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MICROPLASTIC DETECTION IN BEACH SAND USING IMAGE PROCESSING AND MORPHOLOGICAL SEGMENTATION

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Abstract:

The presence of microplastic waste in coastal areas is an extreme ecological hazard due to its persistence and microscopic size, making it indistinguishable from natural particles, such as grains of sand. The paper presents a powerful image processing and deep learning environment for precisely identifying and categorizing microplastics in beach sand. The system utilizes a microplastic-specific dataset specifically designed for use in computer vision. Due to microplastic particle segmentation, the preprocessing phase utilizes binary image thresholding and morphology to segment the microplastic particles effectively. To enhance feature selection, a saliency attention mechanism is combined, enabling the model to focus on the most critical areas of the image. Data on amplitude and phase holography are merged to enhance the ability to differentiate microplastics from other materials with similar appearances. The output of improved features is fed into the Guided Convolutional Neural Network (AG-CNN) to make gradable predictions. Standard performance measures, accuracy 92.3%, precision 91.0%, recall 90.5%, and F1-score 90.7% are used to evaluate the proposed approach and show better detection rates and fewer false positives than traditional types of methods. Such a mixed solution promises the potential of a robust, automated track of microplastics that can aid in the coastal management of the world and help with the reduction of microplastic pollution within marine environments.

Keywords: Detection of microplastic, image fusion, attention-guided CNN, holography dataset, analysis of beach sand, deep learning, environmental geospatial monitoring, image classification, amplitude-phase images, plastic pollution.

1. INTRODUCTION

This fact is strongly supported by the widespread concern about the use of fiber shredding as the primary source of microplastics contributing to water pollution, and indeed, there is an apparent need for identification procedures. The newly going-live Holography Microplastic Dataset will be a useful point of reference for comparison in testing deep learning optimization to distinguish microplastics from other types of rubbish. The present work builds upon earlier experiments in this direction, aiming to further enhance and continue the quest for data efficiency by exploring increasingly advanced models of picture mapping, as well as other advanced models of deep learning, to achieve better detection results [1]. Understanding the buildup and movement of microplastics smaller than 1 mm close to coastal areas is crucial, as microplastic contamination is a global issue. The kinds of plastics that seep into the environment and break down over time determine the many different types of microplastics that are found there [2]. With the increasing hazard posed by plastic waste to marine ecosystems, the authors conducted fieldwork sampling and analysis to determine the number of microplastic particles present in sediment and seawater samples. The article highlights the origin, routes, and duration of microplastics that are typically present in such coastal areas. The primary purpose of the research is to present a comprehensive overview of information that will be crucial in guiding policymakers and environmental managers in developing efforts to reduce microplastic contamination and safeguard the biodiversity of Colombia's coastal environments [3]. The shortcomings of traditional microplastic identification techniques, which are usually based on visual testing, include being time- and labour-intensive, as well as prone to error. By adopting the best deep learning strategies, we developed an efficient system that accurately segmented and labeled various types and dimensions of microplastics in microscopic images. The paper demonstrates how the automation of the microplastic analysis process can significantly enhance detection rates and subsequent evaluation of the environmental impact of plastic pollution [4]. Microplastic images that are specifically labeled and tailored towards the detection as well as segmentation of microplastics in sewage. In the paper, the authors emphasize the need for standardized datasets to train and validate machine learning models that will aid in automating the analysis of microplastics. The authors aim to support research on microplastic pollution in urban wastewater streams by providing high-resolution images with precise segmentation and detection labels [5].

Objectives

- To create an innovative image-processing methodology able to identify and classify microplastics in the samples of beach sand and deal with issues related to the size and innate similarity to other particles.
- To apply image fusion methods, which could be used to merge the amplitude and the phase images of the Holography Microplastic Dataset, to produce clear three-channel images that would increase the visibility of features of microplastic.
- To achieve more accurate segmentation, an Attention-Guided Convolutional Neural Network (AG-CNN) that prioritizes microplastic areas and spatial salience while reducing background interference
- To prove the effectiveness of the suggested fusion-attention network in terms of accuracy and robustness in detecting microplastics, compared with single-modal inputs and following traditional deep CNNs.
- To present a useful, user-friendly, non-toxic, scalable tool allowing us to measure microplastics accurately, and to facilitate automated environmental diagnostics, pollution monitoring, and coastal cleanup efforts.

The remaining content is divided into the following main sections. Section II lists the ongoing research projects on Microplastic Detection in Beach Sand Using Image Processing and Morphological Segmentation, carried out by various authors. In Section III, the procedure of the proposed technique is explained. Section IV presents the findings of a comparison between the proposed Microplastic Detection in Beach Sand Using Image Processing and Morphological Segmentation model and the traditional approach. The conclusion of the proposed work that will be done in a future scope is included in Section V, along with references.

2. RELATED WORK

The author cites **Lorenzo-Navarro et al. (2021)** A DL network-based method for automatically identifying and classifying 1–5 mm microplastic particles in photos taken with a smartphone or digital camera that has at least 16 million pixels is proposed in this research. The first level of the suggested architecture, which is implemented using the U-Net neural network, is responsible for segmenting the image's particles. Following their isolation, the various particles are categorized into three groups using a second step that uses the VGG16 neural network: fragments, pellets, and lines.

