CSI3006 Soft Computing Techniques

J Component Project

UNDERWATER GARBAGE DETECTION USING YOLOv8 FOR REAL-TIME MARINE TRASH IDENTIFICATION

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ABSTRACT

Marine pollution is an increasingly pressing issue, severely impacting aquatic ecosystems and marine biodiversity. Manual monitoring and cleanup efforts are time-consuming, costly, and inefficient, especially in underwater environments with poor visibility and vast coverage areas. This project proposes an automated system using the YOLOv8 (You Only Look Once version 8) deep learning model to detect various types of underwater garbage in real time.

We have trained our model using a custom YOLOv8-compatible dataset titled "Underwater Garbage Detection.v1i.yolov8", which includes **15 annotated classes** such as **'Mask', 'can', 'cellphone', 'electronics', 'gbottle', 'glove', 'metal', 'misc', 'net', 'pbag', 'pbottle', 'plastic', 'rod', 'sunglasses', 'tire'**. The model was trained with appropriate data augmentation techniques, batch sizes, and hyperparameters optimized for performance on limited hardware resources. The project ensures accurate detection with minimized false positives, leveraging the advanced detection architecture and anchor-free object recognition capabilities of YOLOv8.

Our objective is to develop an effective and scalable system capable of being deployed on real-time underwater vehicles or drones to support marine conservation efforts. The model's accuracy is evaluated using standard metrics like mean Average Precision (mAP), precision, and recall. This system aims to provide a foundation for future integration into augmented reality applications that could assist divers by displaying detected trash directly on smart goggles.

This project demonstrates that real-time underwater trash detection is not only feasible but can significantly aid in maintaining ocean cleanliness and raising environmental awareness using modern deep learning techniques.

1. INTRODUCTION

1.1 Background

The health and sustainability of marine ecosystems are under severe threat due to increasing levels of underwater pollution. Human-generated waste, such as plastics, glass, metals, rubber, and electronic items, is being continuously deposited into oceans, rivers, and lakes. This not only poses significant risks to aquatic organisms through ingestion or entanglement but also affects biodiversity, water quality, and the global food chain. Current manual cleanup methods are labor-intensive, costly, and cover only limited areas, often missing micro and deeply submerged pollutants.

With the advancement of artificial intelligence and computer vision, particularly deep learning, it is now possible to detect and classify a variety of objects in real-time with impressive accuracy. This project aims to harness these capabilities to tackle underwater pollution by building an automated underwater garbage detection system using YOLOv8 — one of the latest and most powerful object detection models available.

1.2 Motivations

The project is motivated by the need to protect aquatic life and the broader ecosystem through smarter, more scalable technological solutions. Traditional underwater monitoring relies heavily on human divers or remotely operated vehicles (ROVs), which are limited by cost and time constraints. By introducing automation into this space, we aim to:

- Enable real-time, accurate identification of underwater waste items.
- Support eco-friendly robotic cleanup operations.
- Assist in long-term ocean health monitoring.
- Lay the groundwork for augmented reality (AR) applications that could assist divers or underwater drones in identifying and reacting to waste dynamically.

1.3 Scope of the Project

This project will focus on:

- Preparing a curated dataset of underwater trash items, annotated across 15 object classes (e.g., plastic bottles, cans, nets, electronics, masks, etc.).
- Implementing a YOLOv8-based object detection model and training it on this dataset.
- Evaluating the model using standard metrics such as mAP (mean Average Precision), confusion matrix, precision-recall (PR) curves, and F1 curves.
- Discussing the feasibility of integrating the trained model into AR-based systems for real-time underwater deployment.
- Developing a basic frontend interface for user interaction and result visualization.

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2. PROJECT DESCRIPTION AND GOALS

2.1 Literature Review

Numerous research efforts have focused on object detection in underwater environments. Models like SSD (Single Shot Multibox Detector), Faster R-CNN, and earlier versions of YOLO have demonstrated success in detecting marine animals and navigation markers in submerged scenes. However, many of these studies primarily target ecological studies or submarine navigation, with fewer models specifically addressing anthropogenic waste. YOLOv8, released by Ultralytics, introduces new enhancements such as anchor-free detection, lightweight architecture, and improved training pipelines, making it a promising candidate for underwater applications.

