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Detecting Floating Marine Macro Litter (FMML) Using Deep Learning Models

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Abstract:

Floating plastic debris on water surfaces poses both immediate and long-term threats to the environment. Therefore, identifying and monitoring plastic pollution is crucial for understanding its location and scale. This article presents a framework for detecting and tracking floating plastic debris in inland waters using optical satellite image time series, leveraging the advantages of multitemporal Earth observation data. The detection process begins with a rule-based approach that analyzes variations in signal intensity, temporal patterns, spectral characteristics, and information fusion to identify potential plastic candidates. Once sensitive areas are detected, they can be continuously monitored, and the extent of plastic coverage at a subpixel level is estimated using spectral unmixing. The method requires only a specified time frame and area of interest as input parameters, eliminating the need for manually selecting specific images or outlining regions of interest. Several case studies demonstrate the successful application of this workflow, developed as a Google Earth Engine application, to identify highly affected areas in full Sentinel-2 scenes. These examples span different continents and environmental contexts, capturing floating plastic debris of varying types and dynamics.

2. Introduction:

Plastic debris pollution has become a critical environmental challenge worldwide, particularly affecting aquatic ecosystems. The extensive use of plastic in daily life, its economic importance, inadequate waste management, and its long-lasting durability have all contributed to the continuous release and persistence of vast amounts of plastic in the environment [1] [2] [3]. This pollution is transported through atmospheric processes, surface runoff, and water bodies, leading to widespread accumulation in various ecosystems. Plastic debris has been documented in freshwater systems, coastal areas, floating garbage patches in ocean gyres, and even deep-sea environments [6] [7]. Significant accumulations have been recorded and studied across major water bodies, including the Atlantic Ocean, the Indian Ocean, and even the Antarctic region[12].

The environmental threats associated with plastic pollution include risks to marine and terrestrial organisms through ingestion and entanglement, bioaccumulation of toxic substances in the food chain, leakage of harmful additives, and disruptions to ecosystem services. Research by Lebreton et al. estimated that between 1.15 and 2.41 million metric tons of plastic enter the ocean from rivers annually, with 67% of these emissions originating from just 20 major rivers—15 of which are located in Asia. Meijer et al. later refined these estimates, suggesting that emissions from smaller rivers had been significantly underestimated, and that over 1,600 rivers contribute to 80% of global riverine plastic pollution, totaling between 0.8 and 2.7 million metric tons.[5] [6] Additionally, Van Calcar and van Emmerink found that rivers in Asia transport up to 30 times more plastic than their European counterparts, with much of this plastic retained within river catchments until extreme hydrological events trigger its release into the ocean[12].

Detecting and monitoring plastic debris in these ecosystems is crucial for developing effective mitigation strategies. Understanding the volume of plastic accumulation and the extent of plastic washed away by floodwaters is essential for informed decision-making. Advances in remote sensing technology, combined with the increasing availability of open satellite data and enhanced big-data processing capabilities, offer significant potential for comprehensive and continuous monitoring of plastic pollution through Earth observation (EO)[15]. Furthermore, highlighting the visibility of floating plastic debris from space can help raise public awareness of the severity of plastic pollution[16], potentially driving mitigation efforts.

This article presents a framework for detecting and monitoring plastic debris in inland waters using time-series data from open remote sensing sources and information fusion techniques[22] [23]. The study explores the opportunities and challenges associated with monitoring floating debris using current spaceborne missions, which vary in spectral and spatial resolution, revisit frequencies, and data accessibility. High-resolution EO imagery clearly captures the presence of plastic debris, as demonstrated in case studies across three continents: Guatemala, Bosnia, and Egypt. In each of these locations, plastic accumulation is linked to dams regulating inland water flow. This study aims to detect and monitor floating plastic debris in such cases using lower spatial resolution data while leveraging the higher temporal resolution provided by open-data satellite programs, such as the Copernicus initiative[18].