Astel et al. (2023) A feature identification procedure using open-source software was proposed and evaluated in the current work. A combination of image processing and microscopic expertise was used to identify form descriptors, such as length, breadth, and item area, for a collection of digital images of microplastic objects found in fish organs. The built-in Moti Connect software was used to calculate the corresponding values after the edge points required for calculating form features were manually defined in digital pictures taken by the camera and binocular.

Figueredo et al. (2025) In this study, we proposed an inexpensive analytical technique that increases the temperature from 25 to 220 degrees Celsius in less than five minutes to identify, measure, and separate MPs from non-plastic particles using image-based analysis. Using a smartphone camera and an advanced algorithm, it is possible to effectively analyse semi-crystalline and non-crystalline MPs, such as polyethylene, polypropylene, and polystyrene, to ascertain if they melt or alter size.

According to **Faltynkova et al. (2023)**, the authors of this paper used the Hyspex SWIR-320me imager to generate a spectrum database of consumer goods, marine plastic waste, and pre-product particles. Using the SIMCA model, MPs were found in hyperspectral pictures for four different kinds of polymers: polypropylene, polyethylene, polyethylene terephthalate, and polystyrene. Using fluorescent microscopy, we assessed the size estimate accuracy for PS MPs larger than 1000 μm. Additionally, we looked at how photooxidation affected the NIR-HSI identification of plastics (PE, PP, PS, and PET) and the SIMCA model's subsequent prediction of these polymers.

Kim et al. (2024) The MP-solutions are inserted into the Syringe after the paper-based 3D-PGNP was combined with a syringe filtering apparatus. In the absence of pretreatment, MPs may be effectively identified through subsequent detection Herbalist with surface-enhanced Raman scattering (SERS). The simulation carried out using Finite-difference time-domain shows that the interface and volumetric hotspot generation of 3D-PGNP surrounding the recorded MPs, enhance the sensitivity a great deal. Images of a portable Raman spectrometer SERS mapping are then turned into descriptive digital signals by employing a machine learning method so as to determine and quantify the MP dispersion.

Using X-ray micro-computed tomography (micro-CT), this study sought to ascertain if non-destructive 3D imaging might be utilized to identify microplastics in fish. The authors state that **Parobkova et al. (2025)** used micro-CT to analyse the distribution of microplastics in the colon after administering spherical microplastics made of polyethylene (30–110 μm). The results showed that the particle size distribution determined by micro-CT closely matched the data from conventional laser diffraction analysis.

This study, by **Bakir et al. (2023)**, presents the results of one of the research and development projects tracking the amount and concentration of microplastics within the seafloor sediments during a predetermined number of years and justifies the need to create a national program of monitoring microplastics in the seafloor sediments in the UK (England and Wales). The 1D-screening technique that uses Nile Red staining of the polymers coupled with a 1D-FTIR was confirmed through the 1D-FTIR-FPA. All 189 pooled sediment samples across the spectrum of 15 sites picked across the United Kingdom in each study year carried microplastic particles.

In the author **AR, Nisari et al. (2024),** The main attention of the first baseline study attempt was the distribution pattern of Microplastic and the change with the biochemical make-up of Kol-sediment residue. The density-separation approach, which involves visual counting and classification using a compound microscope while taking size, type, and colour into consideration, was used in the MPs dissociation procedure. Additionally, the chemical characterizations and validation were carried out using SEM-EDAX analysis and Fourier Transform Infrared (FT-IR) spectroscopy. In every analysed sample, micro debris was considered a complex moiety of priority.

The authors of this study, **Guedes-Alonso et al. (2021)**, address this issue by providing an analytical methodology founded on the ultrahigh-performance liquid chromatography tandem mass spectrometry and ultrasound-assisted extraction so that it is possible to identify 13 steroid hormones adsorbed on the pellets and microplastic particles. Other parameters that influenced the extractive procedure such as the volume of the solvent and the time period of extraction were optimized.

Da Silva Ferreira et al. (2025). The purpose of this study is to investigate how the morphometrical determinants function as independent factors in influencing the MP distribution on the nearby sandy beaches. Six ML models Random Forest, Gradient Boosting, Lasso and Ridge regression, Support Vector Regression, and Partial Least Squares regression were tested and evaluated using remote sensing images of beach face slope and orientation, calibrated by in situ topographic profiles acquired through GNSS positioning, and laboratory analyses.

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Table 1 Comparison of Microplastic Detection in Beach Sand

References No	Authors & Year	Focus Area	Methods	Main Findings
16	Hierl et al. (2021)	Coral interaction	Lab exposure, microscopy	Scleractinian corals can incorporate microplastics
17	Azaaouaj et al., (2025)	Beach sediments	Sampling, visual ID, FTIR	Identified the presence, distribution, and types of microplastics
18	Sajorne et al. (2022)	Beach sand	Field sampling, density separation, and microscopy	High abundance, varied characteristics
19	Mandal et al., (2023)	Marine water, beach sand, and fish	Sampling, visual sorting, and microscopy	Significant pollution in all compartments
20	Munz et al., (2023)	Multiple compartments	Near-infrared imaging spectroscopy	High-resolution detection method for microplastics
21	Bentaallah et al. (2024)	Recreational beaches	Field sampling, density separation, and microscopy	Assessed abundance and potential impacts
22	Botterell et al. (2025)	Turtle nesting beaches	Global sampling, visual/micro-analytical	Global status of microplastic pollution
23	Sivaraman et al. (2024)	Beach sand	Solvent extraction, thermal degradation	Effect of particle size and depth on abundance
24	Tasnim et al., (2023)	Surface beach sediment	Seasonal sampling, density separation	Spatiotemporal trends in debris distribution
25	Nchimbi et al. (2022)	Beach & seabed sediments	Field sampling, lab analysis	Microplastic presence in both zones

