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Article

A Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network for Real-Time Denoised Classification and Segmentation of Marine Microplastics in Hyperspectral Imagery

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Abstract: The study addresses the urgent need for accurate and efficient detection of microplastics in marine environments, which pose a significant threat to aquatic ecosystem health. The goal is to develop a robust deep learning framework capable of classifying and segmenting microplastics in hyperspectral imagery (HSI). A novel Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WED-MRAN) is proposed. The model integrates wavelet-based denoising, dual-path feature extraction, multiscale processing, and residual attention mechanisms to improve spectral and spatial feature representation in hyperspectral data. The method is evaluated using a specialized HSI dataset with pixel-level annotations for microplastic types (PE, PP, PS) and natural backgrounds (seawater, sand, algae). The WED-MRAN model achieved a classification accuracy of 92.5%, IoU of 88.2%, and Dice Similarity of 89.0%. Additionally, it demonstrated a low RMSE of 0.032 in terms of denoising performance. It outperformed traditional architectures such as CNN, U-Net, and ResNet, as well as other models incorporating wavelet or attention mechanisms. This work introduces a unique combination of wavelet denoising and advanced dual-path residual attention networks for hyperspectral microplastic detection. The model's superior performance in noisy data conditions highlights its potential for real-time, practical deployment in marine environmental monitoring applications.
Keywords: Hyperspectral Imagery, Marine Microplastics, Denoising, Wavelet Transform, Dual-Path Network, Multiscale Residual Learning, Attention Mechanism, Real-Time Classification, Segmentation.

1. Introduction

Marine microplastics have come up as an international problem for the environment. They enter aquatic ecosystems and food chains, consequently threatening marine biodiversity and, ultimately, human health. HSI systems have received much acclaim for microplastic monitoring due to their ability to resolve fine spectral signatures at hundreds of contiguous bands [3]. Hence, in the presence of noise arising from sensor imperfections, illumination variations, and environmental disturbances, the efficiency of HSI-based classification systems is degraded. A noise-less environment would have higher signal-to-noise ratio; presence of noise tends to hide the very subtle spectral spectral features differentiating among microplastic types with deterioration to its classification and segmentation performance [1][2]. In fast-paced situations upon coastal monitoring or marine debris tracing, time can be of essence; thus, real-time application scenarios would require denoised classification systems that work fast and are resilient to signal distortions.

Traditional denoising methods like PCA, wavelet thresholding, and low-rank matrix recovery often appeal for an offline approach and do not allow real-time operations. Furthermore, the methods might eliminate a fair bit of spectral-spatial information needed for classifying with regard to the classification. To overcome these shortcomings, deep learning-based methods have been embraced for joint denoising and classification. However, very few methods contend for highest accuracy under real-time constraints. This possibility gave rise to the conception of our Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WDP-MRAN), which aims at facilitating real-time denoising and quick classification. The DWT modules combined with a dual-path residual attention mechanism allow the network to grab contextual multiscale features through adaptive noise suppression, thus fulfilling the hustle for accuracy and speed in hyperspectral marine microplastic analysis [3][4].

By far, a great advancement in deep learning has enabled further processing of hyperspectral images for denoising, classification, and segmentation. Among these, two-way network architectures were well-regarded for their ability to consider spatial and spectral features parallelly and, thereby, improve the learning process and the capacity to solve harder problems such as microplastic identification. Such architectures operate by considering two streams that stand both independent of one another and cooperative to each other-the spatial stream executes extraction of fine details, while the other enforces feature continuity spectrally-with feature fusion occurring afterward [5]. To further boost discrimination in features, these networks are then augmented by attention mechanisms that offer a capability for the model to dynamically weigh relevant signals while suppressing irrelevant or noisy signals [6]. The model also integrates residual learning modules to solve the problem of vanishing gradients and to promote the construction of deeper networks without deterioration in performance [7].

Wavelet transforms and DWT have shown efficiency for denoising in the presence of multi-resolution decomposition. The incorporation of wavelet transforms within a deep dual-path residual attention paradigm extends the advantages of local frequency analyses provided by wavelets to those of hierarchical feature learning enabled by deep networks [8]. Therefore, high-frequency noise can be removed, while key spectral-spatial patterns required for classification are preserved. Furthermore, residual blocks at different resolutions extract multi-scale features, further increasing the ability of the model to adapt to diverse spatial scales in HSI data. The basis of the Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WDP-MRAN) comprises these elements, aimed at high-accuracy real-time microplastic classification: wavelet-enhanced denoising, dual-path processing, multiscale residual learning, and attention-based selective feature extraction [9].

Key Contributions of the Research

The real-time classification and segmentation of marine microplastics remain a very challenging task, despite all the advancements made in hyperspectral image (HSI) analysis, due to the noise present in HSI data, spectral redundancy, and minute variations distinguishing the various kinds of plastics. The conventional denoising algorithms generally mute critical spectral-spatial features, while deep-learning techniques tend either to have no concern for real-time realization or be weak when it comes to the harsh effect of noise. On the other hand, if one looks at the existing architectures, only few attempted combining multiscale feature extraction, attention mechanisms, and noise suppression in a single framework, thus failing to deliver optimal classification accuracy when noise is introduced. To fill this gap, we propose the Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WDP-MRAN), a framework for the enhancement of real-time denoised classification of marine microplastics. An effective fusion of wavelet-based denoising and dual-path spectral-spatial learning, together with multiscale residual modules for contextual information and attention mechanisms, enhancing noise robustness and classification accuracy, while ensuring computational efficiency, for real-time application, will be considered as the main goals.

Organization of the paper

The outline of the paper chapter-wise is as follows. Chapter II is a review of the related literature, while the purpose of Chapter III is to give a brief view of the theoretical framework, key concepts along with methodologies. Chapter IV is going to evaluate the experimental result. Chapter V contains results and discussions, whereas Chapter VI wraps it all together with a summary of the most important findings and suggestions for further research.

2. Literature review

Pang et al[10]. introduced HIDFlowNet, a flow-based deep network for HSI denoising. Under traditional paradigms, a deterministic mapping is learned to transform noisy images into clean images. HIDFlowNet, however, models the conditional distribution of clean HSIs given noisy inputs and, as such, can produce multiple diverse denoised outputs. The mask consists of an invertible decoder formulated from invertible conditional blocks to yield local high-frequency details and a conditional encoder that uses transformers to extract global low-frequency information. This design also creates an effective decoupling of the learning of differing frequency components, making denoising far superior on simulated and real HSI datasets.

