerning S2 marine litter detection and deep learning-based image segmentation. Section 3 details the proposed model and justifies the choice of its architecture. A detailed performance analysis of the proposed model alongside similar approaches is given in Section 4, comparing both qualitative and quantitative results. The dataset used for training and evaluation is also described in this section. Finally, Section 5 summarizes the main conclusions and outlines directions for future work.

2 Related Work

As mentioned in the introduction, the traditional marine litter detection and monitoring approach involves human expeditions conducted at different times and locations, in which floating litter is visually identified and subsequently sampled to study its properties [46]. Although simple and effective, this method is not efficient, and its reliance on human labor introduces several limitations. The requirement for personnel to remain constantly vigilant for floating debris is often impractical and costly [57]. To reduce the dependence on manual observation, some alternatives have been proposed, such as installing multiple motion cameras on the bows of fishing vessels [12, 57]. These cameras produce photo timelapses at intervals of a few seconds, resulting in near-continuous data from the surveyed region. However, human involvement is still necessary for data collection, and the acquired images must be further processed to analyze the quantity and type of plastics present.

To overcome these limitations, considerable research has focused on detection and monitoring using UAVs and satellite imagery. On one hand, UAV-based missions are less intrusive than boat expeditions and do not disturb the marine ecosystem [36, 13]. Drone-acquired data is usually georeferenced, allowing for more precise detection of plastics and the identification of potential accumulation zones [36]. Nevertheless, despite the growing accessibility of UAV technology, no standardized processing pipeline exists for analyzing drone imagery. Image processing methods often vary according to project-specific goals, making it difficult to establish a unified framework for UAV-based marine debris detection [35].

On the other hand, satellite data, despite its lower resolution, offers the advantage of providing long-term observations over extensive areas without the need for direct human intervention. Satellite sensors have proven highly valuable for plastic detection. Topouzelis et al. [53] proved that the detection of certain types of plastics requires multi- and hyperspectral imagery, as their reflectance is easily detected in the NIR wavelengths. Several satellites have been employed in the literature to detect and study marine litter, such as WorldView-3, used to observe plastics in the Great Pacific Garbage Patch [40]; PRISMA, applied to study the Greek island of Lesvos [49]; and Sentinel-2, which has been widely used in different scenarios [53, 8, 50].

2.1 Sentinel-2 Marine Litter Detection

The Sentinel-2 (S2) mission, part of the Copernicus program of the European Space Agency (ESA), is particularly attractive due to its high spatial resolution when compared to other satellites and the open-access policy of the program. The mission consists of two twin satellites orbiting the Earth, providing a 5-day revisit cycle at the equator [14]. S2 satellites acquire imagery in 13 spectral bands: four at 10 m resolution, covering the visible and NIR spectrum; six at 20 m resolution, including several within the SWIR range; and three additional bands at 60 m resolution—see Figure 1. While the coarser bands

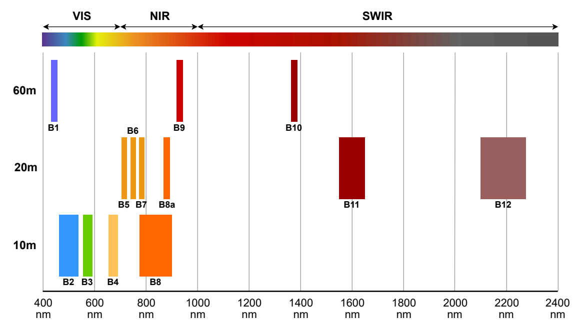

Figure 1: Distribution of the Sentinel-2 bands across the wavelength spectrum.

provide less spatial detail, they capture unique spectral information that can be highly valuable for specific applications.

One of the first studies to investigate the use of S2 imagery for marine litter detection is [53]. Serving primarily as a proof of concept, the study combines unmanned aerial systems with Sentinel-2A imagery to detect artificially deployed floating plastic targets. The detection is performed manually, with an emphasis on identifying the wavelengths that best highlight the targets.