3. Related Works:

Various methods are available for monitoring plastic pollution in rivers and freshwater systems[21]. Traditional approaches typically focus on localized monitoring, including tracking plastic debris using GPS devices, active sampling with nets, passive sampling through floating booms or garbage collectors, visual counting from bridges or vessels[24] and using installed cameras or autonomous aerial vehicles (AAV) for airborne surveys[19]. While these methods offer valuable insights, they are often limited in spatial coverage and scalability. In contrast, satellite-based Earth Observation (EO) technologies provide a more extensive geographic reach, faster revisit times—such as approximately one week with Sentinel-2 data—and the ability to monitor aquatic environments on a larger scale. Detailed reviews of these methodologies are provided by Topouzelis et al. and Waqas.

Effective satellite-based monitoring of marine and coastal plastic debris requires distinguishing between shoreline and in-water detection, as the latter presents challenges due to infrared signal attenuation and temporal variability. Research suggests quantifying the signal-to-noise ratio for accurate detection of both submerged and floating debris. Optical Sentinel-2 satellite data has been widely used for identifying floating plastic debris in marine and coastal environments [27]. One of the most commonly applied spectral indices for detecting macroplastic is the Floating Debris Index (FDI), designed to identify plastic accumulation on clear water surfaces[30].

Hu explored the capabilities and limitations of Sentinel-2 data for remote sensing of marine debris, concluding that while large debris patches can be detected effectively due to Sentinel-2's balance between resolution and coverage, interpreting the data requires caution due to variations in spatial resolution across different spectral bands. Additionally, researchers working on the MARIDA dataset found that relying solely on spectral features limits plastic detection from space. To improve classification performance, they integrated spatial information, including textural features.

Sentinel-2 imagery enables inland and coastal water analysis at a ground sampling distance (GSD) of 20 meters, or 10 meters when using three visible bands and band 8 in the near-infrared range. However, extracting spatial features from affected areas remains constrained at this resolution. Ruburm et al. applied U-NET and U-NET++ deep learning architectures trained on MARIDA and the Floating Objects database to detect nearshore marine debris in Sentinel-2 images, demonstrating improved performance over a random forest (RF) baseline model[7],[8].

Hu also highlighted that while Sentinel-2 is widely used for marine debris detection, mixed band resolutions and subpixel debris coverage necessitate careful spectral data interpretation to minimize misclassifications. The study emphasized the importance of pixel averaging and subtraction techniques in designing effective detection algorithms.

The Plastic Litter Project investigated remote sensing of floating plastic debris using both unmanned aerial systems (UAS) and Sentinel-2 satellite imagery[3],[7]. Findings demonstrated that high-resolution UAS imagery enhances the geospatial accuracy of satellite observations and that artificial plastic targets can serve as useful references for calibrating and validating remote sensing algorithms[16],[17]. The study confirmed that floating plastic debris can be detected with Sentinel-2 under specific conditions, taking into account plastic type, coverage fraction, biofouling, and submersion effects.

Furthermore, Taggio et al. demonstrated a combined approach for detecting floating plastic debris using a mix of unsupervised (K-means) and supervised (light gradient boosting model) classification applied to pan-sharpened hyperspectral PRISMA data. This approach further highlights the potential of integrating different classification techniques for improving plastic debris detection from space.

4. Methodology:

This section outlines the workflow used to analyze multitemporal optical satellite data over a specified period. The process is divided into time steps to identify potential plastic accumulation areas based on spectral variations. The detection of floating debris relies on changes in spectral intensity when plastic appears on water surfaces. Key factors considered include:

- The initial presence of water,
- Increased signal intensity when plastic is present, particularly in the infrared spectral range,
- Filtering out false positives from clouds and urban areas,
- Ensuring a sufficient spatial extent to detect plastic accumulation over time at the given Ground Sampling Distance (GSD).

The initial identification of plastic candidate regions enables further detailed monitoring, allowing for refined analysis of plastic accumulation dynamics through subpixel-level evaluation.[4] This approach is particularly valuable for studying plastic debris in narrow water channels. Additionally, it facilitates large-scale screening for less prominent plastic accumulations on water surfaces.