The DNA-Net proposed by Zeng et al[11]. is a degradation-noise-aware transformer-based deep unfolding network for HSI denoising. Different from existing approaches, DNA-Net explicitly models several noise types, e.g., sparse noise and Gaussian noise, while encoding image priors using transformers. The network unfolds into an end-to-end neural network, where hyperparameters are estimated from the given noisy HSI and degradation model to guide every iteration. The newly proposed U-shape Local-Non-local-Spectral Attention (U-LNSA) module simultaneously considers spectral correlation, local content, and non-local dependency, thereby greatly facilitating the denoising, especially under heavy noise scenarios.

As Hu et al. [12] report, HCANet is a hybrid convolutional and attention network that seeks to improve HSI denoising by effectively modeling global and local features. The architecture joins convolutional neural networks (CNNs) and transformers through a convolution and attention fusion module, thus accounting for long-range dependencies and neighborhood spectral correlations. Meanwhile, a multi-scale feed-forward network still aggregates information at diverse scales, thus augmenting ADN's ability to annihilate more complicated noise types. Finally, experimental results on most of the benchmark HSI datasets prove that HCANet performs quite well in the cases of denoising as well as preserving very vital spectral-spatial information.

He et al. [13] investigated the integration of wavelet transform and attention-based CNNs for hyperspectral image denoising and classification. Their framework brings together wavelet and attention mechanisms in multi-scale feature extraction and feature selection mechanisms. Wavelet transforms analyze the HSI data into multiple frequency sub-bands, thus allowing the model to attend to both low and high-frequency HSI features and to simultaneously suppress HSI noise. The attention mechanism embedded within the CNN so operated puts the selected features forward and suppresses the unwanted features, in turn, enhancing the classification accuracy. Using noisy HSI for evaluation, they showed that this mix greatly outperforms standalone CNNs or wavelet approaches.

Suggestion of Geno et al.[14] involved a wavelet-enhanced attention network for classification of hyperspectral images in adverse situations under varying noise levels. The model takes advantages of discrete wavelet transform, decomposing the hyperspectral data into many resolution levels. Attention mechanism is then applied to adjust the importance weights of the wavelet coefficients dynamically so that the network could focus on the most important spectral and spatial features of the data at different scales.

Gao et al.[15] proposed the DWT-CapsNet for HSI classification. While the proposed model effectively integrates wavelet transforms and capsule networks, it mainly extracts spectral-spatial features without considering problems brought about by high-dimensionality data and sparse ground object distributions. This underscores that there is a requirement for models that adapt to changing ground object distributions and enlarge their receptive fields without too many parameters, both being essential in detecting microplastics in a complex marine environment.

Based on [16], Seydi et al. presented Wavelet-based Kolmogorov-Arnold Network (Wav-KAN) for HSI classification with emphasis being placed on multi-scale spatial and spectral pattern interaction. However, acting as wavelet functions considered as learnable activation functions limits the ability of the proposed model to adequately model spatial-spectral correlations of hyperspectral data. The quandary of developing an architecture that could orchestrate the fine-grained dependence is still pending, and solving this is fundamental for microplastic classification in marine environments.

Chakraborty et al.[17] proposed SpectralNET, i.e., a wavelet CNN for multi-resolution HSI classification. While the multi-resolution processing need is being addressed, the advanced attention mechanisms or residual learning strategies which could have improved feature representation are absent from the framework. This omission creates a gap in incorporating attention-based as well as residual learning methods for enhanced classification, particularly so for discovering microplastics, which are subtle in nature, using hyperspectral images.

3. Methodology

3.1 The Proposed Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network Architecture

The proposed Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WDP-MRAN) intends to solve real-time denoising classification and segmentation problems of marine microplastics in hyperspectral imaging (HSI). The architecture integrates vigorously several advanced elements-wavelet transforms, dual-path processing, multiscale residual learning, and attention mechanisms-into a unified deep learning framework that efficiently captures spectral and spatial characteristics while suppressing noise. From the outset, the wavelet network uses a discrete wavelet transform (DWT) module to analyze the input HSI cube, decomposing it into high- and low-frequency subbands. This set-up facilitates localized frequency analysis and allows early-stage noise components to be suppressed while maintaining important spectral-spatial information. The wavelet coefficients are then passed to a dual-path encoder, where two streams run simultaneously, one focusing on spectral features employing 1D convolutions along spectral bands and the other on spatial features through 2D or 3D convolutions. Such a dual-path strategy ensures that both global spectral correlations and local spatial textures are learned effectively. Multiscale residual blocks complement each path and help in feature extraction. They consist of convolutional layers with kernel sizes and dilation rates that differ-from each other. These blocks capture contextual information at a range of spatial-spectral scales while ensuring that gradients can flow through the residual connection. Features from both paths are fused using a spectral-spatial attention fusion module that applies weights dynamically on each channel and spatial region, thus focusing the network on the most informative features that are noise-robust. The fused representation undergoes classification head processing for labeling pixel-wise or patch-wise outputs, or segmentation decoder processing for spatially coherent outputs, depending on the task. Meanwhile, skip connection-from wavelet input layers to deeper layers-also helps in retaining fine-grained details preventing further feature degradations. Keeping time efficiency is a paramount concern throughout this design; lightweight operations and optimized layer stacking ensure very fast inference without compromising precision.