Subsequent studies incorporate detection algorithms to automate the task. Some employ classical methods, such as [51], which applies a spectral signature detection procedure that extracts plastic target signatures through inverse spectral unmixing followed by matched filtering on S2 imagery, and others adopt machine learning techniques. Among the latter, Biermann et al. [5] introduced the FDI index and use it, together with NDVI and remote sensing reflectance values from S2 imagery, as inputs to a Naive Bayes classifier in order to assign pixels to different material classes—water, seaweed, timber, plastic, foam and pumice. In [3], the authors evaluate the floating plastic detection performance of two unsupervised (K-means and fuzzy c-means) and two supervised (support vector regression (SVR) and semi-supervised fuzzy c-means) classification algorithms, concluding that the supervised ones, especially SVR, achieve the best results. Similarly, [47] compares the effectiveness of SVR and Random Forest (RF) in the same task using different combinations of input data comprising Sentinel-2 bands and spectral indices. More recently, in [39], the authors expand on the work of Briemann et al. by using the NDVI together with the FDI and selected S2 reflectances to derive spectral fingerprints. These features are then fed into a Naive Bayes classifier to categorize pixels into the same material classes.

The use of deep learning-based schemes for marine debris detection using S2 imagery has also been explored. For example, [37] trains and evaluates a U-Net convolutional neural network to classify the pixels of S2 imagery into five material classes, matching those defined in [5]. In [23], a deep learning-based Generative Adversarial Network-Random Forest is shown to outperform the traditional machine learning algorithms RF and SVR for large-scale marine pollution detection using S2 imagery. Solé et al. [19] focuse on detecting plastic debris in rivers by adapting the image segmentation procedures U-Net and DeeplabV3+ to the S2 setting. Similarly, the authors of [44] perform marine debris detection using the aforementioned segmentation scheme U-Net and an enhanced version, U-Net++, that replaces the encoder by a residual-network feature extractor.

2.2 Attention Mechanisms in Remote Sensing Image Segmentation

In recent years, semantic segmentation networks have incorporated attention mechanisms [58, 31, 24] to extract the main features, relying on the fact that attention mimics the human eye: it ignores irrelevant parts of the image to focus on the main characteristics. From a quantitative point of view, architectures with attention modules have been proven to be more accurate [43].

In particular, we highlight the increasing use of attention mechanisms in remote sensing segmentation networks. Li et al. [28] combine a channel attention module; to learn the relationships between channels, with a spatial attention one; to aggregate spatial information, which useful when detecting smaller objects. Cui et al. [11] introduce channel attention and residual modules in the encoder, a multi-feature fusion mechanism in the decoder, and improved sub-pixel convolution for upsampling, achieving superior accuracy and efficiency in remote sensing semantic segmentation compared to U-Net and other baselines.

However, more refined attention mechanisms have been used. Ben Salah et al. [4] introduce a multi-head attention mechanism [54], which enables the network to focus on different parts of the input image simultaneously to improve the spatial details of roads and paths. Others, such as Liu et al. [30] rely on transformer-based architectures. They propose building a segmentation network using channel and spatial attention blocks after each U-shaped residual block to make up the encoder and decoder. They also add a Swin Transformer with two multi-head self-attention modules installed at the skip-connections. The Swin Transformers were previously used by Cheng et al. [7] to develop *Mask2Former*, which incorporates a pixel decoder to upsample the low-resolution features produced by the encoder and a transformer decoder that generates object queries from image features. Then, the resulting mask is decoded from per-pixel embeddings from the object queries obtained from the transformer decoder.

2.3 Spectral Indices for Plastic Detection

All models can benefit by using spectral indicies as additional inputs of the proposed architectures. While this procedure may seem redundant, it is a common strategy in satellite-based marine litter detection. Even though the spectral indices are computed using the bands which are already fed into the model, it has been argued that this addition better guides the detection of specific materials and increases performance [37]. Let us give a summary of the indices more commonly used for this purpose.

The Floating Debris Index (FDI) introduced in [5], was specifically designed for marine litter detection. Its precise formula in terms of S2 bands is

$$\mathrm{FDI} = B8 - \left(B6 + (B11 - B6) \cdot \frac{\lambda_{B8} - \lambda_{B4}}{\lambda_{B11} - \lambda_{B4}} \right), \tag{1}$$

where here and throughout this subsection Bn denotes the corresponding S2 band and λ_{Bn} its central

