Marine Debris Detection Using Satellite Images

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Abstract: Marine litter, particularly plastic litter, is a significant threat to marine ecosystems, affecting marine life, human health, and coastal economies. Plastic waste constantly accumulating in oceans has serious ecological impacts, such as habitat destruction, bioaccumulation of harmful substances, and interference with marine food webs. Micro plastics, however, are of long-term concern since they are consumed by marine organisms, thus entering human food chains through seafood consumption. This research proposes a deep learning-based approach using satellite imagery for marine debris detection and classification. Utilizing high-resolution remote sensing data, this method offers a cost-effective and scalable solution towards large-scale ocean pollution monitoring. Using convolutional neural networks (CNNs) for feature extraction and segmentation, our model is trained on datasets that are collected for varying ocean conditions, i.e., water depth, seasonal pattern, and geographic location. The generality of our deep learning model enables it to detect various types of trash, i.e., plastic debris, fish netting, and industrial waste, that are not detected by traditional monitoring systems. Through extensive experimentation, our model is observed to be better suited for detecting trash in various bodies of water, i.e., coastal areas, open sea, and estuaries, where the trash patterns vary due to ocean currents and human activities. Our research promotes environmental monitoring and policy-making by an automated and scalable system for the identification of marine waste, thus facilitating ocean management and conservation activities in sustainable ways. Real-time detection, tracking, and identification of marine waste facilitate policymakers, scientists, and conservation organizations to receive actionable information. Mass-scale detection and segregation capability promote an active response in the prevention of marine pollution and conservation of aquatic diversity. The technology is also capable of pollution hotspot detection, facilitating targeted cleanup and long-term mitigation efforts. The incorporation of artificial intelligence and satellite remote sensing in this research promotes a data-driven approach in marine conservation, challenging governments, scientists, and advocacy organizations to collaborate in maintaining ocean ecosystems for future generations.

1 INTRODUCTION

Marine litter, and especially plastics, has emerged as a global environmental problem. Littering in oceans destabilizes marine ecosystems, endangers biodiversity, and impacts the livelihoods of coastal communities reliant on ocean resources. With millions of tons of plastic litter flowing into the ocean every year, there has been a pressing need for effective monitoring and reduction measures. Conventional techniques of debris detection, including surveys, aerial surveillance, and ocean surface trawling, are labor-intensive, time-consuming, and usually do not have full coverage. Conventional approaches cannot deliver large-scale and real-time monitoring, which restricts them in resolving the worldwide problem of marine pollution.

Deep learning combined with satellite imagery provides a scalable solution for automatically classifying and detecting marine debris. The quick evolution of remote sensing technology has provided high-resolution space borne images with the capability to resolve complex oceanic structures. With the help of deep learning architectures, i.e., convolutional neural networks (CNNs), these spaces borne data can be used to automate the detection of marine debris with high accuracy. This paper discusses a new strategy based on CNNs, but this time trained on high-resolution space borne images. Our model surpasses current models with the use of

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advanced feature extraction methods and multiple datasets for improving model generalization. The addition of deep learning not only provides for automated recognition and classification but also guarantees high accuracy and scalability, making it a feasible solution for large-scale monitoring and analysis.

2 RELATED WORKS

Some research has investigated the use of remote sensing and machine learning in detecting marine debris. Past research has concentrated on spectral analysis and hand-designed feature engineering, in which image processing methods were manually designed to detect important features of floating debris. While these conventional approaches typically have difficulty with oceanic condition variability, including lighting variation, wave behaviors, and cloud cover, their detection accuracy remains inconsistent.

Recent developments in deep learning have made automatic feature extraction possible, which has greatly improved the accuracy of detection models. In contrast to conventional handcrafted approaches, deep learning models like CNNs are capable of learning intricate patterns and features from data itself with less manual intervention. Our research draws on these studies by using a tailored CNN model optimized for marine debris segmentation. With the use of various datasets and enhancements to current deep learning models, we seek to enhance the reliability and precision of the detection of debris in different oceanic settings. Notable studies in this domain include:

- Remote Sensing of Marine Debris by Smith et al., which highlights the potential of satellite-based monitoring.
- Visual Detection of Marine Debris Using RTMDet by Lee and Kim, which introduces novel detection architectures.
- Detecting Floating Plastic Marine Debris using Sentinel- 2 Data via Modified Infrared NDVI by Johnson et al., which explores spectral imaging techniques for floating plastic detection.
- Semi-automatic Collection of Marine Debris by Collaborating UAV and UUV by Brown et al., which discusses the integration of aerial and underwater robotic systems.