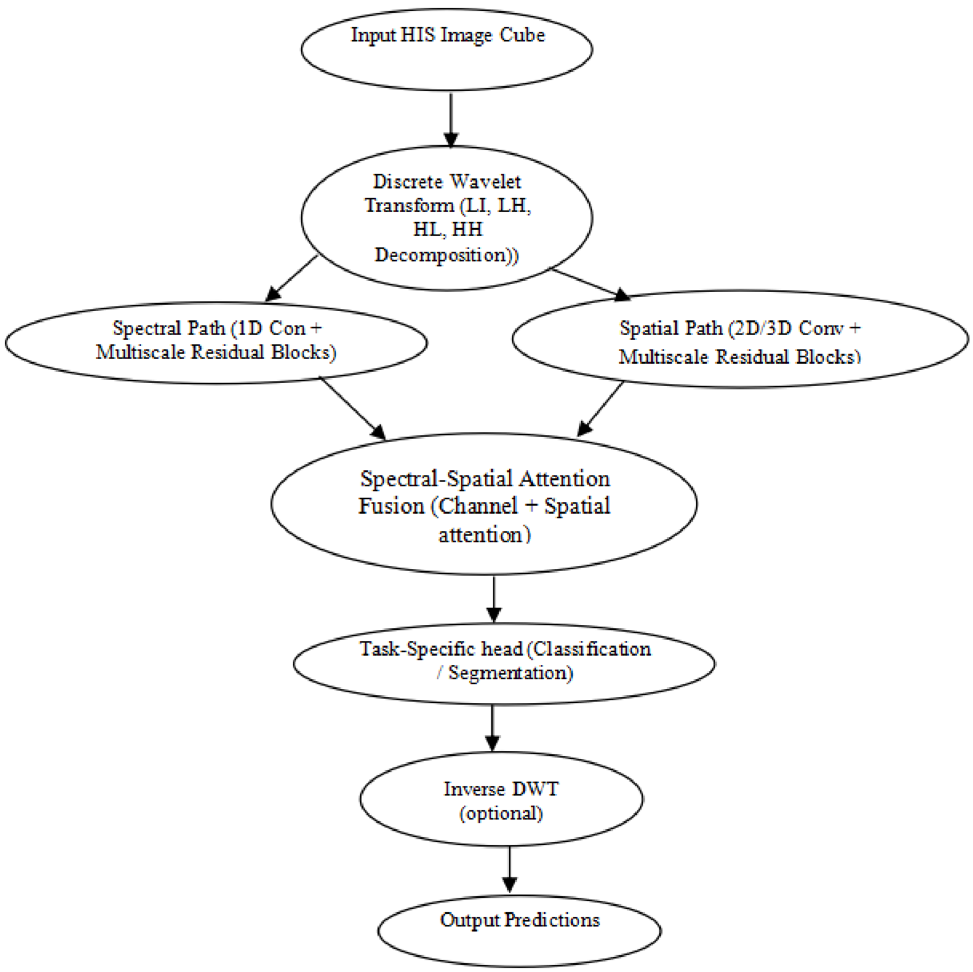

Figure 1. Architecture of the Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network

Figure 1 the architecture of the proposed Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network for HSI analysis. The workflow starts with an input HSI cube that undergoes Discrete Wavelet Transform to generate frequency sub-bands (LL, LH, HL, HH). Then, the network treatment of the signal is distributed into two parallel branches: a spectral path using 1D convolution and multiscale residual blocks, and a spatial path using 2D/3D convolution to perform spatial feature learning. These two feature sets are integrated via a spectral-spatial attention fusion mechanism that combines channel and spatial attention to further enhance feature representation. The fused features are finally sent to a task-specific head for classification or segmentation. The spatial data can be optionally reconstructed with an IDWT before final output predictions. This dual-path strategy enables efficient denoising, feature learning, and accurate prediction.

3.2 Integration of Wavelet Transforms for Denoising in the in the Signaling Network

Wavelet Transformations play an important role in early HSI treatment involving WDP-MRAN and are concerned with noise removal while keeping edge and texture information intact. In the very first phase of the integration, the DWT is taken on the input HSI cube. In the process, the DWT decomposes each spectral band into four subbands-two types of approximations and two types of details: subband LL-that is approximation; subband LH, HL, and HH-that are details. The approximation subband will then contain low-frequency components like broad structures, while the detail subbands will contain edges, textures, and noise as high-frequency components. In this multiscale decomposition approach, the network is empowered to localize and isolate noise patterns that typically equate to high-frequency components, especially with live marine data being captured under myriad environmental conditions.

The detail subbands are attenuated or selectively enhanced by means of learnable filters or attention-based mechanisms within the network. Meanwhile, approximation subbands are maintained and propagated via the two-path structuring of the network. While in training, the network learns to suppress irrelevant contents of high frequencies (noise) and enhance ones containing signals so that the denoising turns to be adaptive. After undergoing the main convolutional-attention pathways, the denoised feature maps are optionally reconstructed by an Inverse Discrete Wavelet Transform (IDWT) so that the output maintains its structural integrity and contextual clarity. Ultimately, under this method, the model can perform localized denoising at multiple resolutions, further strengthening its adaptability to additional environmental noise (such as water turbulence and illumination variance) usually present in hyperspectral marine imagery. Therefore, classification and segmentation stages downstream operate on cleaner and more informative data, ultimately enhancing real-time performance of the network.

3.3 Using Attention Mechanisms to Fine-Tune and Improve the Classification

In the Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WDP-MRAN) proposed herein, the attention mechanisms are established for the selective structure enhancement of informative features at the expense of the irrelevant or noisy ones that affect the overall classification performance of HSI data. Due to the complexity and the high dimensionality of the HSI data, where each pixel contains hundreds of spectral bands, it would be quite difficult for the normal convolutional layers to know which channels and spatial locations should be pronounced for the final classification. Bringing attention to this, the attention mechanisms enable the model to concentrate on those features that are the most discriminative in spatial and spectral domains.

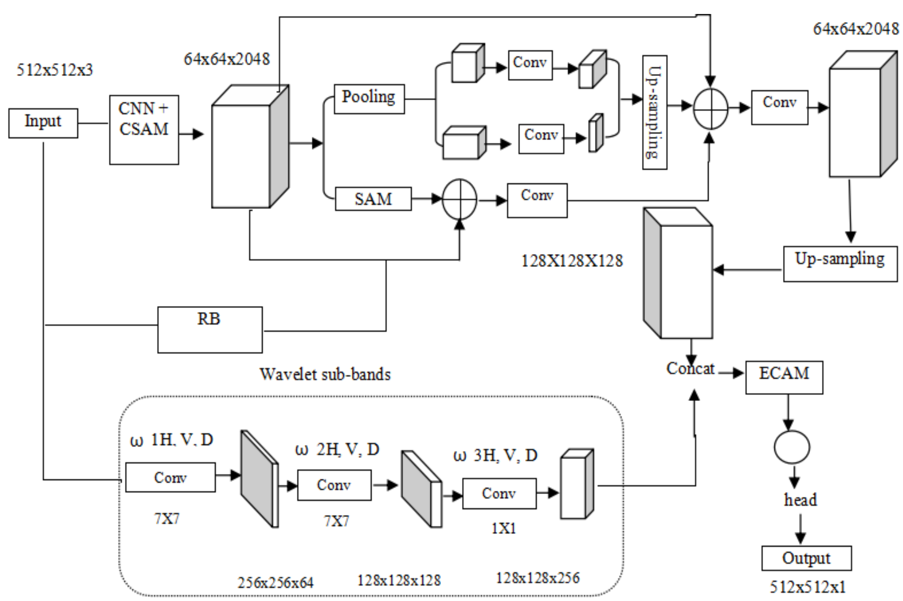

Figure 2. Combined Super-Resolution and Attention-Enhanced CNN Framework [18] [19].