A. Image Time-Series Selection

The process begins with filtering the Sentinel-2 image archive within a specified time frame, selecting a point of interest, and determining the number of images required. Case study examples (see Section III) illustrate this selection process.

1. Sorting by Cloud Cover:
   - The available images are sorted based on cloud cover percentage.
   - The image with the least cloud coverage is selected.
2. Avoiding Consecutive Acquisitions:
   - A 15-day time window is applied around the chosen acquisition date to prevent selecting images too close in time.
   - This threshold is based on global testing and serves as a balance between minimizing cloud cover and maintaining an adequate temporal sampling rate.
3. Iteration:
   - The algorithm repeats this selection process until the required number of image tiles is obtained.

B. Water Masking

Since the goal is to detect floating plastic, the analysis is restricted to water surfaces where plastic debris is assumed to be absent in at least one image from the time series.

Based on the Normalized Difference Water Index (NDWI) but modified using the NIR-Green band combination, which improves water body detection and vegetation differentiation. Sentinel-2 bands 8 (NIR) and 3 (Green) are used due to their high spatial resolution[31].

To enhance reliability, a composite image is created by taking the minimum intensity values for each pixel across the time series. A pixel is classified as water[31].

- 0.06 for large water bodies (dams, lakes, and wide rivers), as suggested by previous studies.
- 0.3 for small water channels, where mixed water-land pixels are common.

For specific contexts, the threshold can be manually adjusted to optimize accuracy.

C. Spectral Characteristics of Plastic

Plastic debris exhibits distinct spectral properties, appearing more prominently in the infrared range compared to shorter wavelengths. To enhance detection, an additional spectral

check is applied:

- The NIR band (Sentinel-2 Band 8) must have a higher intensity than Bands 4–7 (red and red-edge channels).
- Bands 5–7 (20m resolution) are also considered for refining classification.

The resulting binary masks are summed across all time steps to produce the final spectral- based detection mask. This methodology integrates spectral, temporal, and spatial analysis to improve floating plastic debris detection, particularly in inland waterways. By combining water masking, intensity change detection, and spectral validation, it ensures robust identification of plastic accumulation while minimizing false positive.

5. Existing System:

The detection and monitoring of **Floating Marine Macro Litter (FMML)** are vital for protecting marine biodiversity and maintaining healthy ecosystems. Existing systems primarily rely on a combination of **manual surveys**, **aerial and satellite imagery**, and **underwater video footage** to identify and track marine litter.[11] These systems typically involve the following components:

1. **Data Acquisition:**
   Data is collected from various sources, including:
   - **Aerial imagery** using drones or aircraft.
   - **Satellite images** capturing wide-range ocean surfaces.
   - **Underwater cameras** mounted on buoys, remotely operated vehicles (ROVs), or autonomous underwater vehicles (AUVs).
2. **Annotation and Labeling:** The collected visual data is manually annotated by experts to label marine litter. This process is often labor-intensive and time-consuming, especially when large datasets are involved[14]. These annotations are later used for training machine learning or deep learning models.
3. **Traditional Image Processing:** Conventional image processing techniques such as **thresholding**, **edge detection**, **color-based segmentation**, and **contour analysis** are applied to detect visible litter. While these methods are relatively simple and computationally light, they lack the ability to adapt to complex underwater and surface conditions[13].
4. **Manual Inspection and Reporting:** In many scenarios, trained personnel manually review images and videos to identify floating debris. The results are then compiled into reports for further analysis or action[10]. This process is not only time- consuming but also subject to human error and fatigue.
5. **Challenges in the Existing System**
   - **Environmental Variability**: Varying lighting conditions (e.g., glare on water, cloud cover) and water clarity (e.g., turbidity, reflection) affect image quality, making detection less reliable.
   - **False Positives/Negatives**: Marine litter often resembles natural objects like seaweed, driftwood, or marine fauna, leading to misclassification.
   - **Lack of Real-Time Detection**: Most systems operate offline, with data analyzed post-collection, resulting in delays in response and intervention.
   - **Scalability Issues**: Manual surveys and image labeling are not scalable for large-scale or long-term monitoring efforts.
   - **Cost and Resource Intensive**: High-resolution satellite data and underwater monitoring equipment are costly to deploy and maintain, especially in remote or deep-sea locations.