Table 1 investigations encompass various research studies on microplastics along the coasts and seas. A single study focused on coral interactions, indicating that microplastics can be ingested by corals, particularly scleractinian corals. The beach sedimentations and sands were also studied in other literature materials with the requirement of abundance, distribution, and seasons, where sampling, microscopy, and FTIR were taken as technical requirements. The advanced detection of near-infrared imaging spectroscopy has been proven in another study. During the research, measurements of effects on recreational beaches were also provided, and over time, an overview of microplastics on turtle nesting beaches was given. Further works were conducted to investigate the impacts of the depth of particles and resulting particle sizes, along with the presence of microplastics in the seabed sediments.

3. PROPOSED METHODOLOGY

The proposed methodology will utilize image processing, morphological segmentation, and deep learning to detect microplastic content in beach sand samples. The first process involves sampling beach sands and cleaning them, followed by imaging at constant interface conditions. Various methods of preprocessing are used, which distinguish microplastic particles and non-microplastic components: binary thresholding, morphological operations (erosion, dilation). A saliency-based attention mechanism is proposed to enhance feature selection, enabling the system to focus on the most significant areas in any image. Additionally, amplitude and phase holography data are also incorporated into the process images in an attempt to integrate structural information as well as phase-based information to enhance more accurate detection. With the improved features, the final detection and classification are restocked by a Guided Attention Convolutional Neural Network (AG-CNN) that makes an accurate prediction. Performance measures, such as accuracy, precision, recall, and F1-score, are used to assess the model to obtain strong and sound outcomes.

Figure 1: Proposed Block Diagram

3.1 Microplastic Dataset for Computer Vision

The extensive application of the dataset under review, known as the Microplastic Dataset, can address pressing environmental and industrial needs. In terms of ocean cleanup, it enables computer vision models to recognize and detect the location of microplastic pollution in ocean water samples, allowing for targeted cleanup of specific conditions and providing details on the location of microplastics within the marine ecosystem. The model can be incorporated into sorting structures to identify and separate microplastic remnants in waste flows in recycling facilities, ensuring their disposal and treatment that reduces leakage into the environment. Another way researchers can utilize it is through the automated detection and analysis of microplastics in their samples, as a subset of research on the effects on ecosystems and human health. Additionally, industries can utilize the model to track the presence of microplastics in their supply chains, promoting greener and more environmentally friendly manufacturing practices, as shown in Figure 2. Lastly, the dataset facilitates consumer education, enabling the creation of mobile applications that allow users to detect possible microplastic contamination in everyday products, such as cosmetics or food packaging, thereby motivating informed decisions and alerting users to microplastic pollution.

Figure 2: Microplastic Particles in a Petri Dish for Computer Vision Dataset

3.2 Preprocessing Algorithm using Binary Image Thresholding & Morphological Operations

The preprocessing algorithm for detecting microplastics in beaches using binary image thresholding and morphological methods detects tiny plastic materials found on beaches. First, a sample image of the beach is taken. The contrast is then enhanced through preprocessing. Thresholding of the binary image converts the image to black and white and individualizes the microplastics and background. Erosion and dilation (morphological operations) are used to remove noise and enhance the shape of the particles. This improves the accuracy of detection because microplastics are pointed out. This is one of the ways to automate analysis, which is less time-consuming than manual inspection and is very useful in monitoring coastal pollution.

$$B(x,y) = \begin{Bmatrix} 1 \ \ if \ I(x,y) > T \\ 0 \ if \ I\ (x,y) \leq T \end{Bmatrix} \qquad (1)$$

A grayscale image $\mathrm{I}(\mathrm{x},\mathrm{y})$ intensity at pixel x,y, T threshold value,1 foreground (microplastic),0 background (sand).

$$\sigma_b^2(T) = w_1(T)w_2(T)[\mu_1(T) - \mu_2(T)]^2 \qquad (2)$$

Otsu's algorithm finds an optimal threshold T that maximizes $\sigma_{\mathrm{b}}^2(\mathrm{T})$, $\mathrm{w}_1, \mathrm{w}_2$ class probabilities μ_1, μ_2 class means.