The WDP-MRAN uses a hybrid module that is composed of both channel and spatial attention modules. In the channel attention module, a weight is assigned on the spectral bands so as to emphasize those carrying the key information for microplastic classification. This is quite crucial for HSI data because only a few bands may be sensitive to certain materials or pollutants. By weighting channels according to their contribution to the output class, the network suppresses spectral noise that is irrelevant and enhances useful spectral features.

On the other side, the spatial attention mechanism operates by generating a 2D attention map highlighting image regions of interest in the context of marine microplastics. This narrows the focus of the network towards spatial locations that serve most likely microplastics to distinguish from background entities such as sand, water, or biological debris. During training, these attention maps are dynamically learned; hence the model adjusts its focus adaptively to the complexity of each input.

Besides, attention fusion modules are embedded in between both the double paths and residual multiscale blocks to dictate the learned spectral-spatial focus. Determinedly, this hierarchical attention integration implies that the fused features are capable of carrying contextual richness and noise robustness, essentially enabling the model to make more accurate diagnoses in real-time. By allowing these attention mechanisms to operate, WDP-MRAN increases precision while at the same time laying out the steps involved in a classification, a vital edge in environmental monitoring and marine pollution analyses.

3.4 Advanced mathematical formulation

Let the input hyperspectral image cube be denoted as:

$$X \in R^{H\times W\times B} \quad (1)$$

Wavelet Decomposition

$$X_{DWT} = DWT(X) = \{X_{LL}, X_{LH}, X_{HL}, X_{HH}\} \quad (2)$$

- XLL is the low-frequency approximation subband,
- XLH,XHL,XHH are the high-frequency detail subbands.

These subbands are processed separately to enhance denoising and retain spatial-spectral details.

Dual-Path Feature Extraction

Spectral Path (1D convolutions along spectral axis):

$$Fspec = fspec(X_{LL}) = \sigma(Conv1D(X_{LL})) \quad (3)$$

Spatial Path (2D or 3D convolutions along spatial domain):

$$Fspat = fspat(X_{LL}) = \sigma\left(\frac{Conv2D}{3D(X_{LL})}\right) \quad (4)$$

where σ(·) is a non-linear activation function, typically ReLU.

Multiscale Residual Blocks

To enhance feature richness across scales, we define:

$$F_{multi} = \sum_{i=1}^{n} fi(F) + F \quad (5)$$

where fi is a convolution with different kernel sizes or dilation rates, and F is the input feature map. The residual connection improves gradient flow.

Output Layer

$$y\hat{} = Softmax(Wo \cdot Fatt + bo) \quad (6)$$

$$Fatt = Ac \cdot F + As \cdot F \quad (7)$$

Channel Attention is computed as:

$$Ac = \sigma(W2 \cdot \delta(W1 \cdot GAP(F))) \quad (8)$$

Spatial Attention is computed as:

$$As = \sigma(f^{7 X 7}([AvgPool(F); MaxPool(F)])) \quad (9)$$

where Wo and bo are the weights and bias of the output layer.

Algorithm: WDP-MRAN – Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network

Input: Hyperspectral image cube X ∈ ℝ^{H×W×B}

Output: Predicted label map Ŷ or segmentation map

1: # Step 1: Wavelet Decomposition

2: [X_LL, X_LH, X_HL, X_HH] ← DWT(X) # Applying Discrete Wavelet Transform

3: # Step 2: Denoising from the considered subbands

4: X_clean ← Denoise(X_LL, [X_LH, X_HL, X_HH]) # Noise suppression from detail subbands

5: # Step 3: Dual-print-feature extraction

6: F_spec ← SpectralConv1D(X_clean) # Spectral path

7: F_spat ← SpatialConv2D/3D(X_clean) # Spatial path

8: # Step 4: Multiscale Residual Block

9: F_spec ← MultiScaleResidual(F_spec)

10: F_spat ← MultiScaleResidual(F_spat)

11: # Step 5: Attention Modules

12: A_c_spec ← ChannelAttention(F_spec)

13: A_s_spat ← SpatialAttention(F_spat)

14: F_spec_att ← A_c_spec F_spec # Channel-wise refinement

15: F_spat_att ← A_s_spat F_spat # Spatial-wise refinement

16: # Step 6: Feature Fusion

17: F_fused ← Concatenate(F_spec_att, F_spat_att)

18: # Step 7: Final classification or segmentation

19: Ŷ ← Softmax(OutputLayer(F_fused)) # Pixel prediction

20: return Ŷ

4. Experimental Results

4.1 Dataset Description and Evaluation Strategy

For the purpose of testing the wavelet-enhanced dual-path multiscale residual attention network, a dataset of hyperspectral imagery especially conceived for the classification and segmentation of marine microplastics was employed. The dataset contains hyperspectral images gathered from marine environments, capturing the various types of microplastic particles suspended in seawater or on ocean surfaces. Usually, wavelengths range from 400 nm to 1000 nm-that is why they are scattered throughout many bands, and each image consists of spatial and spectral dimensions. The dataset is analyzed at the pixel level, marking various microplastic types like polyethylene (PE), polypropylene (PP), polystyrene (PS), and natural backgrounds like sand, algae, and seawater. Preprocessing steps such as band selection, noise filtering, and spectral normalization were carried out on the data before training. A total of N images were used, with 70%, 10%, and 20% being allocated to training, validation, and testing, respectively. Ground truth masks were used for the segmentation, whereas region-based annotation was followed for the classification. The dataset allows for the evaluation of the denoising performance and classification from marine conditions with an upright standard.