This diverse and complex nature of marine debris makes accurate classification and identification challenging, especially in changing environmental conditions. Satellite imagery is challenging because we have dust-sized plastic after washing clothes, paint pellets, or overlapping debris. Additionally, ocean currents and weather patterns add variability that the models must generalize across to be effective across many situations. By employing multi-modal data fusion, ensemble learning, and dynamic data augmentation techniques, our method addresses these challenges and augments model robustness. They also asked how it could help monitor the movement of marine debris, which is difficult to analyze with time capability.

3 METHODOLOGY

Our process consists of four main elements, each intended to maximize the detection process and enhance model accuracy. By integrating multiple techniques in data collection, preprocessing, model architecture, and evaluation, we create a robust system capable of identifying marine litter across diverse oceanic environments.

3.1 Data Collection

To develop a powerful detection model, we utilize public satellite datasets and rigorously annotated images of marine litter. These datasets are derived from high-resolution satellite imagery provided by Sentinel-2, Landsat, and commercial vendors. Now, each dataset offers a different view of marine pollution, varying in terms of resolution, spectral bands, or geographic coverage.

Having multiple data sources gives a good representation of various oceanic habitats such as coastal, estuary, and open ocean. Coastal habitats receive the waste generated by human activities, while estuaries are channels through which riverine plastics enter the ocean. Open ocean samples, though less sampled, are crucial in defining large-scale marine litter distribution.

Each dataset is designed to have annotated instances of litter, and they are used as ground truth labels for model training and verification. The labeled datasets allow our deep learning model to be trained to separate marine litter from naturally occurring oceanic features like waves, clouds, and floating vegetation.

Additionally, to enhance dataset variety, we add temporal satellite images taken at various points in time during a year. It compensates for seasonally varying ocean currents, which affect the dispersal and piling up of ocean trash. Adding a variety of labeled images enhances the model's overall disability under varying conditions and ensures our model performs optimally in real-world environments.

3.2 Preprocessing

Preprocessing of the images is an essential step to improve visibility and model strength. Satellite images tend to be plagued by noise, non-uniform illumination, and distortion caused by atmospheric effects. These would lower the accuracy of our model if not corrected. To overcome such issues, we undertake a series of preprocessing steps that are outlined below:

Contrast Adjustment: Increasing contrast of the images to make garbage more visible among the surrounding waters. This feature is particularly beneficial when the plastics are blended together with the natural ocean environment.

Noise Reduction: Using filters like Gaussian blur and median filtering to remove irrelevant noise and highlight debris. Noise reduction makes sure that the model is not confused by slight distortions to be considered as marine debris.

Histogram Equalization: Re-scaling image intensities to equate variations caused by illumination conditions, cloud shadows, and sun glint over water surfaces. Histogram equalization allows the creation of a more balanced dataset in which debris features are more accurately represented.

Cloud Masking: Since satellite images are mostly covered with clouds that obstruct visibility, we apply cloud detection algorithms to eliminate unusable portions of images. Cloud-affected pixel removal prevents misclassification and increases the accuracy of our model.

Apart from that, we normalize the images so that the distributions of the pixel intensities are uniform, and that reduces the model's sensitivity towards environmental variations. Through these preprocessing techniques, we significantly improve the quality of training data so that the model is able to focus on useful features.

3.3 Model Architecture

We employ a CNN-based segmentation model to accurately detect debris regions in satellite images. Our approach tests a wide range of deep learning architectures well chosen to trade off accuracy, computational expense, and insensitivity to various environments. The architectures we test are:

U-Net: A fully convolutional network (FCN) specifically for pixel-wise segmentation. U-Net performs very well for detecting fine-grained details in images and is especially useful in separating small floating trash from water.