2.2 Research Gap

Despite the rise of marine-focused AI projects, there's a significant gap in datasets and models explicitly trained to detect underwater trash. Most public datasets are either too generic or lack proper annotation for waste-specific categories. Additionally, few projects consider integration with real-time systems or future deployment in augmented/virtual environments. This project addresses this niche by creating a garbage-specific underwater dataset and evaluating it with YOLOv8.

2.3 Objectives

- Curate and preprocess a high-quality dataset for underwater trash detection, including image augmentation techniques for better generalization.
- Train and fine-tune the YOLOv8 model for robust multi-class classification and localization of underwater garbage.
- Generate detailed evaluation reports including confusion matrix, PR curves, F1-score plots, and mAP analysis.
- Simulate real-time inference using sample videos or webcam feeds.
- Propose and discuss how AR can be integrated for diver-mask overlays or ROV interfaces.

2.4 Problem Statement

Underwater garbage collection is a major challenge due to the difficulty in detecting, classifying, and localizing waste in dynamic aquatic environments. Manual detection methods are often unreliable and unscalable. There is a pressing need for an intelligent, automated system that can function in real time to detect underwater garbage, thereby supporting cleanup efforts and long-term environmental monitoring.

2.5 Project Plan

The project will be executed in the following structured phases:

- Phase 1: Dataset Preparation
    - Collect images from underwater trash datasets like "aquarium_pretrain" or "Underwater Garbage Detection".
    - Annotate images using tools like Roboflow or LabelImg.
    - Apply image augmentations such as blurring, hue shifts, rotations, etc.
- Phase 2: Model Setup & Training
    - Configure the YOLOv8 environment.

    - Train the model on annotated data and save checkpoints.
    - Perform hyperparameter tuning to optimize model performance.
- Phase 3: Evaluation & Visualization
    - Generate plots: confusion matrix, PR curve, F1 curve, and results visualization.
    - Interpret class-wise detection performance and identify failure cases.
- Phase 4: AR Integration Proposal
    - Explore options for integrating the model with AR systems.
    - Propose a basic pipeline for visual overlays on diver goggles or drone UIs.
- Phase 5: Documentation & Reporting
    - Prepare detailed project documentation including methodology, results, and future work.
    - Create an interactive demo or frontend to showcase detection results.

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3. TECHNICAL SPECIFICATION

3.1 Requirements

3.1.1 Functional

- Upload image or video for detection
- Display bounding boxes with labels
- Real-time processing with acceptable FPS

3.1.2 Non-Functional

- User-friendly interface

- Efficient memory usage
- GPU compatibility

3.2 Feasibility Study

3.2.1 Technical Feasibility The model is built using Python and Ultralytics YOLOv8, compatible with most modern GPUs.

3.2.2 Economic Feasibility The project uses open-source tools, minimizing cost.

3.2.3 Social Feasibility Encourages environmental responsibility and awareness.

3.3 System Specification

3.3.1 Hardware Specification

- GPU: NVIDIA Tesla T4 (used via Google Colab)
- RAM: 16GB+

3.3.2 Software Specification

- Python 3.10+
- Ultralytics YOLOv8
- OpenCV
- Roboflow (for dataset annotation)