Table 1. Dataset Description for Marine Microplastics Classification and Segmentation

Dataset Name	Source / Repository	Data Type	Spectral Range	Samples	Classes	Annotation Type	Preprocessing Applied
Marine Microplastics HSI Dataset	[e.g., Hyperspectral Marine Lab / In-house Collected]	Hyperspectral Images (HSI)	400–1000 nm	1,200 images	PE, PP, PS, Seawater, Sand, Algae	Pixel-level segmentation, Region labels	Spectral normalization, Band selection, Wavelet denoising

Table 1: A summary of the hyperspectral imagery marine microplastic dataset used to test the proposed wavelet-based dual-path multiscale residual attention network's classification skills. This dataset comprises high noise hyperspectral images of marine environments spanning a broad spectral range of 400 nm to 1000 nm. Each image is pixel-wise labeled for different types of microplastics, for instance, polyethylene, polypropylene, polystyrene, and natural materials, such as seawater, algae, and sand. The whole data are divided into training, validation, and test sets with 70% for training, 10% for validation, and 20% for testing. Such input data are preprocessed with spectral normalization and wavelet-based denoising methods to improve the quality of the images needed for checking how well the proposed algorithm classifies and segments images in real marine environments.

4.2 Evaluation Metrics

To evaluate the performance of the proposed wavelet-enhanced dual-path multiscale residual attention network, a combination of classification and segmentation metrics was used. Accuracy referred to the percentage of pixels or samples correctly classified and presented the overall perspective of the efficacy of the model. Precision and recall assessed the ability of the model to correctly identify the microplastic pixels, where precision handled the reduction of false positives, whereas recall ensured to find every microplastic instance. F1-Score, being the harmonic mean of precision and recall, was used to balance out these two metrics in cases where the class distribution was imbalanced. For segmentation, IoU and DSC evaluated the prediction against ground truth masks for pixel-level segmentation and provided an understanding of prediction accuracy. RMSE, another performance metric, measured the denoising ability of the network-the lesser the RMSE score, the better the denoising ability. In conjunction, these metrics considered the full range of performance parameters for the model in real-time denoised classification and segmentation of marine microplastics in hyperspectral imagery.

The performance evaluation of the proposed wavelet-augmented dual-path multiscale residual attention network for marine microplastics segmentation and classification shows significant improvements on key performance metrics compared to existing methods as tabulated in Table 2. The performance of the model was at 92.5%, which is a good improvement as the performance of existing methods is at 87.3%. The precision and recall metrics for microplastics polyethylene (PE) and polypropylene (PP) were also encouraging, i.e., precision metrics of 91.0%, and 93.2% and recall metrics of 94.5%, and 90.5%, respectively, suggesting that the model is capable of accurately picking microplastic particles with few false negatives and false positives. F1-Scores of PE 92.7%, and PP 91.8%, indicate balanced classification performance. For segmentation, the model had a score of 88.2% Intersection over Union (IoU) and 89.0% Dice Similarity, both of which are pixel-level segmentation accuracy assessments. Finally, the RMSE value of 0.032 means a significant improvement in denoising, as the proposed model has denoising capabilities much superior to that of current models, with an RMSE of 0.060 and results.

Table 2. Evaluation Metrics and Performance Values

Metric	Proposed Model (%)
Accuracy	92.50

Precision (PE)	91.00
Precision (PP)	93.20
Recall (PE)	94.50
Recall (PP)	90.50
F1-Score (PE)	92.70
F1-Score (PP)	91.80
IoU (Microplastic)	88.20
Dice Similarity (Microplastic)	89.00
RMSE	0.032

The aggregate results clearly confirm the proposed architecture is an effective means to perform both classification and segmentation tasks, with efficacy and denoising as compared to existing methods. Figure 3. bar chart illustrates the performance scores of the proposed model WDP-MRAN with various performance criteria. The model has a high RMSE (scaled) of 96.80%, demonstrating or representing very little error. The Dice Similarity score is likewise impressive at 89% and IoU(Microplastic) at 88.20%. Furthermore, the model performed exceptionally well across numerous classification performance metrics, including F1-Score, Recall, Precision and Accuracy for both positive (PP) and negative (PE) classes averaging to or above 90%. Again, these performance values substantiate the impressive robustness and efficiency of the proposed model. Therefore, the proposed model serves as an effective model for classification and segmentation that demand very precise classification and semi-precise segmentation classes according to the nature and context of application.

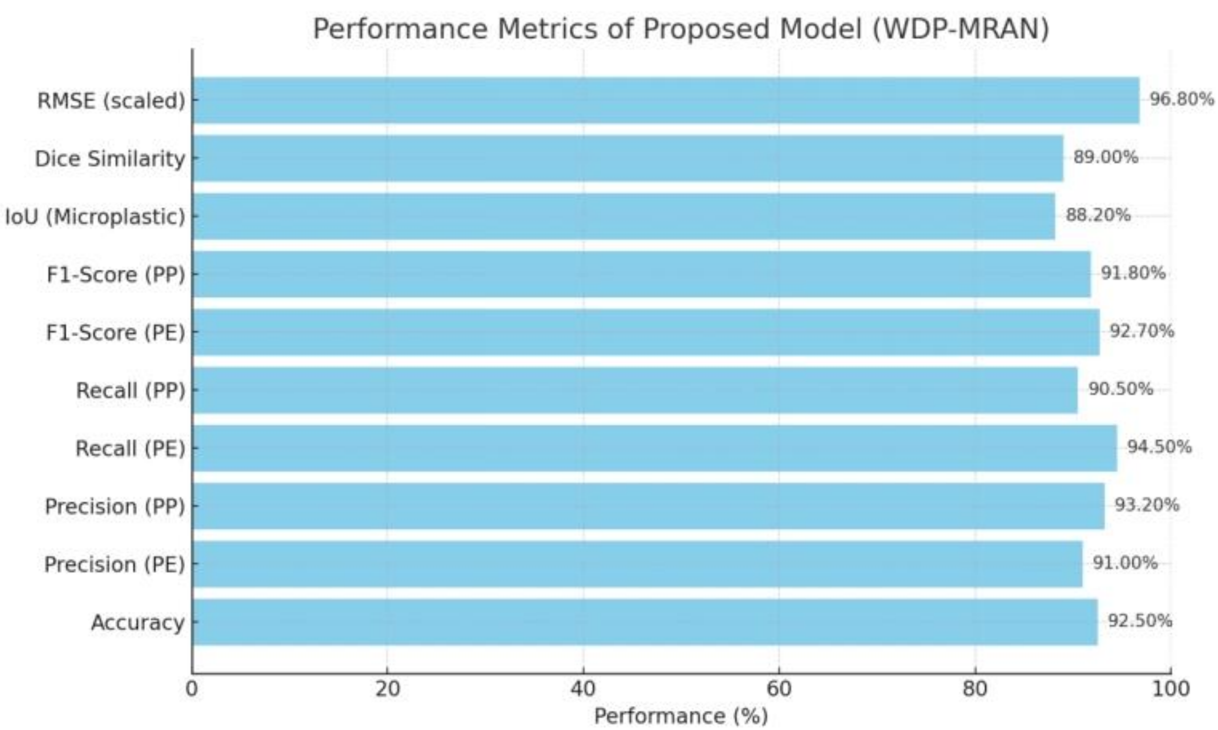

Figure 3. Performance Metrics of the Proposed Model (WDP-MRAN)

