Detection of Plastic Litter on Beaches

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I. Introduction

Plastic pollution is one of the most critical environmental problems, threatening marine ecosystems, wildlife, and human health. According to Our World In Data, annual plastic production has escalated dramatically, experiencing an almost 230-fold increase from 2 million tonnes in the 1950s to 459 million tonnes in 2019. Specifically during 2019, more than 970 thousand tonnes of plastic waste entered the ocean. The presence of plastic waste on beaches and ocean is troubling due to a higher likelihood of ingestion by marine animals and birds.

Recent research has quantified the mortality risk of plastic ingestion across taxa. The study analyzed more than 10000 necropsies of seabirds, marine animals, and sea turtles. It showed that ingestion of macroplastic, such as hard and soft plastics, rubber and fishing debris leads to acute mortality by obstructing, perforating or twisting the gastrointestinal tract. The study also estimated that ingesting anywhere from 6 to 405 pieces of macroplastic of various sizes can result in a 90% probability of death. These findings strongly emphasized the urgent need of monitoring and mitigating plastic litter in coastal environments.

Detection of plastic litter on beaches offers a versatile and efficient way to measure and monitor plastic litter over the traditional manual surveys, which tends to be time-consuming, labor-intensive, and prone to human error. Consequently, this project utilizes the BePLi v1 dataset, to develop an object detection model to detect plastic litter in an effort to reduce wildlife exposure and environmental risks.

II. Dataset

The dataset used in this project is the BePLi v1 dataset, which consists of 3709 images of beach plastic litter collected from beaches in Yamagata Prefecture, Japan. Each image is accompanied by manually annotated labels. The dataset contains only a single class, which is plastic litter. The dataset is organized into two directories: images and labels. The image directory is subdivided into original_images, train, test, and val folders, containing 3709, 2226, 742, and 741 images, respectively. The labels directory contains JSON files corresponding to the train, test, and val splits in a partially modified MS COCO format.

III. Modeling

This project uses a pre-trained model, which is the You Only Look Once (YOLO) model, specifically YOLOv8n as the main model. This model is chosen due to its balance between speed and accuracy, making it suitable for real-time applications. The architecture is divided into three main components, which is Backbone, Neck, and Head.

1. The Backbone utilized Convolutional Neural Network (CNN) to extract multi-scale features from the input image.
2. The Neck aggregates the extracted features using an optimized version of the Path Aggregation Network (PANet), improving the detection of objects at different sizes and scales.
3. The Head predicts the bounding box coordinates, confidence score, and object class based on the extracted features.

The model was fine-tuned on the BePLi v1 dataset using hyperparameters such as 200 training epochs, a batch size of 32, and an input image size of 640x640. Furthermore, the fine tuning process is illustrated in Figure 1.