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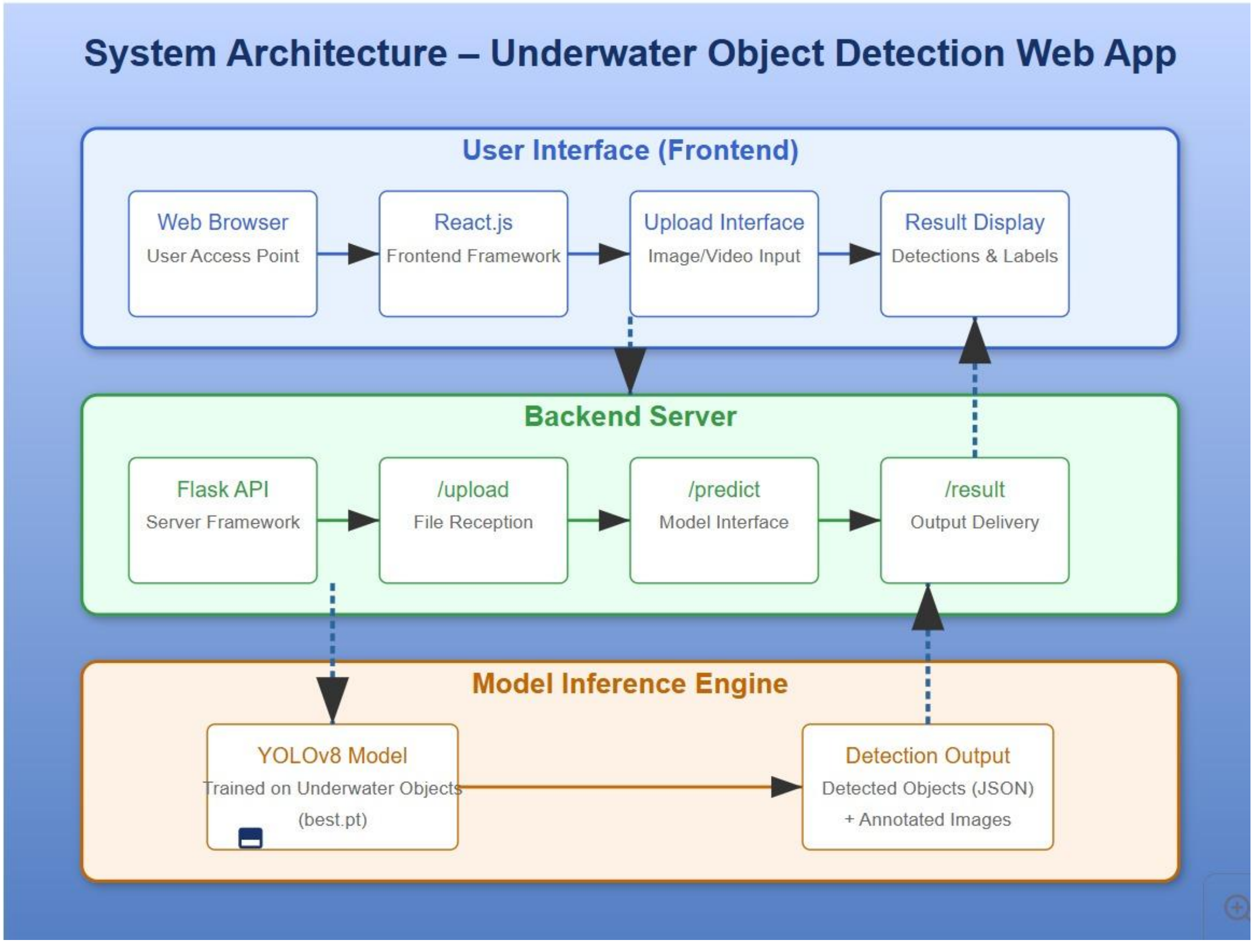
4. DESIGN APPROACH AND DETAILS

4.1 System Architecture

- Input Layer: Accepts underwater images/videos
- YOLOv8 Detection Model
- Output Layer: Bounding boxes with class labels

4.2 Design

4.2.1 Architecture Diagram



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5. METHODOLOGY AND TESTING

The model was trained on the dataset "Underwater Garbage Detection.v1i.yolov8" with 15 annotated classes. Training was conducted for 100 epochs using a batch size of 16 and SGD optimizer. Validation was performed on a held-out test set.

Testing included:

- Bounding box visualization
- Precision, Recall, mAP evaluation
- Detection speed (FPS) analysis