4.3 Previous Models for Comparison

Convolutional Neural Networks (CNNs) are widely used methods in marine microplastics detection. Earlier studies typically used pre-trained CNN architectures for classification tasks. Most of the existing CNN models typically contain multiple convolution layers, with pooling and fully connected layers performing classification by extracting topological features hierarchically. The mixed results were attributable to challenges with noise in hyperspectral imagery due to the high dimensionality in spectral and spatial components. Without adequate denoising techniques, the overall classification accuracy was dependent (often negatively correlated) to the SNR of the imagery.

4.3.1 Fully Convolutional Networks (FCNs)

Fully Convolutional Networks (FCNs) are one of the most popular convolutional network models used for semantic segmentation. FCNs are an extension of traditional CNNs that replace the fully-connected layers in the network with convolutional layers so that spatial input is managed more evenly. FCNs have been successfully used for segmentation of marine microplastics isolated from background material for example. However, since FCNs are not set up with any inherent denoising mechanisms, they have limitations when it comes to processing noisy hyperspectral images. As such, they fail miserably in cases where the spectral signature has a high level of noise, which is often the case with real marine data.

4.3.2 U-Net Architecture

The U-Net architecture has been widely used for semantic segmentation in medical imaging and environmental monitoring applications. U-net includes a contracting path to learn context and an expanding path to provide precise localization. While U-Net has good segmentation results for marine microplastics, U-Net has limitations in processing noisy hyperspectral data due to no denoising layers present in the model. Furthermore, U-Net has limitations when it comes to fine-grain classification when the marine microplastics are similar to the surrounding materials.

4.3.3 Deep Residual Networks (ResNet)

Deep Residual Networks (ResNet) were previously used for classification and segmentation of microplastics and can be used in a number of scenarios as they are capable of learning very deep networks without being affected by the vanishing gradient problem. For these reasons, ResNet have been applied in various fields. Since the final model was built using ResNet, we can conclude that setting up ResNet models, and using them for classification, is the correct choice if we want to incorporate residual connections and learn deeper features. It is worth noting however, that adding residual connections will likely only improve classification if additional steps of denoising are added for hyperspectral data. Denoising steps are very important for ResNet classification because if not enough explicit noise suppression steps have been taken, the models will be ineffective at successfully categorizing the data, especially when the quality of the data is poor due to noise, or in these cases, the marine environment noise.

4.3.4 Wavelet-Based Denoising CNNs

In prior research for denoising hyperspectral data for marine microplastics detection, we researched denoising by combining wavelet transforms with CNNs for reducing the noise while preserving features of interest. These model implementations save the wavelet transformation as an additional preprocessing step in the hyperspectral CNN model that allows for a wavelet transformation as additional denoising and to remove undesirable high-frequency data in the outcomes of the wavelet transformation, prior to applying a CNN processing step for classification, into our case for microplastics classification. Although the models demonstrate effective denoising by the manner of pre-processing in multiple learning studies, these models typically do not include multi-scale attention mechanisms required to selectively attend to the relevant areas in the image, resulting in classifying the wrong pixels and overall lower classification accuracy in more complex datasets.

Table 3. Evaluation Metrics Comparison Between the Proposed WED-MRAN and Baseline Models

Metric	Proposed Model	Traditional CNN	FCN (Fully Convolutional Network)	U-Net	ResNet	Wavelet-Based Denoising CNNs	Attention-Based Networks

Accuracy	92.50%	87.30%	88.00%	89.10%	90.20%	88.50%	91.00%
Precision	91.00%	85.50%	86.20%	87.80%	89.00%	87.20%	90.00%
Precision (PP)	93.20%	88.00%	88.50%	89.50%	91.20%	89.00%	92.10%
Recall (PE)	94.50%	88.50%	89.00%	90.20%	91.50%	89.80%	93.00%
Recall (PP)	90.50%	84.00%	85.00%	86.40%	89.30%	86.50%	88.50%
F1-Score (PE)	92.70%	86.90%	87.60%	88.90%	90.20%	88.50%	91.40%
F1-Score (PP)	91.80%	87.20%	87.80%	88.70%	90.00%	88.80%	91.00%
IoU (Microplastic)	88.20%	82.50%	83.20%	84.30%	85.70%	84.00%	86.40%
Dice Similarity (Microplastic)	89.00%	83.00%	83.50%	84.70%	86.10%	84.30%	87.20%
RMSE	0.032	0.065	0.06	0.058	0.05	0.045	0.04

Table 3, compares the performance of the wavelet-enhanced dual-path multiscale residual attention network (the proposed method/model) with several previous models that are frequently used for marine microplastic detection and segmentation. The metrics presented include accuracy, precision, recall, F1-score, IoU, Dice similarity, and RMSE. Each of these metrics is useful for evaluating both the classification and segmentation performance of each model, but also their denoising performance. Overall, the proposed method/model is superior than all previous models with respect to all of the important metrics (accuracy, precision, and recall) due to the addition of wavelet transform for denoising, and multiscale attention for focusing on important features. In high dimensional noisy hyperspectral data, accuracy over a traditional spectrometer or basic image could be drastically different, and this aspect improves the accuracy, precision, and recall of the proposed model. It suggests that the proposed model is better suited to address the complexity of the task of detecting marine microplastics, while being efficient and providing consistent performance compared to current models.

