Plastic Pollution Detection Using Satellite Images

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***Abstract*—This project is on plastic pollution detection using satellite images. Plastic pollution in oceans is a major challenge in today's world. The detection, classification, and tracking of pollutants need continuous monitoring and powerful machine learning (ML) Algorithms. In this project, I will be reviewing existing works on plastic pollution in oceans as I work towards enhancing the results and also implement measures that trigger an alarm on plastic pollutant occurrence to mitigate it and promote total eradication of plastic pollutants in our oceans.**

Keywords*— Plastic-Pollutant, Machine Learning(ML) Detection, Classification, Tracking, Monitoring, Eradication, Remote sensing, Satellite Imagery.

ADMIN PART

The source code and implementation details can be accessed on GitHub: *https://github.com/KeneKing12/DILL700-TERM-PROJECT*

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I. Introduction

The plastic and cans recycling management in Sweden is something that has caught my attention, and this leaves me with questions about why we still have plastic pollution in the world when Sweden as a country has proven that plastics can be managed and recycled, bringing huge economic benefits to both the users and the manufacturers. As someone deeply concerned about the environmental impact of plastic pollution, I have seen first-hand how this issue affects ecosystems and communities, especially in areas where plastic waste overwhelms natural habitats. The growing accumulation of plastic in oceans, rivers, and landscapes is a pressing problem that demands urgent action. While the problem is widespread, the challenge lies in effectively monitoring and tracking plastic waste across vast, often inaccessible areas.

In addressing this challenge, satellite imagery, combined with machine learning techniques, is used to develop an innovative solution for detecting and monitoring plastic pollution [1Sentinel]. This project aims to create an automated system capable of identifying plastic debris in satellite images, even in complex environments such as water, sand, and vegetation. Doing so will contribute to more efficient and accurate pollution monitoring, which can ultimately support better-informed environmental policies and actions. The goal is to provide a practical tool that can assist in tackling plastic pollution on a large scale, offering a pathway to a cleaner, more sustainable future for our planet.

THE EU AI REGULATION'S IMPACT ON PLASTIC POLLUTION DETECTION USING SATELLITE IMAGES

The EU AI Act is a regulatory framework aimed at ensuring AI systems in the European Union are safe, transparent, and aligned with fundamental rights. The act, in its transparency, ensures that satellite-based plastic pollution detection algorithms are reliable and accountable. this will increase the reliability of the project by users and thus more adoption of the work through the use of AI.

The negative impact of the EU act on this project is due to its necessary compliance on AI-driven research, which comes with a great cost and, as such, slows down the implementation of this project if no external funding is provided.

Finally, since the system is built to trigger an alarm when a pollutant is detected, the system is classified as a high-risk detection and, as such, must comply with strict compliances, such as a human-in-the-loop mechanism, accurate models, data security, and privacy according to EU data protection laws.

II. LITERATURE REVIEW

Plastic pollution, especially in marine and coastal environments, has emerged as a global ecological and socio-economic threat. Traditional monitoring methods, such as manual sampling and aerial surveys, are expensive and often spatially or temporally limited. In response, the use of remote sensing, particularly satellite imagery, has gained traction as a cost-effective and scalable solution for monitoring plastic pollution over large areas [1].

A. *Using CNN on the Sentinel-2 Satellite Images for plastic pollution.*

CNN, an acronym for Convolutional Neural Network, is one of the best neural networks, and it gives automatic feature extraction and efficient spatial pattern recognition, which is very vital to detecting actual occurrence of plastic pollutants. Overall, CNN achieved 95% accuracy when used in the training of the dataset.

B. *Using DETR Transformer on the Sentinel-2 Satellite images for plastic pollution*.

The DETR (Detection Transformer) is a state of the art transformer based model designed for object detection tasks. It can be used effectively for detecting objects like plastic debris in satellite images, such as those from the Sentinel-2 satellites in the MERIDA dataset. It enables end-to-end training without needing separate pipelines for region proposals.

C. *Using Hybrid (CNN and DETR Transformer) Models on the Sentinel-2 Satellite Images for Plastic Pollution*

The CNN handles the local feature extraction, while the transformer captures the global contest, enabling the model to detect and track plastic debris in complex satellite imagery. This provides high-quality and scalable plastic pollution detection.