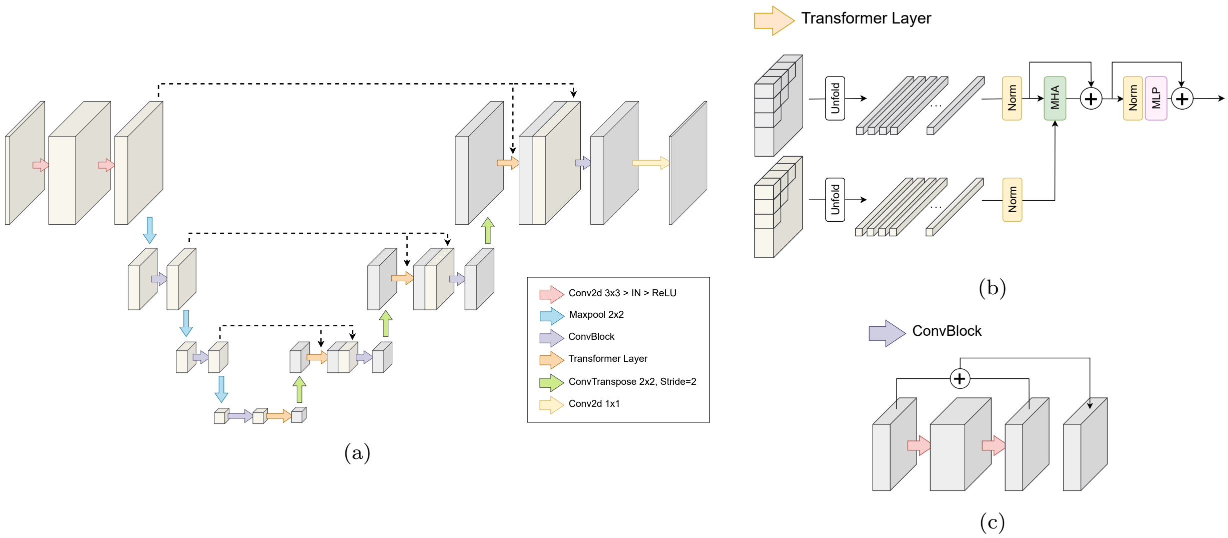

Figure 2: (a) Overall architecture of the TAUNet. (b) Transformer Layer architecture, with the Multi-Head Attention module (c) Residual convolutional block.

wavelength—in practice, $\lambda_{B4} = 665, \lambda_{B8} = 842$, and $\lambda_{B11} = 1610$. We interpret the index as the subtraction of the actual NIR reflectance ($B8$) and the expected NIR reflectance, which is estimated by linear interpolation between the red edge ($B6$) and SWIR ($B11$) bands. This way, FDI measures anomalous NIR reflectance values, which should highlight floating debris, as both plastic and organic material reflect much more NIR than water.

The FDI is often paired with the Normalized Difference Vegetation Index (NDVI), which in a marine context is used for detecting patches of algae and other plant material. This index helps to differentiate floating debris and vegetation patches, reducing false positives [5]. In terms of S2 bands, the NDVI reads as

$$\text{NDVI} = \frac{B8 - B4}{B8 + B4}.$$

Even though FDI and NDVI are the most used for marine litter detection, other spectral indices which are more ad hoc and designed for specific settings are the Plastic Index (PI) [50], which is tailored specifically for plastic detection; the Adjusted Plastic Index, proposed in [45] as an alternative version of PI better suited for detecting plastics in rivers and other watersheds; and the Beached Plastic Debris Index [20], which, as its name implies, has been developed to detect plastic accumulation on beaches.

3 Proposed Model

We propose to use an end-to-end data-driven semantic segmentation model. The model is based on a Deep U-Net architecture [29] and extends the work of Costa et al. [9]. It follows an encoder–decoder structure with skip-connections, while the decoder incorporates Transformer Layers to enhance the extraction of relevant features for marine litter segmentation. The complete architecture of our *Transformer Assisted U-Net* (TAUNet from now on) is shown in Figure 2a.

The model is fed all Sentinel-2 bands except B10, which is mainly used for cirrus cloud detection and does not contain much surface information [14]. In addition, the NDVI and the FDI[5] are used to better guide the segmentation process.

The encoder path follows the design of [29, 9] with three resolution levels. At the lowest level, the feature map is passed through a Transformer Layer with

Table 1: Quantitative metrics obtained by each method. For all metrics, higher values indicate better performance. The best values are highlighted in bold.