3.3 Feature Selection Algorithm Using Saliency-Based Attention Mechanism

The feature selection is dedicated to the microplastic particles in the sand of the beach using the feature selection algorithm and saliency-based attention mechanism. Such a feature selection algorithm drops the irrelevant features and preserves features that indicate the most strongly. This mechanism enhances the accuracy of microplastic detection by allowing the model to focus on the upper regions of the image, specifically areas of significant interest where microplastics are likely to be located, according to the saliency-based attention mechanism. The approach is less computationally expensive and provides a larger amount of training data for machine learning. The pictures of the beach sand samples are in high resolution and were taken, scanned, and then analyzed in a way that automatically detects microplastics. This is applicable in environmental surveillance as well as in the cleanups.

$$\mu = \frac{1}{\mathrm{MN}} \sum_{\mathrm{i}=1}^{\mathrm{M}} \sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{I}(\mathrm{i},\mathrm{j}) \qquad (3)$$

$$H = -\sum_{k=1}^{L} p_k log_2 p_k \qquad (4)$$

3.4 Feature Extraction using Image Fusion of Amplitude & Phase Holography Data

The process of determining the presence of microplastics in beach sand is complicated by the fact that the latter is small in size and resembles natural products, such as sand grains and shell fragments. In this regard, an advanced method of image processing is suggested, involving image segmentation based on morphology and feature extraction. Through the image fusion approach, the intertwining of amplitude and phase types of holography data provides superior and more informative images, efficiently signifying microplastic characteristics. These are falsified data that are then processed using deep learning models capable of identifying microplastics and distinguishing them from background materials. This technique enhances the precision of detection, contributes to environmental surveillance, and aids in pollution control activities in coastal regions.

$$I_f(x,y) = w_1 I_a(x,y) + w_2 I_p(x,y) \quad (5)$$

Where I_f is the fused image, I_a is the amplitude image, I_p is the phase image, and w_1, w_2 are weights.

$$A \ominus B = \{z | (B)_Z \subseteq A\} \quad (6)$$

Where A is an Input binary image, B is a Structuring element, z is a Position vector indicating where the structuring element is placed, $(B)_Z$ is the Structuring element B translated to position z, and $\subseteq$ A The translated structuring element must fit entirely within the object A.

$$A \oplus B = \{z | (B)_Z \cap A \neq \emptyset\} \quad (7)$$

Where A is an Input binary image, B is a Structuring element, z is a Position vector, $(B)_Z$ is the Structuring element B translated to Z, and $(B)_Z \cap A$ is the Intersection between the translated structuring element and the object. $\neq \emptyset$ The Intersection is non-empty, meaning at least one overlap exists.

$$G = \sqrt{G_x^2 + G_y^2} \quad (8)$$

Where G is the Gradient magnitude at each pixel, G_x is the Gradient in the x-direction, Gy is the Gradient in the y-direction.

$$I_T(x,y) = \begin{cases} 1, I\,(x,y) > T \\ 0, other\ wise \end{cases} \quad (9)$$

3.5 Classification using Guided Convolutional Neural Network (AG-CNN)

The microplastics in beach sand are crucial for gaining insights into coastal pollution and its impact on the marine ecosystem, as shown in Figure 3. This technique utilizes sophisticated image processing in conjunction with morphological segmentation to identify small microplastic particles that closely resemble natural substances. The system is trained on the Attention-Guided Convolutional Neural Network (AG-CNN), which enables it to target and ignore surrounding noise by concentrating on the microplastic marks, thereby making detection easier. This strategy will enable scientists to track pollution levels more accurately, assist environmental emergency services in the recovery process, and provide a multipurpose instrument for conducting automated screening of large amounts of microplastic research at a small scale. This can be used to improve environmental protection and waste management procedures.

$$I_{fusion} = f(I_{amplitude}, I_{phase}) \quad (10)$$

Where I_{fusion} fused image, $I_{amplitude}$ amplitude image, I_{phase} phase image, f fusion function.

$$I_{seg} = (I \ominus B) \oplus B \quad (11)$$

Equation 11 is the I_{seg} segmented image, I input image, B structuring element, $\ominus$ erosion, $\oplus$ and dilation.

$$A = \sigma(W * F + b) \quad (12)$$

Where A is the attention map, F is the feature map, W is the learned weight matrix, b is the bias, and σ is the activation

$$F_{AG} = A \odot F\text{n} \quad (13)$$

The equation 13 F_{AG} attention-weighted feature map, $\odot$ element-wise multiplication