Due to these limitations, there is a growing need for **automated, accurate, and real-time FMML detection systems** that leverage advancements in **AI, deep learning, and remote sensing** to enhance the efficiency and effectiveness of marine litter monitoring and management.

6. Proposed System:

To overcome the limitations of existing methods, the proposed system introduces a deep learning-based approach for the detection and classification of Floating Marine Macro Litter (FMML)[8]. The system leverages the powerful capabilities of Convolutional Neural Networks (CNNs) to automatically identify and categorize plastic debris present in marine environments, significantly improving accuracy and efficiency compared to traditional techniques.

This approach is designed to handle a wide variety of plastic litter types under diverse environmental conditions such as varying light levels, water clarity, and background interference[24]. The system aims to function in real-time or near-real-time, making it more practical for deployment in active monitoring and response systems.

Key Components of the Proposed System

A. Data Collection and Preprocessing

The system will be trained on a comprehensive FMML dataset that includes images of various plastic items (e.g., bottles, bags, fishing nets) collected from aerial, satellite, and underwater sources.

Data preprocessing steps include:

1. Resizing and normalization of images to standard dimensions and pixel value ranges.
2. Data augmentation techniques (rotation, flipping, brightness adjustment, etc.) to increase dataset diversity and improve model generalization.
3. Noise reduction and filtering to enhance image clarity.

B. Dataset Splitting

The dataset will be split into three subsets:

1. Training set: Used to train the CNN model.
2. Validation set: Used during training to tune hyperparameters and prevent overfitting.
3. Testing set : Used to evaluate the final model's performance.
4. This split ensures robust and unbiased performance evaluation.

C. Deep Learning Model Construction

1. A Convolutional Neural Network (CNN) architecture will be

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designed or selected based on its effectiveness in image classification tasks.

2. Depending on the complexity, pre-trained models like ResNet, VGG16, or MobileNet may be used and fine-tuned using transfer learning.

The model will be tailored to:

1. Extract spatial and contextual features of plastic debris.

2. Differentiate between litter and natural elements (e.g., seaweed, rocks).

D. Model Training

1. The CNN model will be trained using backpropagation and an optimizer such as Adam or SGD.

2. Loss functions like categorical cross-entropy will be used for multi-class classification.

3. Training will involve multiple epochs, and metrics such as accuracy, precision, recall, and F1-score will be monitored.

E. Model Evaluation

1. Once trained, the model will be evaluated on the test dataset.

2. Performance will be assessed using:

a. Confusion matrix to visualize true vs. predicted classifications.

b. Precision and recall to measure the model's ability to detect litter accurately.

c. ROC-AUC curves (if applicable) for classification confidence.

3. The goal is to achieve high accuracy with minimal false positives and false negatives, ensuring reliable FMML detection in diverse scenarios.

Advantages of the Proposed System

- Automation: Eliminates the need for manual inspection and annotation.
- Scalability: Can be deployed over large areas and on different platforms (drones, satellites, buoys).
- Adaptability: Works under a wide range of environmental conditions due to robust training.
- Efficiency: Provides faster and more consistent results compared to human observers or traditional methods.

7. Result and discussion:

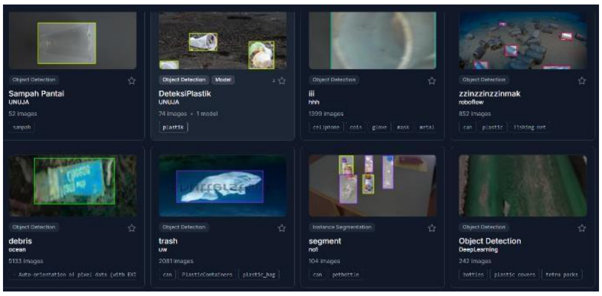

Fig 7.1: Detection and Monitoring Modules

In the Fig 7.1 These modules are used to detect and monitor marine litter, especially FMML. They are often focused on identifying and tracking pollution sources, floating debris, and the movement of litter in the ocean.

