Assignment-04

Object Detection

CSE475 (Machine Learning)

Section: 03

Fall 2024

Submitted By

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2021-2-60-027

Submitted To

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Date of Submission: 8th January, 2025

YOLO-Based Underwater Plastic Detection

Abstract

This report presents the implementation of a YOLOv8-based object detection system designed for identifying underwater plastic waste. Leveraging advanced computer vision techniques, the system aims to address the critical issue of underwater pollution. The study details the methodology, experimental outcomes, and potential applications, along with evaluating the system's strengths and limitations.

1. Introduction

Underwater plastic pollution poses a significant threat to marine ecosystems and biodiversity. This report introduces a YOLOv8-based object detection system specifically designed to identify and localize plastic debris in underwater environments. By utilizing a custom dataset and state-of-the-art machine learning techniques, the study aims to contribute to environmental conservation efforts.

2. Methodology

2.1 **Dataset**

The dataset used comprises images of underwater scenes contaminated with plastic debris. It is divided into three directories: Train, Validation, and Test, containing labeled images for model training and evaluation. Preprocessing techniques such as Dark Prior Channel were applied to enhance image contrast and improve detection accuracy.

2.2 **System Architecture**

The system employs the YOLOv8 Nano model for its balance of efficiency and accuracy. The architecture involves data preprocessing, model training, validation, and prediction. The pipeline ensures optimal performance for detecting underwater plastic debris.

2.3 **Training Configuration**

Key hyperparameters:

- Model: YOLOv8 Nano
- Epochs: 10 [Took 6.5 hours to run 10 epochs, so couldn't increase the epochs]
- Batch Size: 16
- Learning Rate: 0.001
- Image Size: 640 pixels
- Weight Decay: 0.0005
- Augmentation: Random rotations, flips, and color adjustments

3. Performance Evaluation

3.1 Model Metrics

Metric	**Value**
Precision	0.7228
Recall	0.4794
mAP@50	0.5197
mAP@50-95	0.3562
Accuracy	0.6011

3.2 **Prediction Outcomes**

Predictions effectively localized underwater plastic debris with minimal false positives. Annotated visuals were generated for qualitative analysis.