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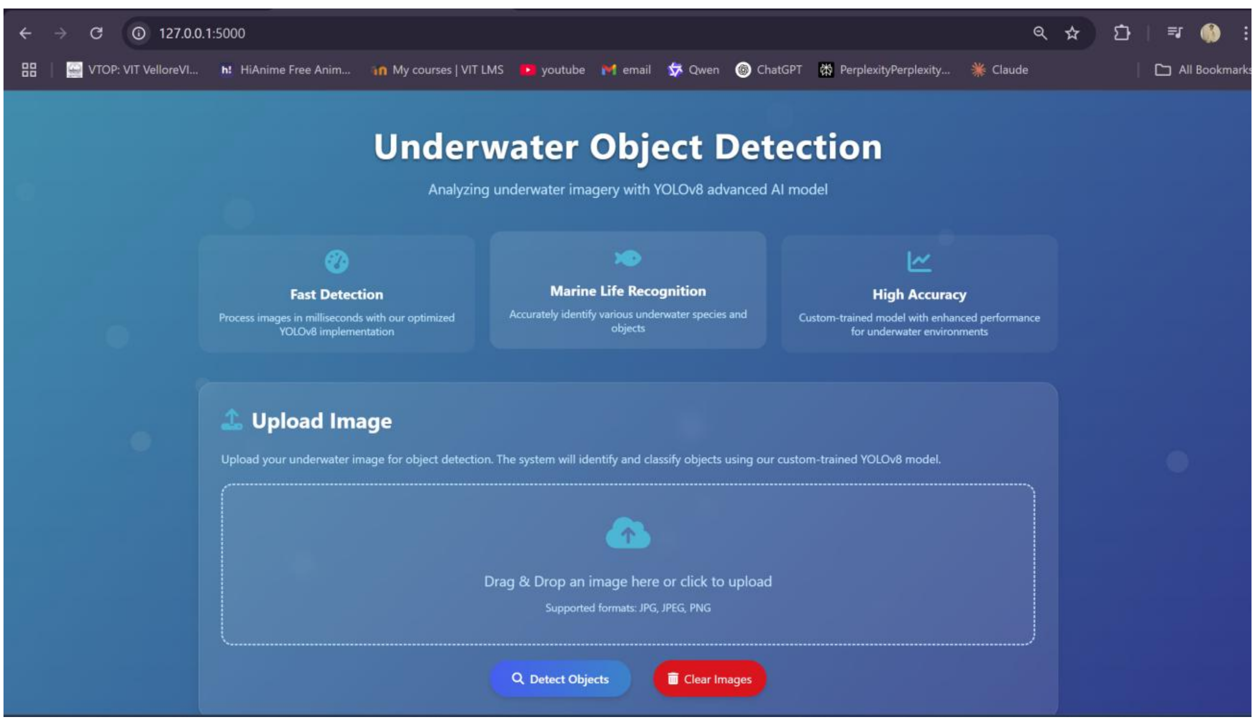
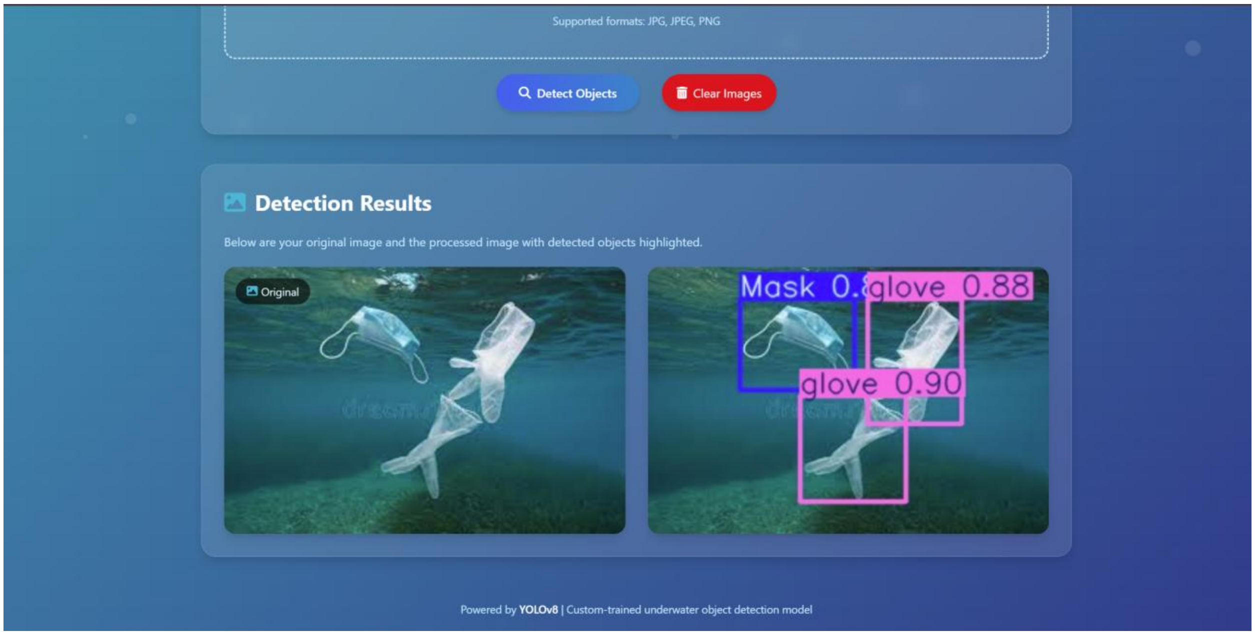