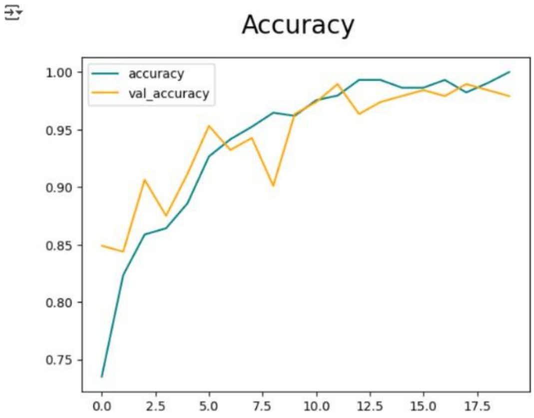

Fig 7.2: Accuracy

In Fig 7.2 The accuracy level can be shown .It can be predicted as 80% of the detection

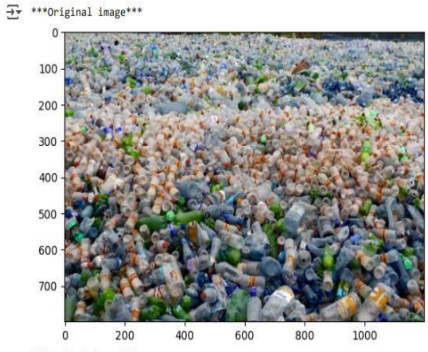

Fig:7.2 original image

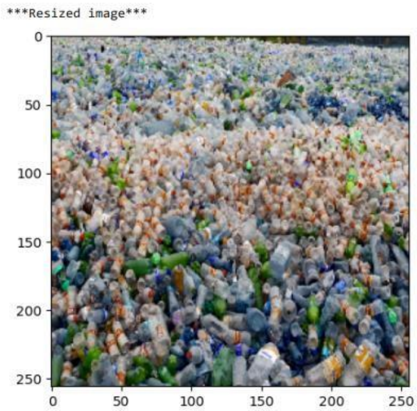

Fig:7.3 resized image

In Fig 7.2 and 7.3 It can be detecting the plastic by using https://universe.roboflow.com/search?q=plastic%2520waste.

It can be detected at the accuracy level of 80%.

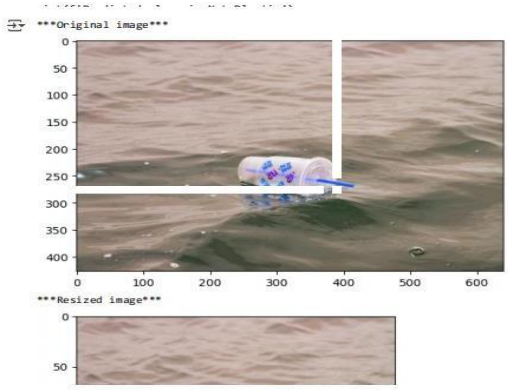

Fig 7.4: plastic in water

Conclusion:

Marine plastic pollution has emerged as a critical threat to the health of our oceans, marine biodiversity, and global ecosystems. Floating Marine Macro Litter (FMML), which includes large plastic items drifting on the ocean surface, poses serious environmental hazards and demands timely and accurate detection mechanisms for effective mitigation. Traditional methods of FMML detection—often relying on manual surveys or basic image processing techniques—have proven to be limited by their dependence on human effort, susceptibility to environmental variations, and lack of scalability.

In this project, we have proposed and developed *plastocean*, an intelligent system that utilizes deep learning models, particularly Convolutional Neural Networks (CNNs), for the detection and classification of FMML from oceanic image data. The project involved multiple crucial phases including data acquisition, preprocessing, model training and evaluation, and visualization of detection results. Through rigorous experimentation and the use of a well-curated dataset containing various types of floating litter under diverse oceanic conditions, we were able to train a model that significantly improves upon the limitations of existing systems in terms of accuracy, consistency, and adaptability.