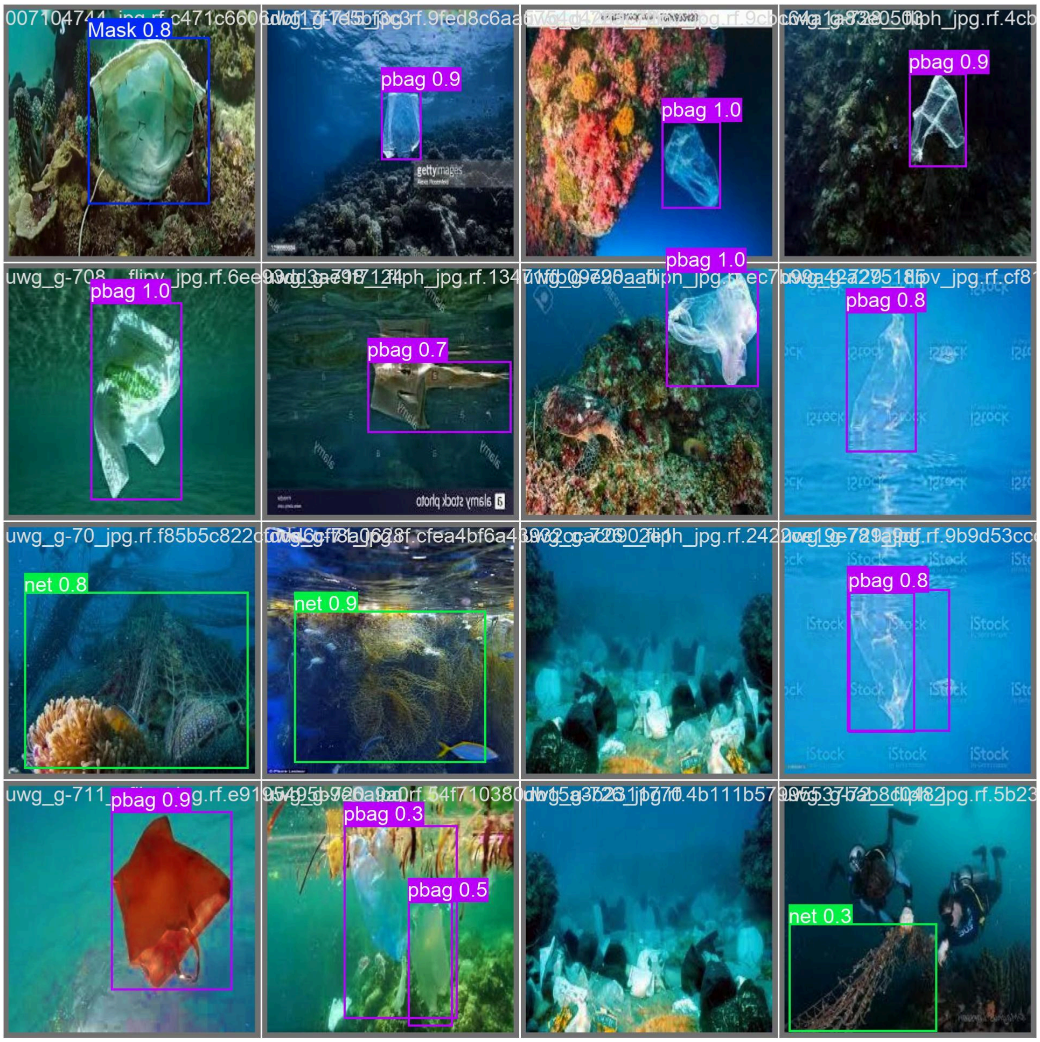

Figure 1: Annotated image showcasing bounding boxes and labels for detected plastic debris.