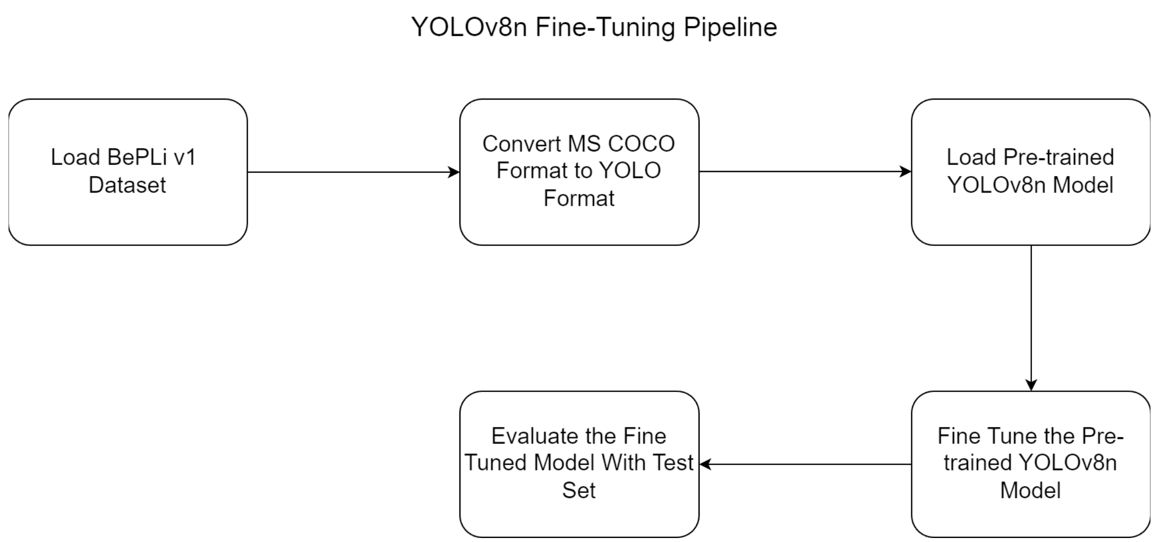

Figure 1. YOLOv8n Fine Tuning Pipeline

The fine tuning process started by loading the BePLi v1 dataset and converting the annotations from MS COCO format to YOLO format, which is required for training the YOLO model. Then, the pre-trained YOLOv8n model was loaded and fine tuned on the BePLi v1 train set. Lastly, the model was evaluated using the test set to obtain the evaluation results, including Precision, Recall, F1 Score, mAP50, and mAP50-95.

IV. Evaluation

The fine-tuned YOLOv8n model was assessed using Precision, Recall, F1 Score, mAP50, and mAP50-95. Precision measures the proportion of the correctly predicted positives among all positive predictions, showing how accurately the model predicts an object. Recall measures the proportion of correctly predicted positives among all actual positives, indicating how well the model detects all positive objects. Meanwhile, F1 Score combines Precision and Recall to measure how the model is able to trade off between precision and recall in a balanced manner. This is because an increase in precision would reduce recall, and vice versa. Furthermore, mAP50 is the mean Average Precision at a single Intersection over Union (IoU) threshold of 0.5, where a detection is considered correct if its IoU is greater than or equal to 0.5. For context, Average Precision measures the area under the Precision Recall (PR) Curve, while Intersection over Union (IoU) measures the overlap between the predicted bounding box and the ground truth bounding box. Lastly, mAP50-95 is the mean of Average Precision calculated at multiple IoU thresholds between 0.5 and 0.95 in increments of 0.05.

The fine-tuned YOLOv8n model evaluation results shows that the model attains Precision of 0.52 and Recall of 0.40. This suggests that approximately half of the positive predictions are correct, whereas only 40% of the actual plastic litter instances are effectively captured. The F1 Score of 0.45 reflects a moderate overall performance, underscoring an inherent trade off between Precision and Recall. Furthermore, the model obtained an mAP50 of 0.39, indicating that the model correctly detects 39% of the litter instances with sufficient overlap. This shows that the model is able to detect many objects, but struggle with localization. Lastly, the mAP50-95 of 0.17 indicates that many predicted bounding boxes didn't precisely aligned with the ground truth bounding box. In conclusion, the model is able to detect the plastic litter moderately but struggles with precise bounding box prediction on smaller or occluded plastic litter.

V. Deployment

The fine-tuned model was deployed as a website application using Streamlit. The application allows the user to upload an image of a beach containing plastic litters, and the model will perform an inference and output the predicted bounding box and the corresponding confidence score as illustrated in Figure 2.

Figure 2. Workflow of Beach Plastic Litter Detection Web Application Using Streamlit

VI. Reflection

This project demonstrates the practicality of utilizing deep learning-based object detection to detect plastic litter on beaches by using BePLi v1 dataset and YOLOv8n model. The model was able to detect plastic litter with moderate accuracy while still being lightweight, making it ideal for real-world deployment. Furthermore, the deployment into a web application using Streamlit highlights the feasibility of employing Artificial Intelligence for environmental monitoring. However, we experienced several challenges in this project.

The evaluation results indicate that the model performed moderately, resulting in low Precision, Recall, F1 Score, mAP50, and mAP50-95, in which the model struggles to detect all plastic litter and localize the bounding box precisely. These challenges could be tackled by expanding the dataset to incorporate more diverse beach conditions, lighting conditions, and plastic litter classes. Furthermore, utilizing larger YOLO variant models may further improve the accuracy. Overall, this project highlights both the potential and the challenges of applying a deep learning-based object detection model to real world environmental problems.

VII. Related Links

The source code for the project is hosted in Github and can be accessed at https://github.com/Alvindra1/Deep-Learning-Beach-Waste-Object-Detection-Using-YOLOV8n.

VIII. References

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