	IoU	κ	Dice
UNet	0.3256	0.3858	0.4808
ResUNet	0.3907	0.4720	0.5633
MANet	0.4187	0.4772	0.5660
DUNet	0.4301	0.5159	0.6087
Ours	**0.4712**	**0.5315**	**0.6257**

self-attention, illustrated in Figure 2b, where both keys and queries are copies of the same input. Self-attention is used here to capture long-range dependencies within the same feature map, enabling the network to model relationships between distant regions of the image. In the decoder, the downsampled features from the encoder are used twice at each level: first, as keys and queries for the Transformer Layer operating on the upsampled feature map with cross-attention; and second, concatenated with the output of this Transformer Layer. Cross-attention allows the decoder to integrate information from the encoder features while refining the upsampled representation, thereby enhancing the reconstruction of fine details. The subsequent upsampling blocks follow the design of Costa et al. [9].

Normalization layers are included throughout the network to improve training stability. We employ Instance Normalization (IN) [51], which rescales and recenters each image in a mini-batch independently. Unlike Batch Normalization (BN) [21], IN computes mean and variance dynamically during inference, making it more suitable for this task due to the strong variability observed in floating object regions.

Finally, following [9], the binary segmentation mask M, which indicates the presence or absence of floating objects, is obtained from the multispectral image together with NDVI and FDI. The output of the TAUNet is passed through an exponential activation function and then thresholded at 0.3 to produce the final mask.

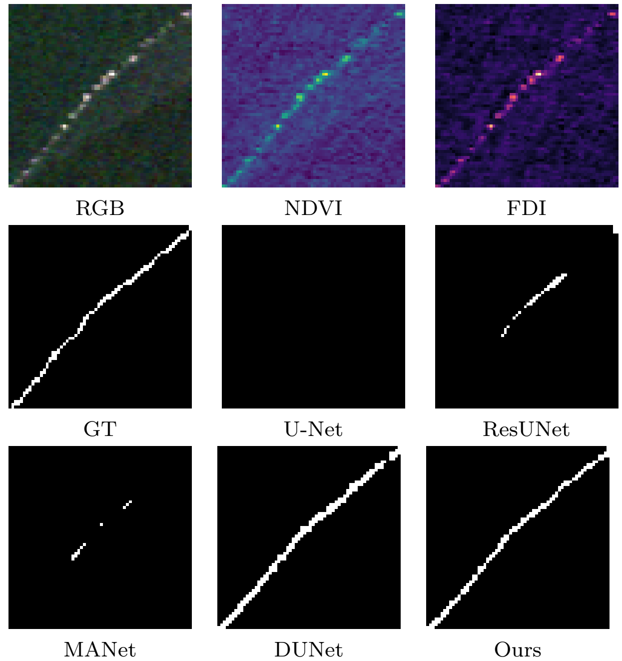

Figure 3: Qualitative comparison of the marine litter segmentation networks. The proposed approach provides the sharpest segmentation mask.

3.1 Implementation details

Concerning the loss function, we employ a combination of two metrics commonly used for semantic segmentation. In particular, it is defined as

$$\mathcal{L} \coloneqq \mathcal{L}_{BCE} + \mathcal{L}_{Dice}, \tag{2}$$

where $\mathcal{L}_{BCE}$ denotes the Binary Cross Entropy (BCE) loss and $\mathcal{L}_{Dice}$ the Dice loss [22]. The BCE loss compares the predicted probability $p \in [0, 1]$ with the ground truth label $y \in \{0, 1\}$, and it is computed as

$$\mathcal{L}_{BCE}(y, p) \coloneqq -\left(y \log(p) + (1 - y)\log(1 - p)\right). \tag{3}$$

The Dice loss is derived from the Dice Similarity Coefficient (DSC), which measures the overlap between predicted and true masks. With a smoothing constant ϵ to avoid division by zero, the DSC is defined as

$$DSC(y, p) = \frac{2yp + \epsilon}{y + p + \epsilon},$$

and the Dice loss is computed as

$$\mathcal{L}_{Dice}(y, p) \coloneqq 1 - DSC(y, p). \tag{4}$$

The smoothing costant is usually set to $\epsilon = 1$ [22].

The proposed model is trained over 50 epochs using the loss function (2). We use Adam optimizer [26] with a learning rate of 10^{-4}.