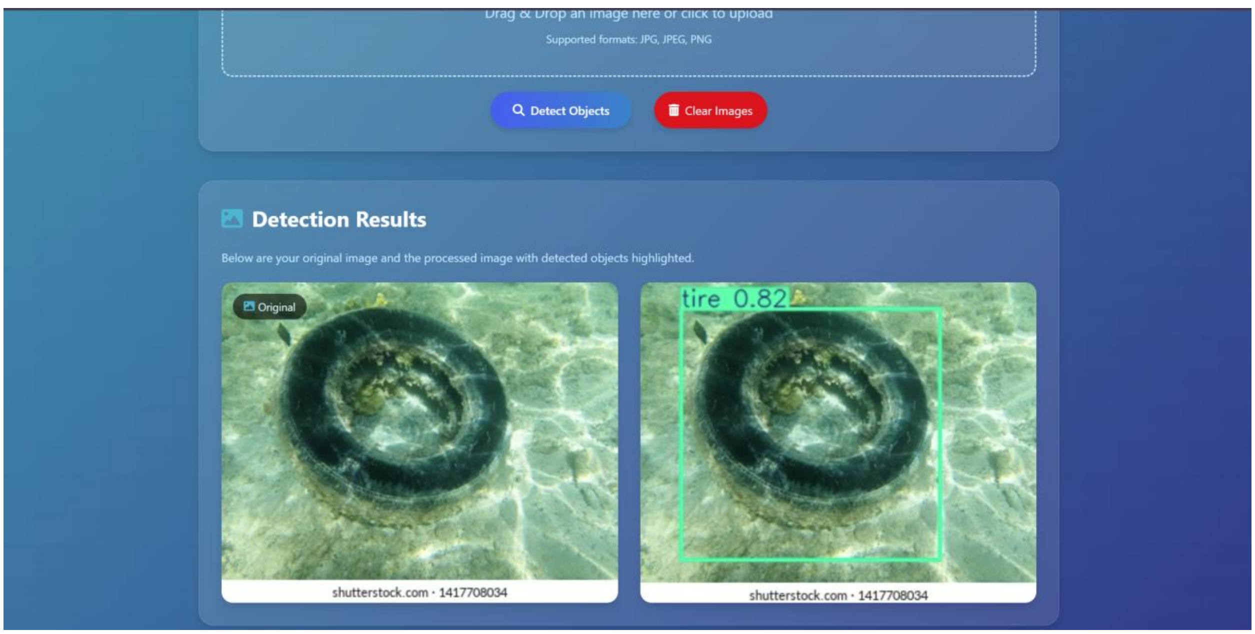
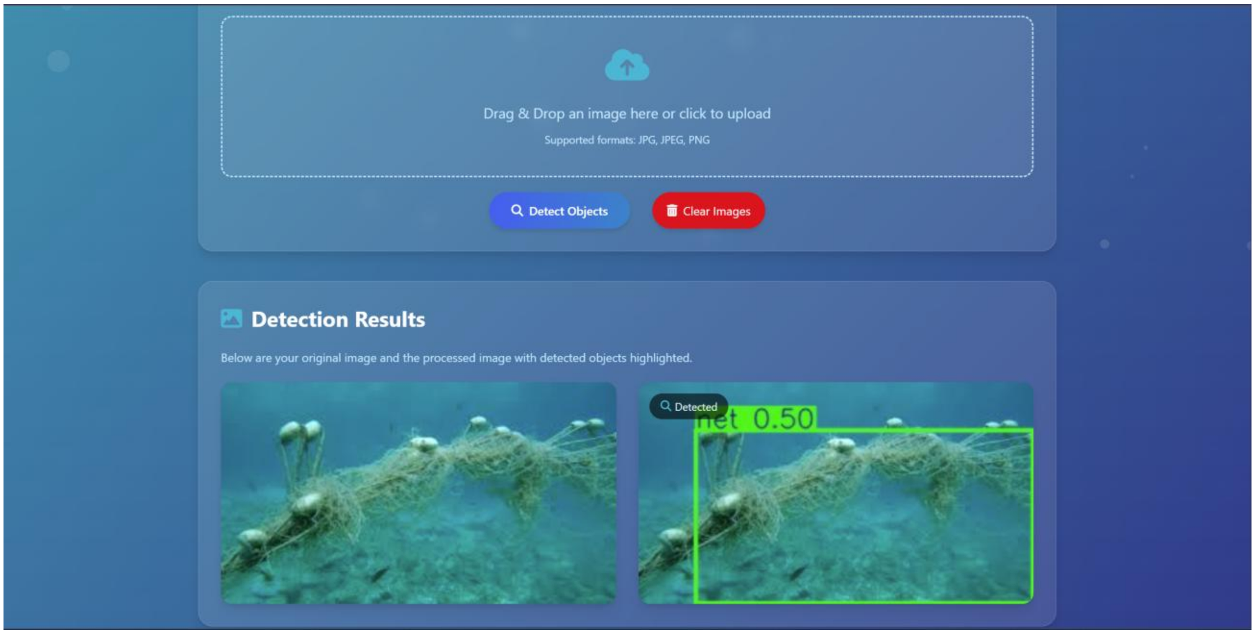
6. PROJECT DEMONSTRATION