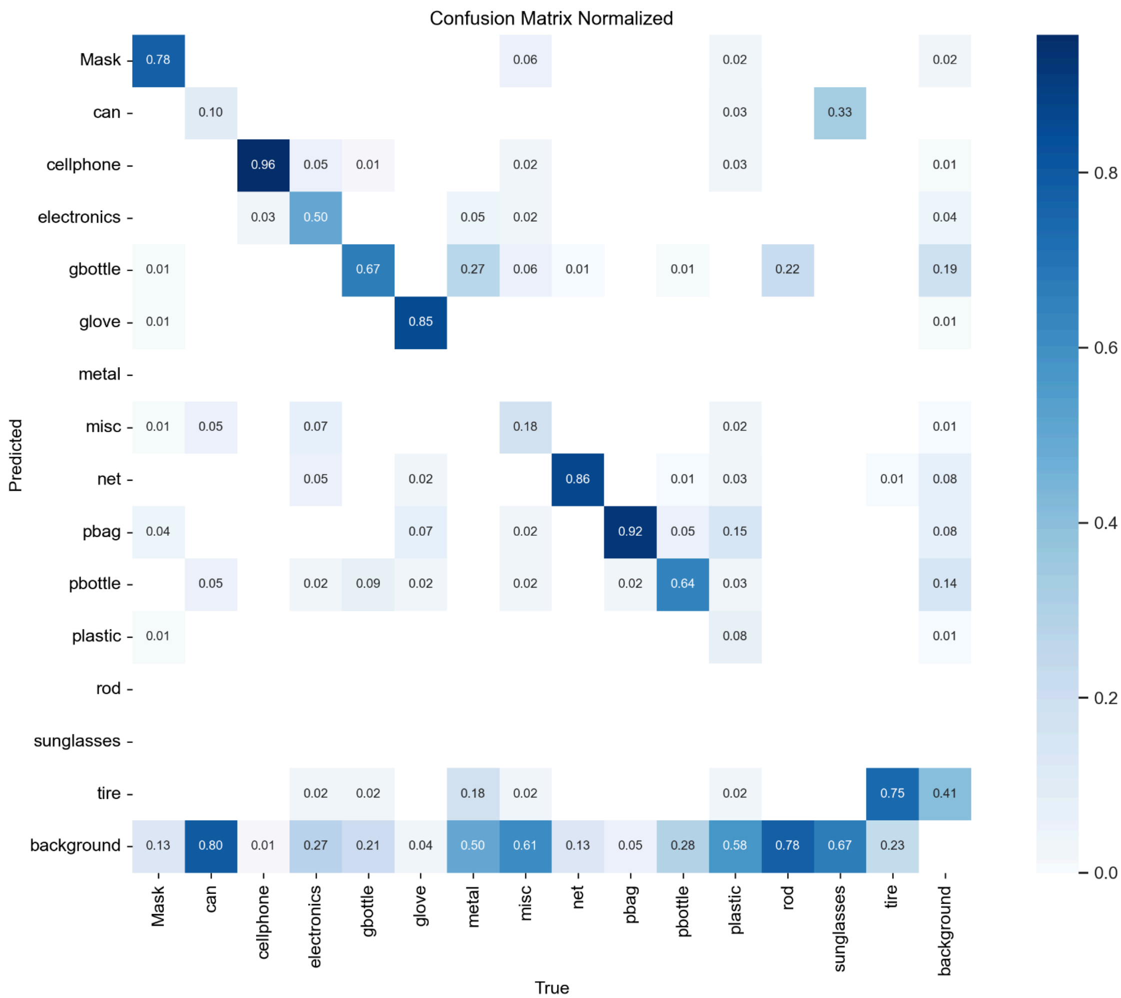

Figure 2: Confusion Matrix Normalized.

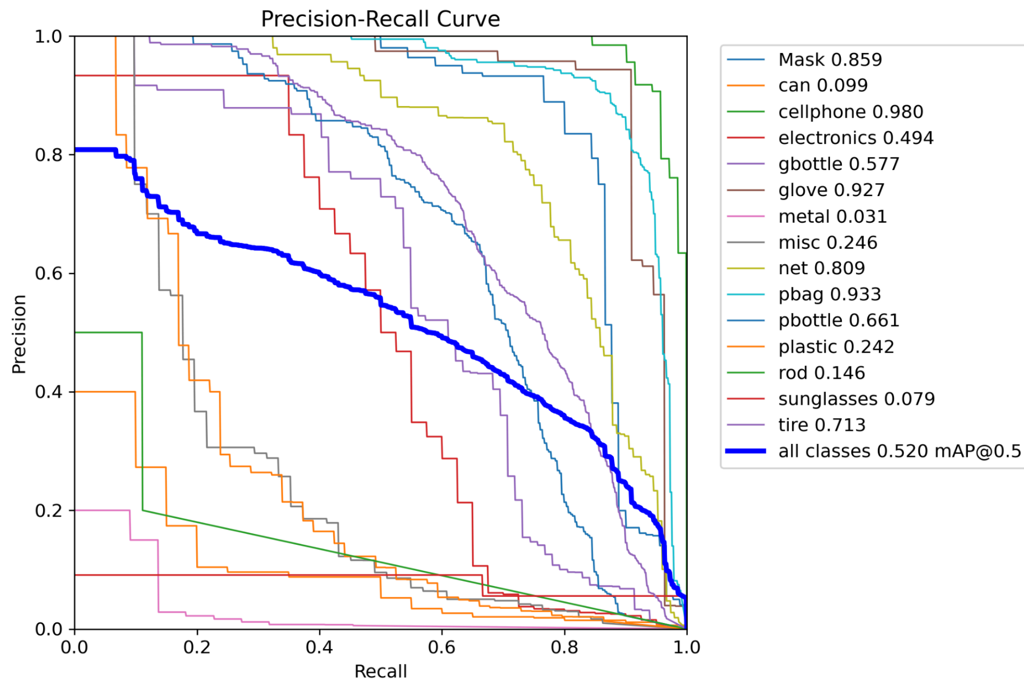

Figure 3: Precision-recall curve demonstrating model performance across confidence thresholds.