4 Results

In this section we conduct a performance analysis of the proposed model for detecting marine litter. For the quantitative comparison, we use the following metrics: Intersection over Union (IoU), which measures the overlap of correctly detected pixels and is widely used in segmentation tasks; Cohen's kappa index (κ), which evaluates performance taking chance into account; and Dice Coefficient (Dice), which is similar to IoU but more sensitive to small objects. For all metrics, higher values indicate better performance, with a maximum score of 1.

We train our model on the FloatingObjects dataset, first introduced in [37] and later expanded in [6], a large-scale hand-annotated dataset of floating objects designed for remote sensing applications. The dataset compromises 26 globally distributed S2 coastal scenes and is equipped with pixel-level binary labels distinguishing floating objects from non-floating objects. All bands are have already been upscaled to 10m. To create the training and test sets, each image was cropped into patches of size 64×64, and then divided into training and test with an 80%-20% ratio.

We compare our model with the deep learning-based models MANet [15], DUNet [9] and ResUNet. This last model is a modified UNet architecture whose details can be found in [41]. Additionally, we compare with two FDI- and NDVI-based methods, in which a pixel is classified as marine litter if the index value corresponding to the pixel exceeds a fixed threshold (in practice the threshold is 0.3).

Specifically, we conducted both a quantitative and qualitative comparison of our results with those obtained by the aforementioned models. Table 1 presents the results across the various metrics, where our model consistently demonstrates the best performance in all of them. Regarding the qualitative comparison, Figures 3 and 4 display the RGB image to be segmented, the FDI and NDVI indices, the reference mask, and the resulting masks obtained by applying the input to all methods.

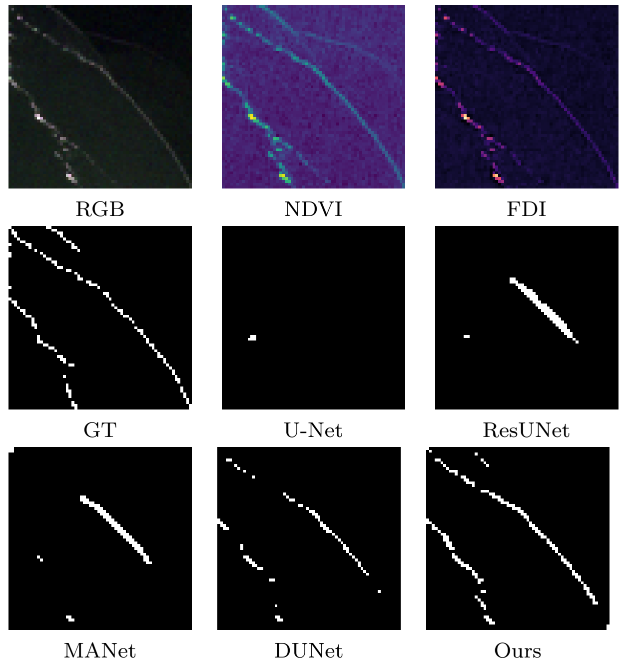

Figure 4: Qualitative comparison of the marine litter segmentation networks. Our prediction is the only one able to detect the floating objects in the top-center of the image.

In Figure 3, the masks produced by our model, together with those generated by DUNet, are the ones that most closely resemble the reference mask. However, in our case, the mask is more clearly defined and encompasses the majority of the target area, whereas DUNet provides a coarser mask.

In Figure 4, the models that achieve the best segmentation of the objects are DUNet and our proposed approach. Nevertheless, for the floating objects in the upper region, only our model is able to segment them. Moreover, our segmentation is considerably more sharply defined.

5 Conclusions

In this article, we have presented a variation of DUNet [29] that introduces attention mechanisms into the decoder. Specifically, we have incorporated a transformer layer in which self-attention is employed at the lowest level, while cross-attention is applied at subsequent levels using the corresponding encoder outputs to compute the attention maps. A comparative evaluation against several state-of-the-art models have demonstrated the superiority of our approach both quantitatively and qualitatively.

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References

[1] Anthony L Andrady. "Persistence of plastic litter in the oceans". In: *Marine anthropogenic litter*. Springer International Publishing Cham, 2015, pp. 57–72.

[2] Eleni Aretoulaki, STAVROS Ponis, GEORGE Plakas, Kostantinos Agalianos, et al. "Marine plastic littering: A review of socio economic impacts". In: *J. Sustain. Sci. Manag* 16.3 (2021), pp. 277–301.