The results demonstrate that deep learning-based models can effectively identify and classify FMML with high precision, even under challenging scenarios such as low lighting, water disturbances, or the presence of visually similar objects. Our system is not only capable of detection but also scalable for integration with UAVs, satellite imaging, or ship-mounted camera systems, making it a promising solution for large-scale, automated marine litter surveillance[14].

Beyond detection, the project also contributes to the larger vision of environmental conservation and sustainable marine resource management. By enabling faster and more reliable monitoring of plastic waste in oceans, *PlastOcean* can assist policymakers, environmentalists, and cleanup organizations in making informed decisions and deploying timely action plans.

Overall, this project establishes a robust technological foundation for intelligent FMML detection. It paves the way for further research in real-time marine pollution tracking and reinforces the critical role of artificial intelligence in environmental protection initiatives. With future enhancements like the incorporation of video-based detection, hybrid deep learning architectures, and real-time processing capabilities, this system can evolve into a comprehensive platform for global marine litter management.

Future Enhancement:

While the current implementation of the *PlastOcean* system marks a significant step forward in the automated detection of floating marine ment. These future improvements can help make the system more robust, real-time, and globally scalable. The following are key directions for future enhancement:

1. Integration of Multiple Data Sources

To improve the comprehensiveness and accuracy of FMML detection, future versions of the system can incorporate data from diverse platforms such as:

- **Satellite Imagery:** Offers wide-area surveillance of ocean surfaces, useful for detecting large-scale litter patterns and pollution hotspots across vast regions.
- **UAV (Drone) Data:** Provides high-resolution, low-altitude imagery for more localized monitoring, especially near coastlines or in remote oceanic areas.
- **Ship-Mounted Camera Systems:** Enable continuous monitoring during marine voyages and can feed real-time data directly into the detection system.

By fusing data from these varied sources, the model can develop a holistic understanding of marine litter distribution and movement, improving both spatial and temporal coverage.

2. Advancing Deep Learning Models with Modern Architectures

The current model primarily uses CNNs for image classification and detection. Future enhancements can explore:

- **Attention Mechanisms:** These help the model focus on specific regions of the image that are most likely to contain FMML, thereby improving precision and reducing false positives.
- **Transformers:** Originally designed for natural language processing, transformers are now revolutionizing computer vision as well (e.g., Vision Transformers or ViTs), offering superior performance in image recognition tasks.
- **Hybrid Architectures:** Combining CNNs with transformers or other models like Recurrent Neural Networks (RNNs) can leverage the strengths of multiple techniques, leading to more robust detection under variable environmental conditions.

Such architectural improvements will make the system more adaptable to diverse marine scenarios, including different lighting conditions, wave patterns, and cluttered scenes.

3. Real-Time Detection and Tracking

A major step forward would be enabling **real-time processing** of video feeds or continuous image streams:

- This can be particularly useful for onboard systems in ships or deployed drones where timely detection can trigger immediate action—such as deploying clean-up devices or alerting authorities.

- Real-time tracking will also allow for continuous observation of litter movement, aiding in predictive modelling and better understanding of how litter disperses across ocean currents.

Implementing lightweight and efficient models (e.g., using Tensor RT or ONNX for deployment on edge devices) will be essential to support real-time applications in resource-constrained environments.

4. Use of Sequential and Temporal Data

Current systems often rely on static image frames. Future developments should focus on:

- **Sequential Frame Analysis:** Using video data can help the model understand temporal continuity—identifying whether an object persists across multiple frames, thereby reducing false positives caused by transient elements like waves or reflections.
- **Motion-Based Detection:** Analyzing movement patterns helps in distinguishing actual floating litter from still ocean surface features. This is particularly beneficial in dynamic marine environments.

Incorporating temporal information through models like RNNs or 3D CNNs can drastically improve detection consistency over time.

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