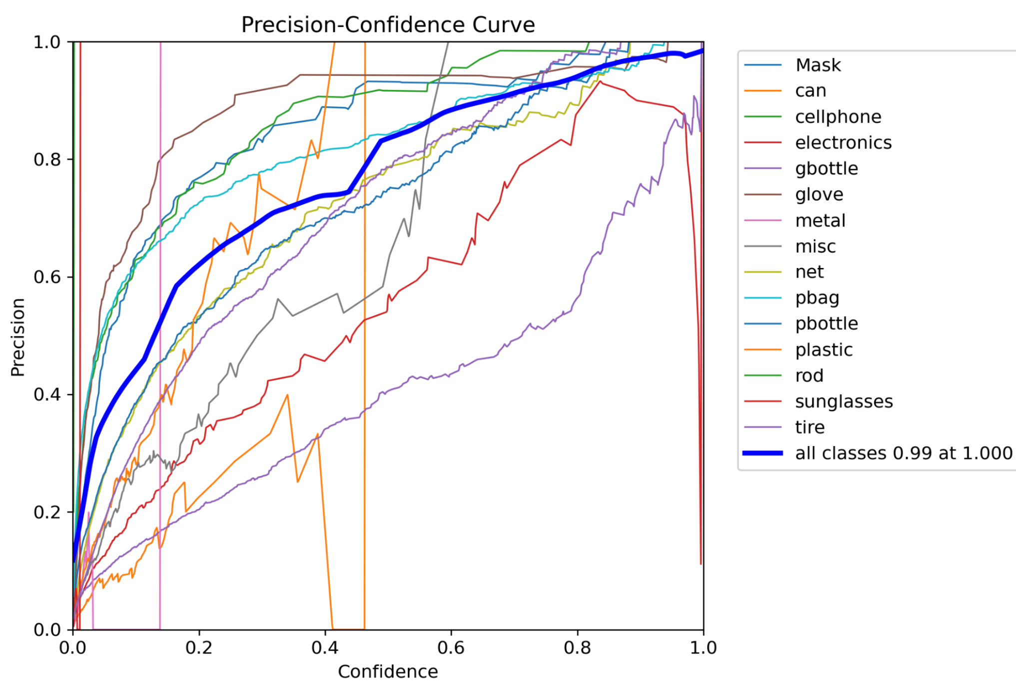

Figure 4: Precision-confidence curve demonstrating model performance across confidence thresholds.

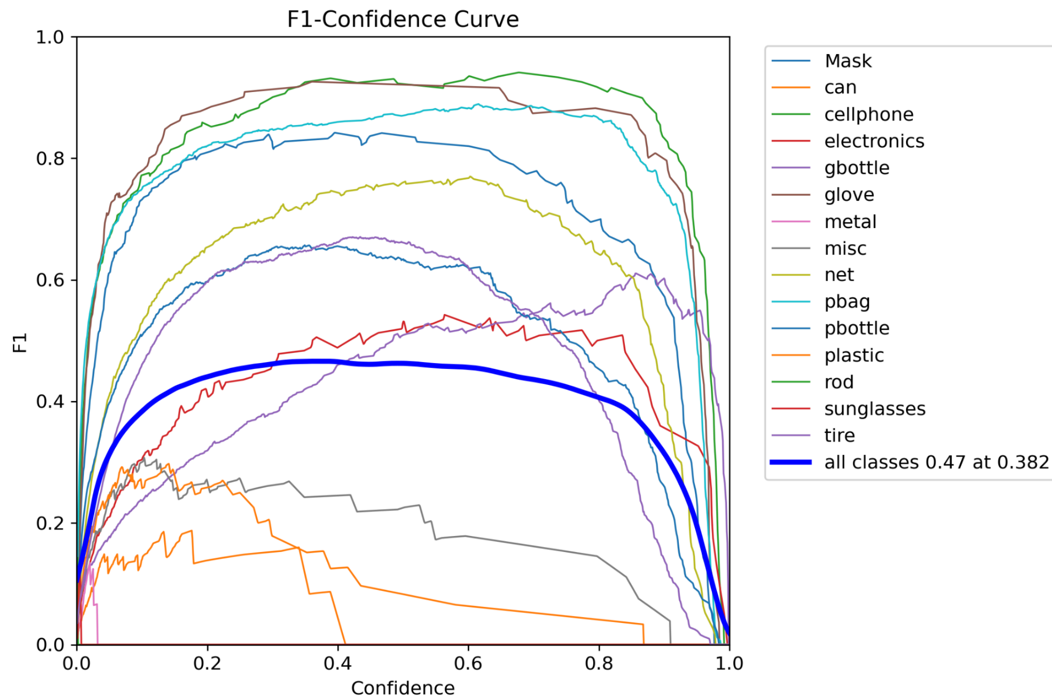

Figure 5: F1-Confidence curve demonstrating model performance across confidence thresholds.