$$y = Softmax(W_c * F_{AG} + b_c) \quad (14)$$

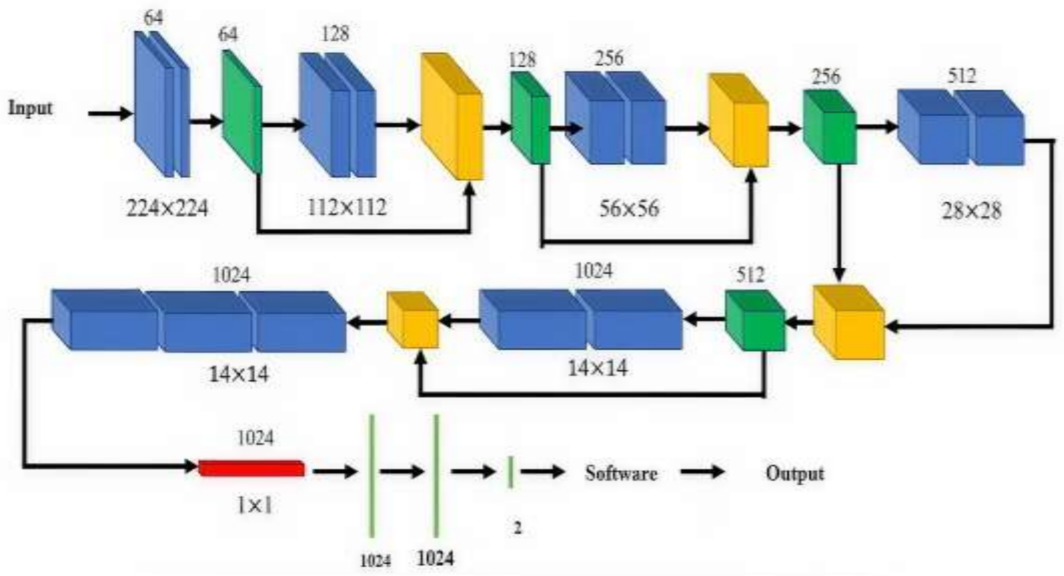

Figure 3: Architecture of Guided Convolutional Neural Network (AG-CNN)

4. RESULTS AND DISCUSSION

The findings show that the suggested approach for identifying microplastics in samples of beach sand is successful. Standard measures including F1-score, recall, accuracy, and precision were used to assess performance. Significant progress is shown when compared to current deep learning models. These results demonstrate how robust and dependable the AG-CNN architecture is for real-world environmental monitoring.

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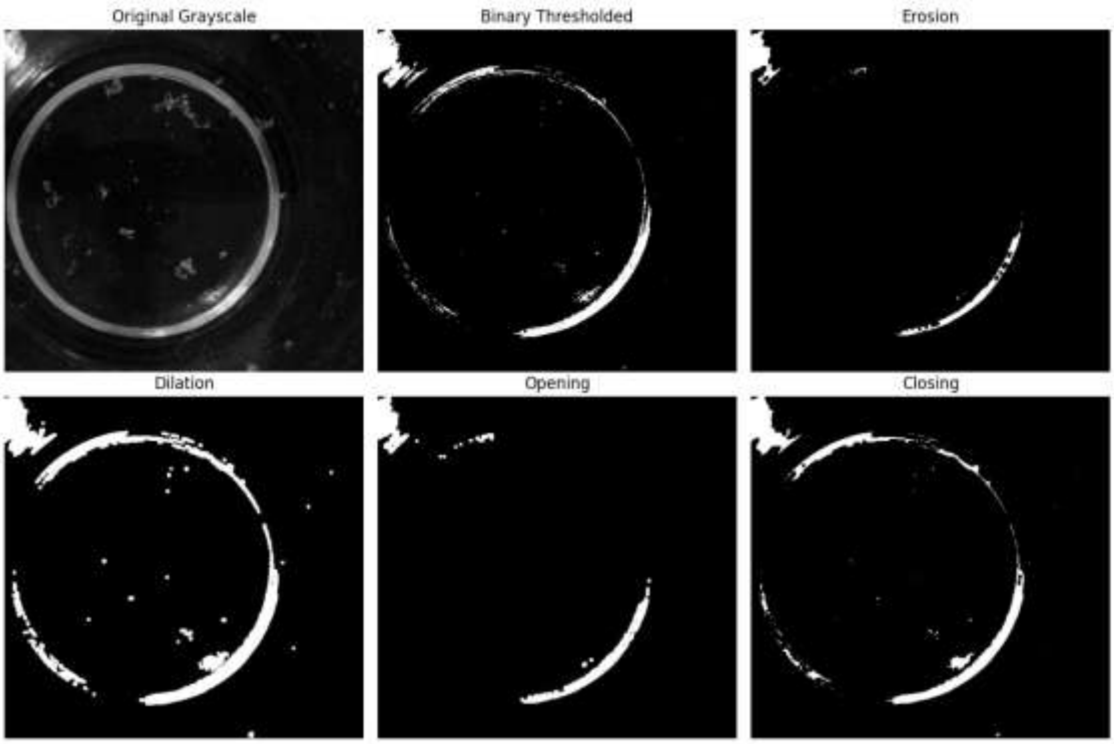

Figure 4: Visualization of Binary Thresholding, Erosion, Dilation, Opening, and Closing Applied to a Circular Object Image

Figure 4 illustrates the results of applying binary thresholding and various morphological operations to a grayscale image. First, the grayscale picture is transformed into a black and white picture through binary thresholding to emphasize essential characteristics, such as edges and particles. Small white noises are removed, and white areas shrink under erosion and are expanded by dilation. Small white spots are removed by opening (erosion followed by dilation), which cleans noise. Small black holes are filled with white areas in a process known as closing (dilation followed by erosion). These operations are necessary to enhance specific structures and contribute to noise suppression. They are crucial for detecting, segmenting, or extracting features in image processing tasks, such as identifying boundaries or microplastics.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

Where TP The number of microplastic particles correctly detected as microplastics by the model, TN The number of non-microplastic particles correctly identified as non-microplastics, FP False Positives, FN False Negatives.

$$Precision \frac{TP}{TP+FP} \tag{16}$$

Precision indicates the number of actual microplastics among the estimated number of particles that are considered microplastics. It gauges the accuracy of the model's positive predictions in equation 16.