III. REQUIREMENT AND DATA ANALYSIS

A. *Dataset*

The MERIDA stands for Marine Debris Archive, and it is a publicly available dataset designed for research in marine plastic pollution detection using remote sensing techniques. The dataset was developed to address the lack of labeled data for training and validating machine learning models aimed at detecting plastic debris in satellite imagery [2].

The MERIDA dataset is collected from the Sentinel-2 satellite images and consists of 11 spectral channels derived from Sentinel-2 bands. The bands include the visible colors (RGB), near infrared(NIR), and the shortwave wavelength. It includes data from different regions and water conditions with plastic debris and natural materials captured from sea surfaces. The images are provided in smaller patches for easier processing and modeling, and each patch has an associated label titled plastic, organic, or background [2].

Image 1 heat maps from the sentinel image captured from the satellite. Once plastic materials are identified, a heat map is created by assigning a color gradient, usually from blue or green for low concentrations to red for high concentrations. The heat map shows areas where plastic debris or pollution is more concentrated. The intensity of the color in the heat map corresponds to the likelihood of plastic being present in that area.

The MERIDA dataset is classified as Plastic and Non-plastic based on the sample collected from the satellite image as recorded in the Sentinel-2 image.

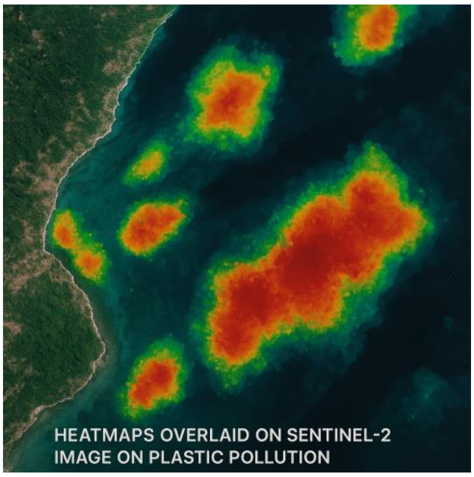

Fig. 1.0: Heat maps of the Sentinel-2 image.

B. *Preprocessing*

The raw satellite data is preprocessed to remove noise and any atmospheric interference. This often involves calibration and correction steps to ensure that the data reflects true surface properties. It includes data from different regions and water conditions with plastic debris and natural materials captured from sea surfaces. The images are provided in smaller patches for easier processing and modeling, and each patch has an associated label titled plastic, organic, or background [2].

C. *Implementing the training*

The Training of the dataset was done using the python environment called Google Colab and this provided a link to seamlessly upload the work on GitHub directly.

D. *Project Specification Requirements*

Specification	Target Value
Accuracy	>=85%
Recall	>=90%
Response Time	< 5s per image
Robustness	Works in varied water conditions

Fig. 2.0: The Project requirements.

To achieve a trusted result, it has to gain public acceptance. The requirements were tailored down to the following requirements:

- Accuracy: We aim for an accuracy greater or equal to 85% but not less.
- Recall: We aim for sensitivity or a true positive of greater or equal to 90%
- Response Time: We aim for the system to take less than 5 secs to process each image; hence, we have thousands of images captured at a time, and a faster response time is needed to process these images.
- Robustness: Most of the data comes in with lots of imperfection, and we want our system to take care of this imperfection and still generalize well. Hence, we aim to achieve high robustness so it can be implemented in any water conditions.

IV. SYSTEM ENGINEERING

System engineering deals with the arrangement of the steps taken to finally arrive at the result (output) to know if the pollution is plastic or non-plastic pollution.