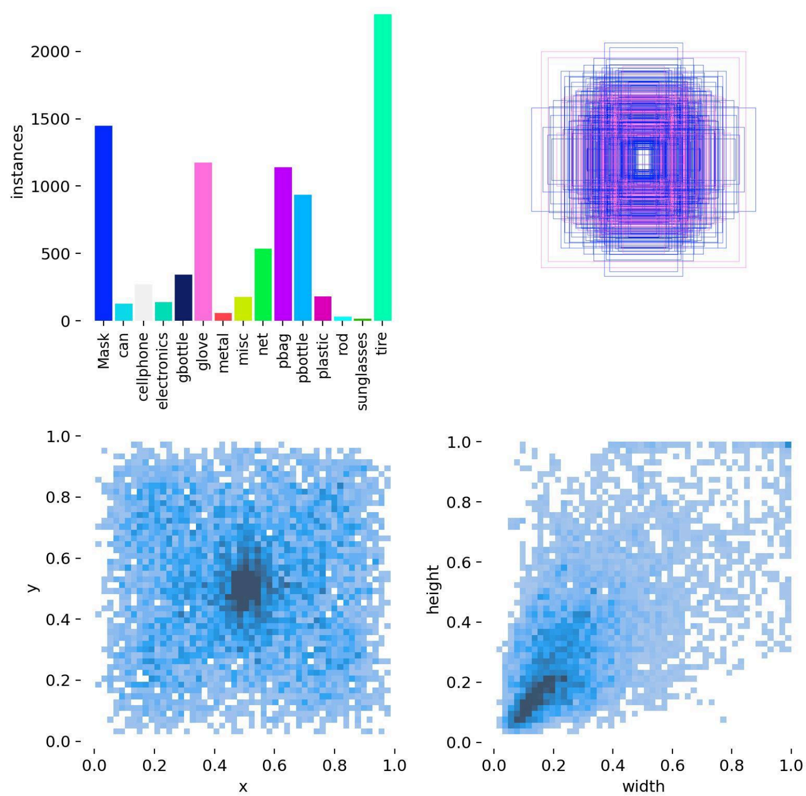

Figure 6: Labels demonstrating model performance across confidence thresholds.