[3] Bidroha Basu, Srikanta Sannigrahi, Arunima Sarkar Basu, and Francesco Pilla. "Development of novel classification algorithms for detection of floating plastic debris in coastal waterbodies using multispectral Sentinel-2 remote sensing imagery". In: *Remote Sensing* 13.8 (2021), p. 1598.

[4] Khawla Ben Salah, Mohamed Othmani, Jihen Fourati, and Monji Kherallah. "Advancing spatial mapping for satellite image road segmentation with multi-head attention". In: *The Visual Computer* 41.4 (2025), pp. 2079–2089.

[5] Lauren Biermann, Daniel Clewley, Victor Martinez-Vicente, and Konstantinos Topouzelis. "Finding plastic patches in coastal waters using optical satellite data". In: *Scientific reports* 10.1 (2020), p. 5364.

[6] Raquel Carmo, Jamila Mifdal, and Marc Rußwurm. "Detecting macro floating objects on coastal water bodies using Sentinel-2 data". In: *OCEANS 2021: San Diego–Porto*. IEEE. 2021, pp. 1–7.

[7] Bowen Cheng, Ishan Misra, Alexander G Schwing, Alexander Kirillov, and Rohit Girdhar. "Masked-attention mask transformer for universal image segmentation". In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2022, pp. 1290–1299.

[8] Achille Carlo Ciappa. "Marine plastic litter detection offshore Hawai'i by Sentinel-2". In: *Marine Pollution Bulletin* 168 (2021), p. 112457.

[9] Ariadna Costa, Eloi Sans, Ivan Pereira-Sánchez, Joan Duran, and Julia Navarro. "Improving marine litter segmentation with limited resolution satellite imagery". In: *2024 International Conference on Machine Intelligence for GeoAnalytics and Remote Sensing (MIGARS)*. IEEE. 2024, pp. 1–3.

[10] Andrés Cózar et al. "Proof of concept for a new sensor to monitor marine litter from space". In: *Nature communications* 15.1 (2024), p. 4637.

[11] Mengtian Cui, Kai Li, Jianying Chen, and Wei Yu. “CM-Unet: A novel remote sensing image segmentation method based on improved U-Net”. In: *IEEE Access* 11 (2023), pp. 56994–57005.

[12] Robin De Vries, Matthias Egger, Thomas Mani, and Laurent Lebreton. “Quantifying floating plastic debris at sea using vessel-based optical data and artificial intelligence”. In: *Remote Sensing* 13.17 (2021), p. 3401.

[13] Gabriela Escobar-Sánchez, Greta Markfort, Mareike Berghald, Lukas Ritzenhofen, and Gerald Schernewski. “Aerial and underwater drones for marine litter monitoring in shallow coastal waters: factors influencing item detection and cost-efficiency”. In: *Environmental monitoring and assessment* 194.12 (2022), p. 863.

[14] European Space Agency. *Sentinel-2 — SentiWiki*. `https://sentiwiki.copernicus.eu/web/sentinel-2`. Accessed: 2025-05-16.

[15] Tongle Fan, Guanglei Wang, Yan Li, and Hongrui Wang. “Ma-net: A multi-scale attention network for liver and tumor segmentation”. In: *Ieee Access* 8 (2020), pp. 179656–179665.

[16] Francois Galgani et al. “Are litter, plastic and microplastic quantities increasing in the ocean?” In: *Microplastics and Nanoplastics* 1.1 (2021), p. 2.

[17] François Galgani, Georg Hanke, and Thomas Maes. “Global distribution, composition and abundance of marine litter”. In: *Marine anthropogenic litter*. Springer International Publishing Cham, 2015, pp. 29–56.

[18] Tamara S Galloway. “Micro-and nano-plastics and human health”. In: *Marine anthropogenic litter*. Springer International Publishing Cham, 2015, pp. 343–366.

[19] Àlex Solé Gómez, Leonardo Scandolo, and Elmar Eisemann. “A learning approach for river debris detection”. In: *International Journal of Applied Earth Observation and Geoinformation* 107 (2022), p. 102682.