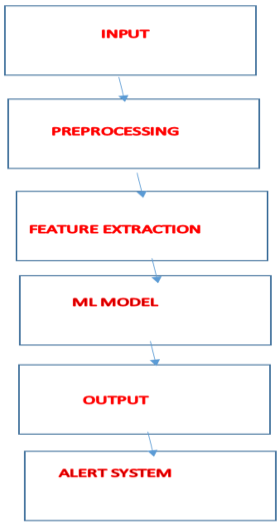

Fig. 3.0: The System block diagram

- **Input:** These are images from the satellite that were captured; they are the raw data that will be analyzed.
- **Preprocessing**: This is the necessary fine-tuning of the raw data to prepare it for processing. the pre-processing involves noise reduction, cloud masking, and contrast enhancement.
- **Feature Extraction**: This involves spectral band analysis, texture descriptors, and color histograms. It helps in reducing the complexity of the data while retaining its attributes.
- **ML Model**: This is the actual machine learning model that was used to train the data set. here, I used CNN(U-NET), DETR transformer and Hybrid (CNN and DETR) in training the model.
- **Output**: This is the final result after training the dataset; it is the classification of the result either as Plastic or Non-plastic alongside a confidence score.
- **Alert System:** This is the system that generates an alert if the plastic pollution surpasses the threshold. It is an automated system whereby a plastic pollution incident is automatically notified through an alarm.

V. ALGORITHM DESIGN USING SPIRAL APPROACH

Using a spiral approach, I adopted two iterations whereby I evaluate models' performance on each of the iterations using predefined specifications and then using the results to improve the models' training with additional requirements to achieve good results.

A. *Iteration 1: Baseline Models*

- **U-Net CNN**: The U-net is specifically designed for semantic segmentation tasks. Here, the model is trained using the training dataset. The U-Net takes the satellite images as inputs and outputs segmentation masks that height regions of marine debris. Each image has a corresponding mask with labels for marine debris. Then, the U-Net was trained, and the model learns to predict these labels by minimizing the loss function during training. The model achieved an accuracy of 88.3%, and this shows how convolutional networks like U-Net can achieve massive feature extraction.

B. *Iteration 2:*Hybrid (CNN and DETR Transformer)

To optimize the results from the first iteration, we employed the combination of the U-net and the DETR-Transformer(detection transformer). The CNN handles the local feature extraction, while the transformer captures the global context, enabling the model to detect and track plastic debris in complex satellite imagery. This provides high-quality and scalable plastic pollution detection.

The result was very impressive as we gained a boost of 90.77% on the analysis from the dataset.

VI. RESULTS

A. *Results from the Models used and comparing them*

MODELS	ACCURACY
CNN(U-NET)	88.3%
DETR-TRANSFORMER	89.2%
HYBRID(U-NET and DETR TRANSFORMER)	90.77%

Fig. 4.0: The model's accuracy outputs

The baseline CNN model achieved an accuracy of 88.3% on the U-Net model. The Detection transformer(DETR) achieved 89.2%, and the Hybrid transformer, which combines the U-net and the DETR (that is, the local features and global context to achieve an accuracy of 90.77%.

VII. CONCLUSION

This project explored machine learning-based plastic pollution detection using satellite imagery. The dataset used here was the MERIDA dataset containing Sentinel-2 images from satellite captured from different regions in the Marine [3].

The CNN U-Net model demonstrated superior performance, achieving an accuracy of 89%, while the DETR Transformer achieved an accuracy of 89.2%. But with Hybrid

(U-NET and DETR), we were able to achieve a far better accuracy of 90.77%

Despite notable progress, challenges such as cloud occlusion, image noise, and dataset imbalance persisted. Addressing these issues through advanced preprocessing, additional training data, and model refinement remains a priority for future research.

VIII. FUTURE CONSOLIDATION OF ATPS AND FUTURE PLAN

Our Hybrid network, which involves the combination of CNN-based U-NET and detection Transformer(DETR-Transformer), gave us an accuracy of 90.77% on the MERIDA dataset. The combination gave us far more achievement above our specific requirements. While the CNN-based U-NET handles the local feature extraction, the DETR-Transformer handles the global context, and this greatly addresses the issues of accuracy and hence will gain public acceptance when the results of plastic pollution are stated and also makes the MERIDA dataset a very robust dataset.

FUTURE WORK

To further improve real-world applicability, Future works will focus on:

- Real-time deployment using edge computing and integrating explainable AI techniques to enhance transparency.
- By leveraging AI and remote sensing, this approach presents a scalable solution for monitoring marine pollution and supporting environmental conservation efforts
- Implementing an automated system to automatically trigger the occurrence of Plastic pollution.

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