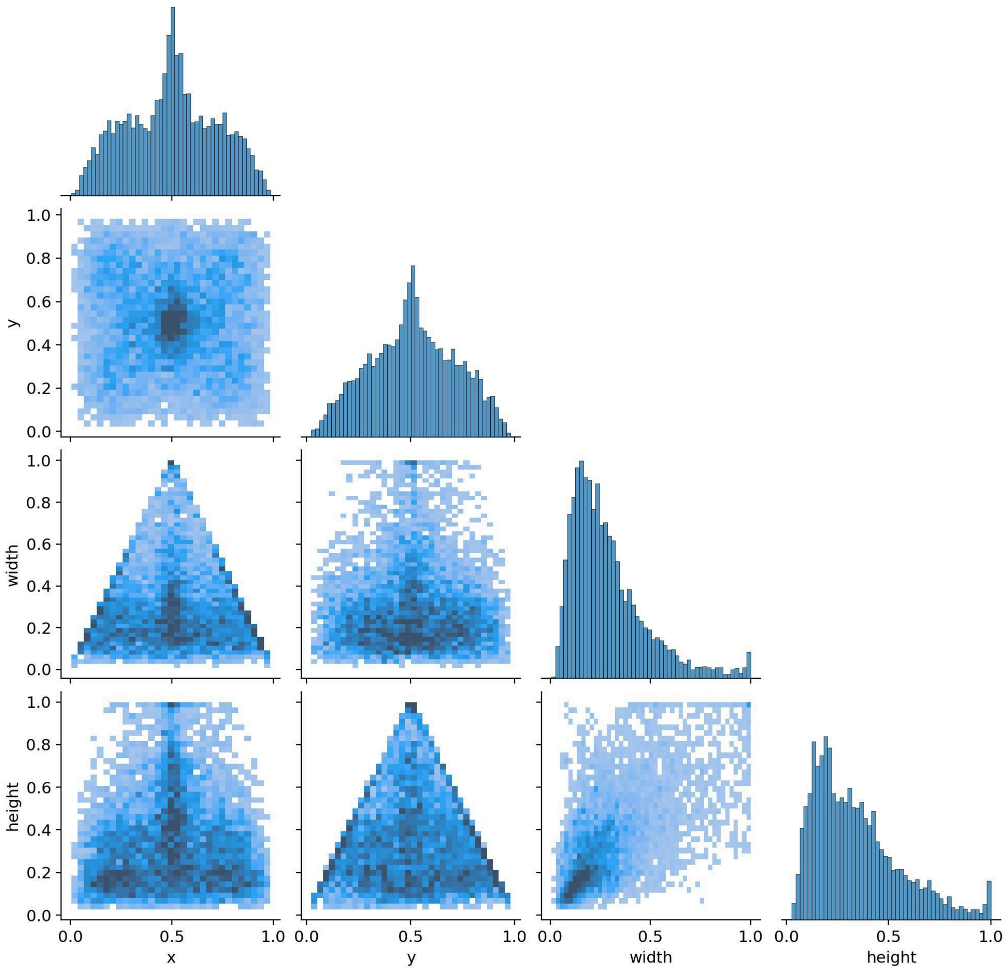

Figure 7: Labels of Correlogram.

4. Results

4.1 Visual Outputs

Annotated images were produced to visualize the model's detection capabilities. Bounding boxes accurately localized various classes of underwater plastic waste.