[20] Jenna Guffogg, Mariela Soto-Berelov, Chris Bellman, Simon Jones, and Andrew Skidmore. “Beached Plastic Debris Index; a modern index for detecting plastics on beaches”. In: *Marine Pollution Bulletin* 209 (2024), p. 117124.

[21] Sergey Ioffe and Christian Szegedy. “Batch normalization: Accelerating deep network training by reducing internal covariate shift”. In: *International conference on machine learning*. pmlr. 2015, pp. 448–456.

[22] Shruti Jadon. “A survey of loss functions for semantic segmentation”. In: *2020 IEEE conference on computational intelligence in bioinformatics and computational biology (CIBCB)*. IEEE. 2020, pp. 1–7.

[23] Ali Jamali and Masoud Mahdianpari. “A cloud-based framework for large-scale monitoring of ocean plastics using multi-spectral satellite imagery and generative adversarial network”. In: *Water* 13.18 (2021), p. 2553.

[24] Katerina Kikaki, Ioannis Kakogeorgiou, Ibrahim Hoteit, and Konstantinos Karantzalos. “Detecting marine pollutants and sea surface features with deep learning in sentinel-2 imagery”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 210 (2024), pp. 39–54.

[25] Katerina Kikaki, Ioannis Kakogeorgiou, Paraskevi Mikeli, Dionysios E Raitsos, and Konstantinos Karantzalos. “MARIDA: A benchmark for Marine Debris detection from Sentinel-2 remote sensing data”. In: *PloS one* 17.1 (2022), e0262247.

[26] Diederik P Kingma. “Adam: A method for stochastic optimization”. In: *arXiv preprint arXiv:1412.6980* (2014).

[27] Susanne Kühn, Elisa L Bravo Rebolledo, and Jan A Van Franeker. “Deleterious effects of litter on marine life”. In: *Marine anthropogenic litter* (2015), pp. 75–116.

[28] Haifeng Li et al. “SCAttNet: Semantic segmentation network with spatial and channel attention mechanism for high-resolution remote sensing images”. In: *IEEE Geoscience and Remote Sensing Letters* 18.5 (2020), pp. 905–909.

[29] Ruirui Li et al. "DeepUNet: A deep fully convolutional network for pixel-level sea-land segmentation". In: *IEEE journal of selected topics in applied earth observations and remote sensing* 11.11 (2018), pp. 3954–3962.

[30] Guangjie Liu, Kuo Diao, Jinlong Zhu, Qi Wang, and Meng Li. "STransU2Net: Transformer based hybrid model for building segmentation in detailed satellite imagery". In: *PloS one* 19.9 (2024), e0299732.

[31] Yanyan Liu et al. "Image semantic segmentation approach based on DeepLabV3 plus network with an attention mechanism". In: *Engineering Applications of Artificial Intelligence* 127 (2024), p. 107260.

[32] Ansje Löhr et al. "Solutions for global marine litter pollution". In: *Current opinion in environmental sustainability* 28 (2017), pp. 90–99.

[33] Clever Mafuta et al. "Drowning in plastics: marine litter and plastic waste vital graphics". In: (2021).

[34] Alistair McIlgorm, Karen Raubenheimer, Daniel E McIlgorm, and Rachel Nichols. "The cost of marine litter damage to the global marine economy: Insights from the Asia-Pacific into prevention and the cost of inaction". In: *Marine Pollution Bulletin* 174 (2022), p. 113167.

[35] Silvia Merlino, Marco Paterni, Andrea Berton, and Luciano Massetti. "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". In: *Remote Sensing* 12.8 (2020), p. 1260.

[36] Silvia Merlino et al. "Citizen science for marine litter detection and classification on unmanned aerial vehicle images". In: *Water* 13.23 (2021), p. 3349.

[37] Jamila Mifdal, Nicolas Longépé, and Marc Rußwurm. "Towards detecting floating objects on a global scale with learned spatial features using sentinel 2". In: *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 3 (2021), pp. 285–293.

[38] C Morales-Caselles et al. *An inshore–offshore sorting system revealed from global classification of ocean litter. Nat. Sustain. 4, 484–493.* 2021.

[39] V Nivedita et al. "Plastic debris detection along coastal waters using Sentinel-2 satellite data and machine learning techniques". In: *Marine Pollution Bulletin* 209 (2024), p. 117106.