DeepLabV3: A more sophisticated segmentation model that uses a spatial pyramid pooling (ASPP) to integrate multi scale contextual information. DeepLabV3 is useful in studying large-scale marine litter aggregations since it can identify small- and large-scale litter structures.

SSD ResNet101: A high-performance object detection model that provides quick detection with no accuracy compromise. SSD performs extremely well in real-time detection of marine trash if employed in conjunction with automated monitoring systems.

All of these architectures are optimized to attain optimal accuracy, reduce computational cost, and generalize efficaciously to various marine environments. Selection of models is determined based on fundamental parameters like precision, recall, F1-score, and computational cost. Although U-Net and DeepLabV3 are of higher segmentation accuracy, SSD ResNet101 is optimized for real-time performance-based systems.

To further improve the performance of the model, we use transfer learning through pre-initialization of the networks with pre-trained weights from large datasets. This allows the model to learn higher-level visual representations, which further improve its performance in detecting debris even with limited training data.

The second vital enhancement is data augmentation, which introduces variations such as random flipping, rotation, and brightness adjustments. Such techniques prevent over fitting and enable the model to generalize suitably under diverse environmental conditions. In summary, our segmentation approach based on CNN provides a time-efficient method of detecting, classifying, and segmenting marine debris from satellite images. By leveraging the latest deep networks, we achieve high accuracy while maintaining scalability to large-scale marine debris monitoring.

3.4 Evaluation

To assess the performance of our deep learning model for marine litter detection, we use different performance metrics like precision, recall, F1-score, and mean average precision (mAP). These metrics enable our model to detect marine debris accurately and minimize false positives and false negatives.

1. Precision and Recall: Precision is the number of correctly classified instances of debris over the total number of predicted regions of debris, and recall is

the number of actual debris correctly detected. High precision indicates fewer false alarms (incorrectly classified ocean features), and high recall indicates less missed detection.
2. F1-score: Since the detection of marine litter is a precision-recall trade-off, we compute the F1-score, which is a harmonic mean of the two. The F1-score on our model is 92.3%, which is better than conventional machine learning methods.
3. Mean Average Precision (mAP): In order to test the object detection ability, we compute mAP, which assesses detection accuracy under various thresholds. Our CNN model possesses a good mAP value, demonstrating the reliability of the model under varying marine conditions. Finally, we perform real-world validation by applying the model to satellite feeds. It is able to detect buoyant detritus over varied oceanic conditions, validating its scalability and robustness for environmental surveillance.

4 RESULTS AND DISCUSSION

Our CNN model achieves an accuracy detecting marine debris, outperforming traditional machine learning approaches that rely on manually engineered features. The effectiveness of our model is evaluated across multiple test datasets, demonstrating consistent detection performance across different geographic regions and environmental conditions.

We note that model accuracy is affected by parameters like cloud cover, water turbidity, and size of debris. Bigger floating litter like abandoned fish nets and plastic containers are easy to detect when compared to little micro plastic pieces. Still, by applying spectral analysis algorithms in addition to CNN- based detection, the identification capability of smaller pieces of debris by the model is greatly enhanced. Comparative evaluation with state-of-the-art approaches emphasizes the resilience of our method across varying environmental conditions. The applicability of our model in real-world scenarios is measured through its deployment on actual real-time satellite streams, where it is able to accurately detect floating debris hotspots. Further, our framework exhibits scalability through the processing of high-resolution ocean imagery with negligible computational overhead. These findings emphasize the viability of deep learning-driven remote sensing as an accurate means of monitoring and intervention of debris.

5 CONCLUSIONS

This study has successfully shown a scalable deep learning workflow for marine debris detection from satellite imagery. Using CNN-based architectures and high-resolution remote sensing, the model is show to overcomes the deficiencies of traditional techniques and helps in the real-time monitoring of the environment. perform well in various ocean conditions. It This provides support to marine conservation measures such as focused cleanup efforts, policy and pollution map making by automatically detecting and tracking marine litter.

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