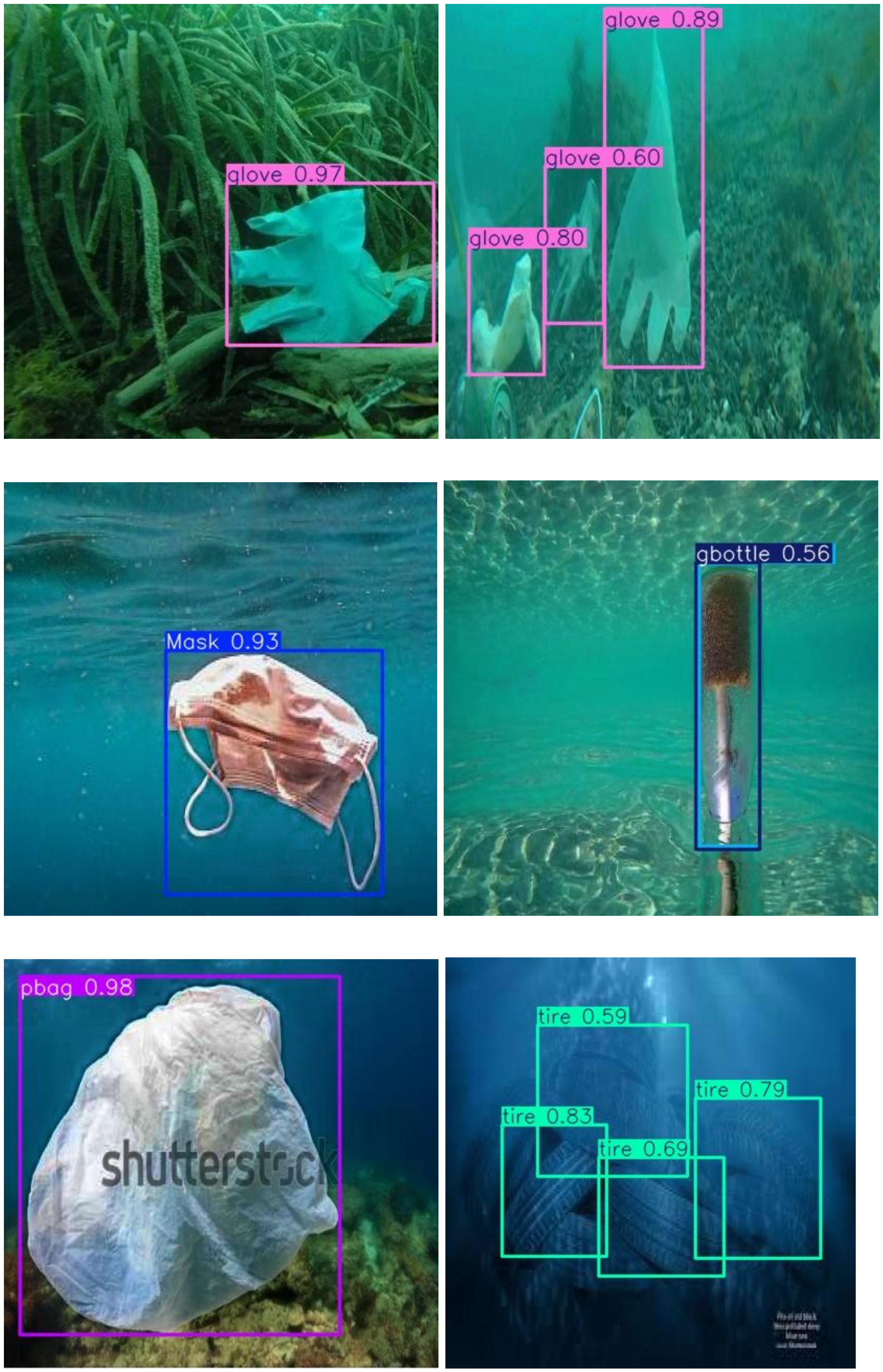

Figure 8: Visuals demonstrating model detection of underwater objects.

5. **Discussion**

The results of the YOLOv8-based system highlight its potential in addressing the critical issue of underwater plastic detection. While the model achieved a precision of 0.7228, indicating a high rate of correct positive detections, its recall of 0.4794 points to challenges in identifying all plastic objects present in the dataset. This discrepancy suggests room for improvement in capturing a more comprehensive range of underwater debris, particularly smaller or occluded objects.

The mAP@50 of 0.5197 and mAP@50-95 of 0.3562 indicate moderate performance in terms of average precision across varying confidence thresholds. These metrics demonstrate the model's capability to generalize across different conditions, though the relatively low mAP@50-95 emphasizes the need for better handling of complex underwater scenarios with diverse object sizes and shapes.

Accuracy, measured at 0.6011, further reflects the system's overall classification capabilities. While acceptable, this value highlights the challenges posed by underwater environments, including poor visibility and noise, which can affect model performance. Visual outputs confirm the effective localization of plastic objects, with bounding boxes accurately marking detected items. However, instances of false negatives and false positives were observed, suggesting the necessity for dataset augmentation and further hyperparameter tuning.

Strengths of the system include its lightweight architecture, enabling efficient real-time processing, and its effective handling of larger, clearly visible objects. However, limitations such as restricted dataset diversity and static hyperparameter settings have constrained the model's adaptability and overall accuracy. To address these issues, future work should focus on:

- Expanding the dataset to include more diverse underwater conditions and object types.
- Exploring advanced preprocessing techniques to mitigate underwater noise and visibility challenges.
- Implementing dynamic hyperparameter optimization to adapt the model to varying data distributions.
- Incorporating additional evaluation metrics, such as F1 scores and ROC curves, for more comprehensive performance analysis.

6. **Conclusion**

The YOLOv8-based underwater plastic detection system demonstrates a promising approach to tackling marine pollution. With a precision of 0.7228, the model reliably identifies plastic debris, contributing to efforts in environmental conservation. While the moderate recall and mAP values underscore the challenges of underwater detection, the system's efficient architecture positions it as a viable tool for real-time applications.

Future enhancements are essential for improving the system's adaptability and scalability. Expanding the dataset to capture diverse underwater scenarios, optimizing hyperparameters dynamically, and integrating real-time capabilities will significantly bolster its utility. Additionally, developing a user-friendly interface for deployment and visualization can further its applicability in real-world scenarios. This study underscores the critical role of AI-driven solutions in addressing environmental challenges, paving the way for sustainable innovations in marine conservation.