[40] Young-Je Park, Shungudzemwoyo P Garaba, and Bruno Sainte-Rose. "Detecting the Great Pacific Garbage Patch floating plastic litter using WorldView-3 satellite imagery". In: *Optics Express* 29.22 (2021), pp. 35288–35298.

[41] ESA PhiLab. *FloatingObjects*. https://github.com/ESA-PhiLab/floatingobjects. GitHub repository. Accessed: 2025-09-30.

[42] Julie Raynaud. *Valuing plastic: The business case for measuring, managing and disclosing plastic use in the consumer goods industry.* UN, 2014.

[43] Jiacheng Ruan, Suncheng Xiang, Mingye Xie, Ting Liu, and Yuzhuo Fu. "Malunet: A multi-attention and light-weight unet for skin lesion segmentation". In: *2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE. 2022, pp. 1150–1156.

[44] Marc Rußwurm, Sushen Jilla Venkatesa, and Devis Tuia. "Large-scale detection of marine debris in coastal areas with Sentinel-2". In: *Iscience* 26.12 (2023).

[45] Anjar Dimara Sakti et al. "Identification of illegally dumped plastic waste in a highly polluted river in Indonesia using Sentinel-2 satellite imagery". In: *Scientific Reports* 13.1 (2023), p. 5039.

[46] Paula M Salgado-Hernanz et al. "Assessment of marine litter through remote sensing: recent approaches and future goals". In: *Marine Pollution Bulletin* 168 (2021), p. 112347.

[47] Srikanta Sannigrahi, Bidroha Basu, Arunima Sarkar Basu, and Francesco Pilla. "Development of automated marine floating plastic detection system using Sentinel-2 imagery and machine learning models". In: *Marine Pollution Bulletin* 178 (2022), p. 113527.

[48] Javier Soto-Navarro et al. "Impact of the marine litter pollution on the Mediterranean biodiversity: A risk assessment study with focus on the marine protected areas". In: *Marine Pollution Bulletin* 165 (2021), p. 112169.

[49] Nicolò Taggio et al. "A combination of machine learning algorithms for marine plastic litter detection exploiting hyperspectral PRISMA data". In: *Remote Sensing* 14.15 (2022), p. 3606.

[50] Kyriacos Themistocleous, Christiana Papoutsa, Silas Michaelides, and Diofantos Hadjimitsis. "Investigating detection of floating plastic litter from space using sentinel-2 imagery". In: *Remote Sensing* 12.16 (2020), p. 2648.

[51] Konstantinos Topouzelis, Dimitris Papageorgiou, Alexandros Karagaitanakis, Apostolos Papakonstantinou, and Manuel Arias Ballesteros. "Remote sensing of sea surface artificial floating plastic targets with Sentinel-2 and unmanned aerial systems (plastic litter project 2019)". In: *Remote Sensing* 12.12 (2020), p. 2013.

[52] Konstantinos Topouzelis, Dimitris Papageorgiou, Giuseppe Suaria, and Stefano Aliani. "Floating marine litter detection algorithms and techniques using optical remote sensing data: A review". In: *Marine Pollution Bulletin* 170 (2021), p. 112675.

[53] Konstantinos Topouzelis, Apostolos Papakonstantinou, and Shungudzemwoyo P Garaba. "Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018)". In: *International Journal of Applied Earth Observation and Geoinformation* 79 (2019), pp. 175–183.

[54] Ashish Vaswani et al. "Attention is all you need". In: *Advances in neural information processing systems* 30 (2017).

[55] Chloe Wayman and Helge Niemann. "The fate of plastic in the ocean environment–a minireview". In: *Environmental Science: Processes & Impacts* 23.2 (2021), pp. 198–212.

[56] John S Woods, Francesca Verones, Olivier Jolliet, Ian Vázquez-Rowe, and Anne-Marie Boulay. "A framework for the assessment of marine litter impacts in life cycle impact assessment". In: *Ecological Indicators* 129 (2021), p. 107918.

[57] Ruofei Yang et al. "Development of a ship-based camera monitoring system for floating marine debris". In: *Marine Pollution Bulletin* 206 (2024), p. 116722.

[58] Guangzhe Zhao, Yimeng Zhang, Maoning Ge, and Min Yu. "Bilateral U-Net semantic segmentation with spatial attention mechanism". In: *CAAI Transactions on Intelligence Technology* 8.2 (2023), pp. 297–307.