$$Recall = \frac{TP}{TP+FN} \tag{17}$$

Recall is an indication of the number of identified actual microplastic particles correctly identified by the model. It indicates the model's ability to detect all relevant cases with positive results.

$$F1 = 2 \times \frac{Precision \times Recall}{Precison+Recall} \tag{18}$$

Table 2: Performance Metrics Comparison of Different Models

Models	Accuracy (%)	Precision (%)	Recall (%)	F1- Score (%)
CNN	82.5	80.2	78.9	79.5
VGG-16	84.7	82.5	81.0	81.7
ResNet-50	86.9	85.0	83.2	84.0
DenseNet-121	88.3	87.0	85.5	86.2
Proposed AG-CNN	92.3	91.0	90.5	90.7

The detection performance of the suggested approach was compared to that of conventional deep learning models using the accuracy, precision, recall, and F1-score of Table 2. The basic CNN had an accuracy rate of 82.5 percent, whereas VGG-16 and ResNet-50 showed accuracy rates of 84.7 percent and 86.9 percent, respectively. DenseNet-121's accuracy was 88.3%. With 92.3% accuracy, 91.0% precision, 90.5% recall, and 90.7% F1-score, the suggested AG-CNN produced the best results.These findings verify that, when it comes to accurately classifying microplastics, the combination of a saliency-based attention mechanism and holography data fusion makes the AG-CNN significantly more capable in its detection than traditional CNN models, confirming its increased robustness and ability to remain reliable in accurate classification.

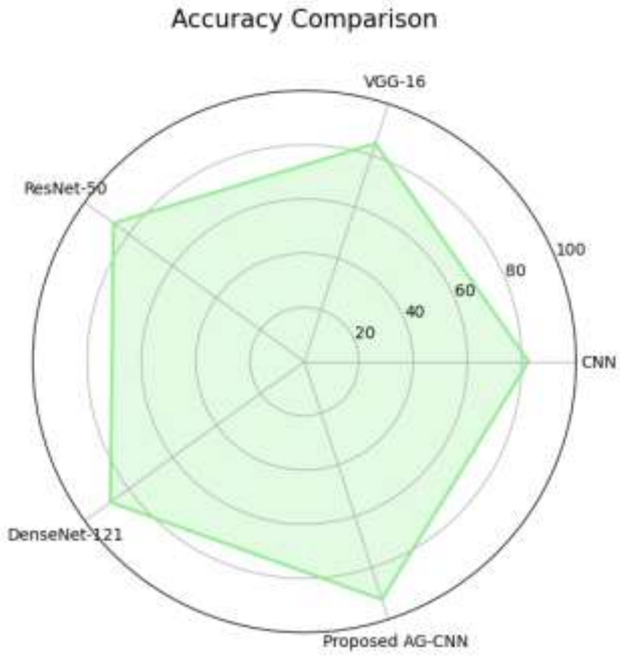

Figure 4: Accuracy Comparison

Figure 4 presents the five types of deep learning architectures, including CNN, VGG-16, ResNet-50, DenseNet-121, and the proposed AG-CNN, in terms of the model classification accuracy for each type. It clearly demonstrates that the proposed AG-CNN outperforms the other models, scoring the highest accuracy of 92.3%. Very close behind them are the ResNet-50 and DenseNet-121, with accuracies of 86.9% and 88.3%, respectively, indicating that these two networks performed very well in terms of accuracy compared to the deeper networks. Moreover, VGG-16 achieves the highest accuracy of 84.7%, while the standard CNN achieves the lowest accuracy of 82.5%. This graphic illustrates the power of the suggested AG-CNN framework to enhance forecasting performance more than traditional models.