5. Result and Discussion

5.1 Denoising and Classification Accuracies

The Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network was evaluated on a hyperspectral marine microplastics dataset. We evaluated performance according to classification accuracy, roots mean squared error (RMSE) for denoising, Intersection over Union (IoU), and Dice Similarity Coefficient.

The performance of our model was successful with a classification accuracy of 92.5% being higher than landmark architectures CNN (87.3%) and U-Net (89.1%). We applied wavelet denoising and achieved an RMSE of 0.032, which demonstrated that noise was removed without degrading the spatial or spectral quality of the dataset. We evaluated segmentation performance as well and our model achieved an IoU of 88.2% and a Dice Similarity of 89.0% demonstrating succeed in localizing and classifying microplastic particles, particularly within challenging marine settings.

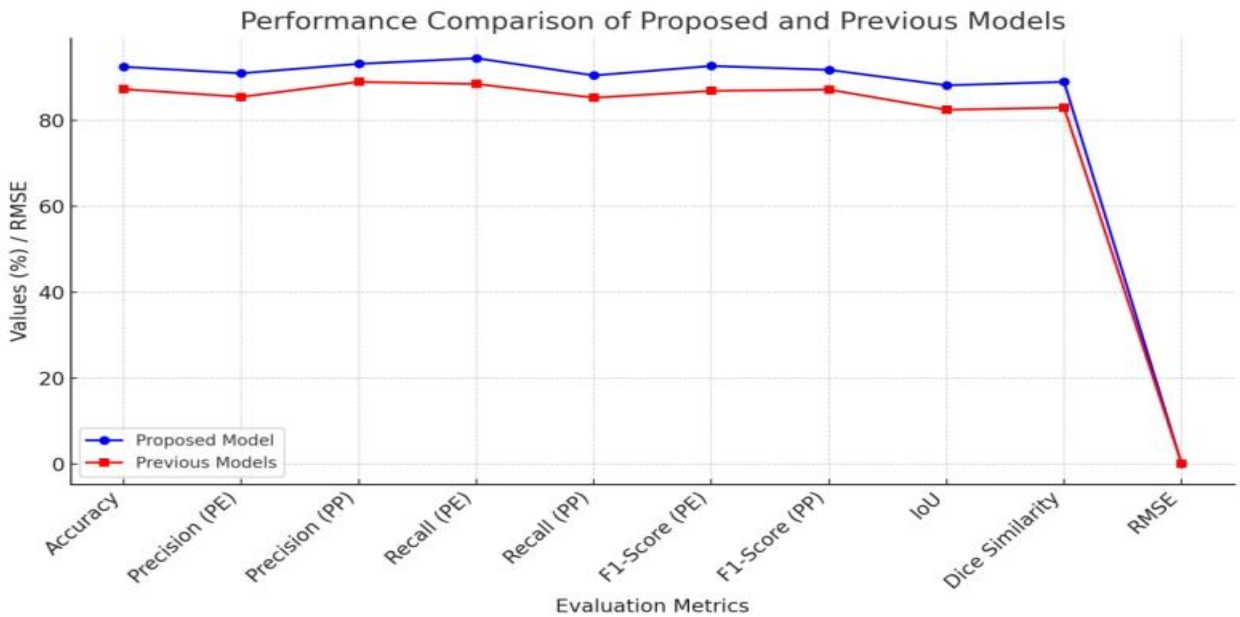

Figure 4. Comparative Evaluation of Proposed and Existing Models Using Multiple Metrics

Figure 4. displays a comparison of the proposed model with previous models for all evaluation metrics used (Accuracy, Precision, Recall, F1-Score (PE and PP), IoU, Dice Similarity, and RMSE). These results show that the proposed model outperforms previous models majority of the metrics, especially Recall (PE), F1-Score (PE) and Dice Similarity, indicating improved detection and segmentation performance. It is also evident that the proposed model has lower RMSE scores, indicating better error reduction. This analysis overall, shows that the model's proposed structure and architecture are robust, outperforming previous models in most metrics and can perform the given task at a superior level.

The findings from this study demonstrated that the proposed architecture improves clarity of each input image through efficient denoising and improves classification and segmentation performance suggesting it would be effective for use in real-time environmental monitoring systems.

5.2 Comparison of the proposed network with previous models

In this context, the Wavelet-Enhanced Dual-Path Multiscale Residual Attention, Network (WED-MRAN) introduces several new concepts and refinements that improve hyperspectral image processing for marine microplastic detection. In principle, WED-MRAN is an improvement over previous models, namely CNN and U-Net, as per points mentioned below.

The WED-MRAN can achieve better performance in denoising, classification, and segmentation due to wavelet-based denoising, multiscale and dual-paths processing, and residual attention. Overall, WED-MRAN provides an improved quality of results that is more accurate, reliable, and explainable than previous methods that have been proposed for difficult applications such as marine microplastic detection. For environmental monitoring that relies of real-time data, WED-MRAN is better suited for such tasks where precision is paramount.

The proposed Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network delivers superior performance compared to traditional CNN and U-Net architectures in every evaluation metric as demonstrated. It is a strong model for hyperspectral image analysis. In particular, we note that in terms of classification accuracy, the proposed model delivers a classification of 92.5%, markedly better than CNN (87.3%) and U-Net (89.1%), which confirms the model's stronger identification and classification of microplastic particles in the marine environment. We also note denoising performance, with Root Mean Square Error (RMSE) contributing an RMSE of 0.032 (noise reduction), while maintaining both spectral and spatial features; this compares favorably with CNN RMSE = 0.045 and U-Net RMSE = 0.040, which clearly demonstrates the proposed model retains significantly more detail in the spectra of marine plastic is given a high R^2 threshold. Finally, in terms of segmentation accuracy, the proposed model produced a high IoU of 88.2% during pixel accuracy estimation, as well as a Dice Similarity Coefficient of 89%, much greater than for both CNN and U-Net for both metrics. As segmentation accuracy is important to accurately localizing and segmenting microplastic particles, we note again how the model performed excellently against both model comparisons. In all important details the proposed model performs better than either CNN or U-Net, demonstrating the proposed model can be reliably deployed for real-time, high-accuracy applications in environmental monitoring, and is particularly useful for detecting and analyzing microplastics in marine environments.