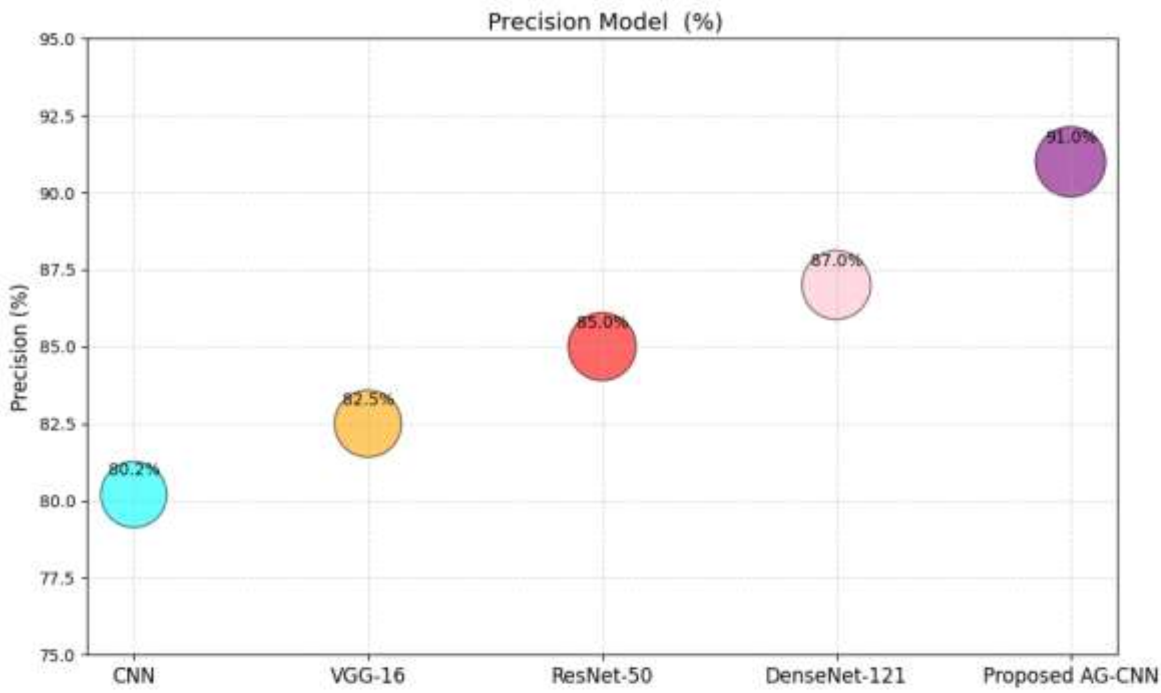

Figure 5: Precision Comparison of Different Models

Figure 5 presents a clear illustration of the accuracy performance of several deep learning models, where CNN, VGG-16, ResNet-50, DenseNet-121, and AG-CNN are employed. Different models, however, are depicted by different-colored bubbles, and their corresponding percentage of accuracy has been formatted inside the bubble to make it easy to refer to. Based on the figure, it can be seen that the basic CNN model records the lowest value of precision, at 80.2%, whereas the proposed AG-CNN has the highest value of precision, at 91.0%. The medium-level models, VGG-16, ResNet-50, and DenseNet-121, show a gradational increase in precision values, at 82.5%, 85.0%, and 87.0%, respectively. This trend indicates that more advanced network architectures are more effective in enhancing classification performance. The fact that the AG-CNN became much more accurate also demonstrates the importance of incorporating saliency-based attention and guided convolution to increase various forms of precision. This kind of comparison emphasises the promise of the proposed model in improving the detection accuracy of microplastics in complex coastlines.

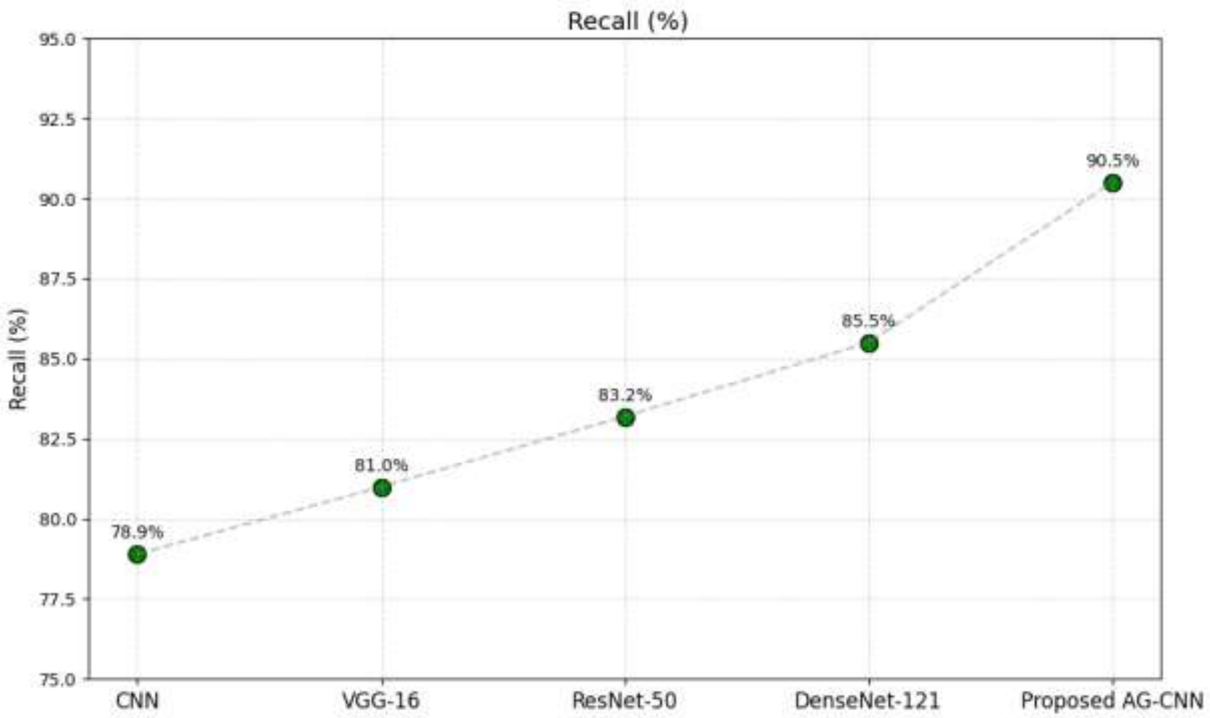

Figure 6: Recall Comparison of Different Models

Figure 6 illustrates the recall accuracy of five different deep learning models, namely CNN, VGG-16, ResNet-50, DenseNet-121, and the proposed AG-CNN. The line graph shows each point representing the percentage of recalls made by each of the models. Based on the the trend line, there is no doubt that there is a a progression in the increase in recall values, and this increase begins with the simplest model of CNN,, which has, a recall rate of 78.9%, and continues to the proposed AG-CNN model,, which achieves the highest recall rate of 90.5%. The VGG-16 model, ResNet-50, and DenseNet-121 exhibit recall rates of 81.0%, 83.2%, and 85.5%, respectively, representing a progressive improvement. This represents a progressive improvement, highlighting the benefits of utilizing more complex architectures and attention mechanisms. The significant improvement in recall rating on the AG-CNN model indicates its advantage in accurately detecting microplastics and reducing the number of false negatives, which is crucial in ensuring effective environmental monitoring practices and the successful management of pollution along the coastline.

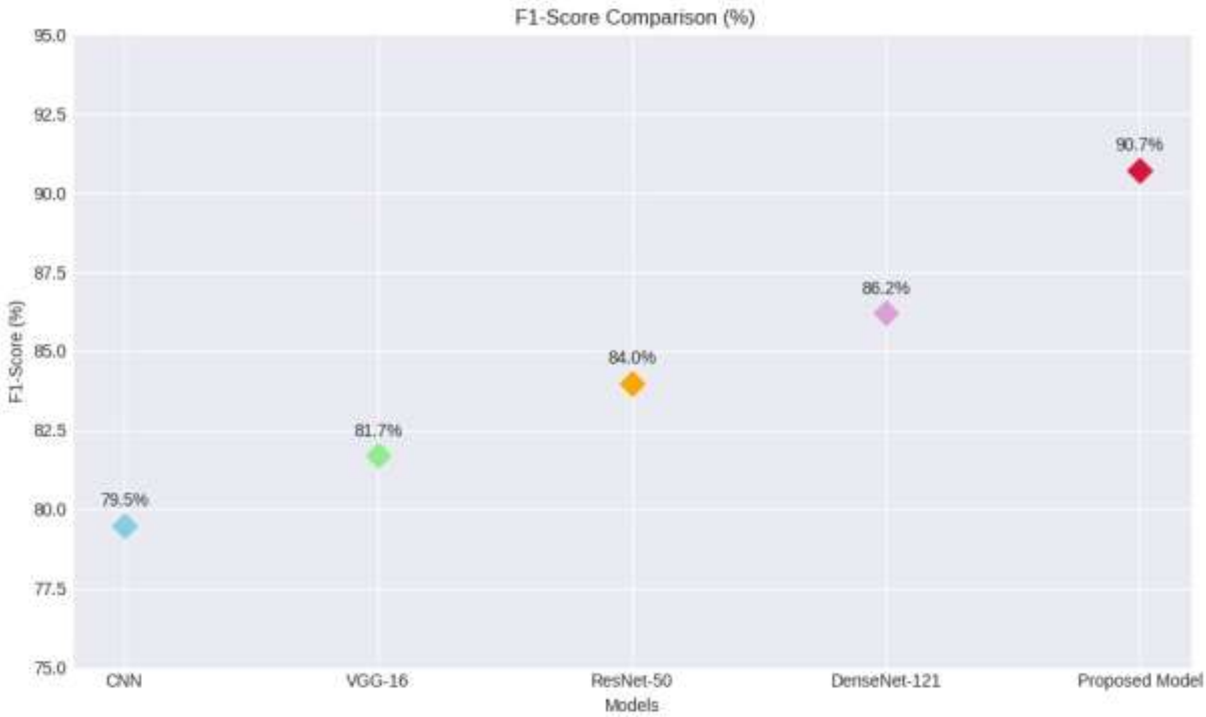

Figure 7: F1-Score Comparison

In Figure 7, the F1-score of five deep learning models is reported, namely: CNN, VGG-16, ResNet-50, DenseNet-121, and the proposed model. The shape of a coloured diamond indicates the F1-score of each model, and the exact figure reads a precise percentage. The graph also shows the F1-score, which suggests that the CNN has the worst performance, recording 79.5%, whereas the proposed model achieves a much better score of 90.7%. The improvements in the intermediate models of VGG-16, ResNet-50, and DenseNet-121 are gradual, with percentage scores of 81.7%, 84.0%, and 86.2%, respectively. This thread line shows clear evidence that the given model offers a better trade-off between precision and recall and, therefore, its overall effectiveness in the task of classification.

CONCLUSION

Finally, the study presents a promising and automated machine learning approach to detecting microplastics on the coast, utilizing advanced image analysis and deep learning in beach sand. By combining the saliency-based attention mechanism with the Guided Convolutional Neural Network (GCNN), the suggested technique allows the model to precisely choose features by concentrating on the most important regions of the picture. Morphological operations and Binary thresholding enable the precise separation of microplastic particles from sand grains. Additionally, combining data on amplitude and phase holography enhances the overall system's ability to identify microplastics more efficiently compared to other similar-looking materials. With accuracy, precision, recall, and F1-score values of 92.3%, 91.0%, 90.5%, and 90.7%, respectively, the AG-CNN model suggested in this study performs better than conventional detection systems. These findings show that both false positives and detection can be significantly decreased and increased, respectively, by using the method. This new technology has high prospects of promoting sustainable coastal management and enhancing programs to manage microplastic pollution in marine environments worldwide.

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