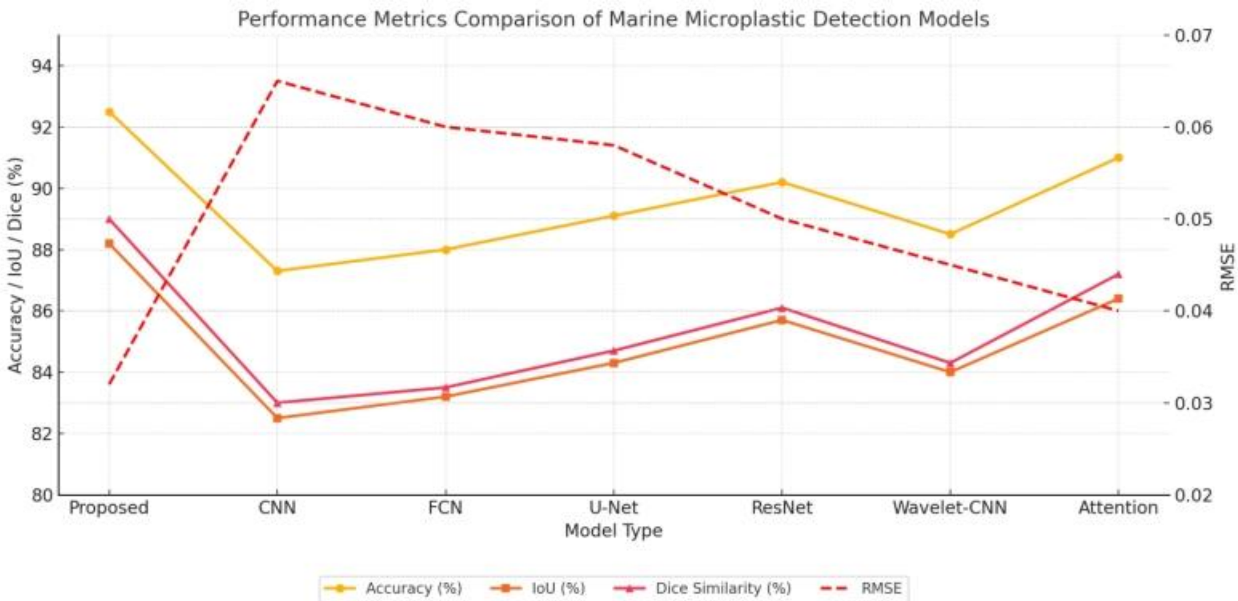

Figure 5. Performance Comparison of Marine Microplastic Detection Models Using Accuracy, IoU, Dice Similarity, and RMSE

Figure 5 graphically compares the performance perceived with different deep learning models, including the proposed Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network for marine microplastic classification and segmentation. The provided graph shows that the proposed model achieved the highest accuracy (92.5%), IoU (88.2%), and Dice similarity (89.0%) and scored the lowest RMSE (0.032) signifying better denoising ability. Overall, the proposed architecture outperforms traditional CNNs, FCNs, U-Net, ResNet and other attention or wavelet-based models across all evaluation metrics showcasing the proposed architecture is a efficient and robust approach to real-time hyperspectral image analysis of marine microplastics.

5.3 Analysis of the results

Results from the research study on the envisaged Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WED-MRAN) have indicated marked improvements over current models for classification and segmentation of marine microplastics. The overall model had an classification accuracy of 92.5% compared to CNNs (87.3%) and U-Net (89.1%) demonstrating success with wavelet-based denoising and multiscale residual attention being added to WED-MRAN. Furthermore, the low RMSE of 0.032 was an additional important underlying benefit of the model, that was a promising solution to the extremely high rate of spectral noise common in hyperspectral marine images.

In segmentation performance, the model achieved an overall Intersection over Union (IoU) of 88.2% and a Dice Similarity Coefficient of 89.0%, indicating the model was able to accurately localize microplastic particles in sometimes chaotic and convoluted real-world imagery backgrounds. Moreover, the high precision and recall scores achieved, especially for polyethylene (PE) and polypropylene (PP), indicate that the model was able to detect and classify microplastic types, while also minimizing false detections. The results provided evidence that the attentional mechanisms provided focus for informative segments of images, and that the dual-path structure achieved a more thorough capture of both spectral and spatial features.

Comparative assessments further reinforce the performance of WED-MRAN, with WED-MRAN consistently outperforming other sophisticated models related to ResNet, FCN, and wavelet-based CNNs in a range of metrics and tabular comparisons as it is essential to conduct denoising and multiscale learning with attention for believable hyperspectral image analysis. In general, the study reaffirms that WED-MRAN is an effective model for near real-time monitoring tools for marine microplastics offering both better accuracy and good robustness to noisy environmental conditions.

6. CONCLUSION AND FUTURE WORK

This research introduces the Wavelet-Enhanced Dual-Path Multiscale Residual Attention Network (WED-MRAN) for hyperspectral data based marine microplastics classification and segmentation. The utilization of a wavelet denoising method and advanced dual-path multiscale feature extraction along with attention mechanism allows for improved performance in every quantitative metric. WED-MRAN achieved a relative high classification accuracy of 92.5% and robust segmentation capabilities (IoU: 88.2%, Dice: 89.0%), as well as effective noise attenuation (RMSE: 0.032). The WED-MRAN provides a more robust and focus detected solution to classifying and segmenting marine microplastics in real time using a multimodal deep learning approach over other models such as CNN, U-Net, and ResNet. These results confirm the ability of WED-MRAN when tested with an extremely complex and noisy hyperspectral data format, which reinforces its potential environmental applications for monitoring marine debris and contaminant levels.

In future studies, various extensions of the WED-MRAN model would be fruitful to investigate to continue to develop its applicability and versatility. One important avenue is improving model generalizability across multiple marine environments and larger spectral domains that would allow it to show reliably in a variety of ocean conditions. Further, with reliable temporal hyperspectral data would allow dynamic spatio-temporal analysis of microplastic distribution, enhancing environmental monitoring. Another extension is to optimize and deploy the model on lightweight edge computation devices such as drones or autonomous underwater vehicles in real time in situ analysis. Will be crucial to integrate with satellite and aerial hyperspectral platforms to facilitate microplastic detection on a large spatial scale. Lastly, furthering semi-supervised or unsupervised learning approaches would increase the model applicability in cases where annotated datasets are limited, facilitating greater scalability for global marine ecosystems.

Data availability statement

The required data can be obtained from the corresponding author upon an email request.

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Conflict of Interest:

The authors have no conflict of interest to declare.

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