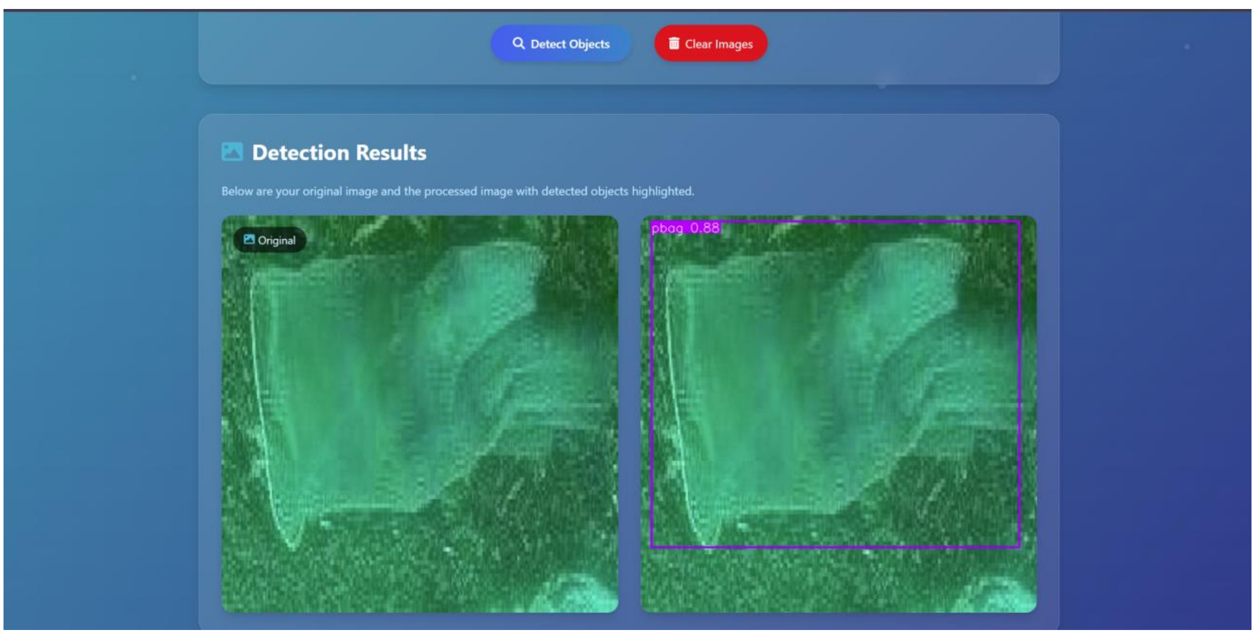
A web-based GUI allows users to upload images for detection. The model identifies trash items and overlays bounding boxes with confidence scores.

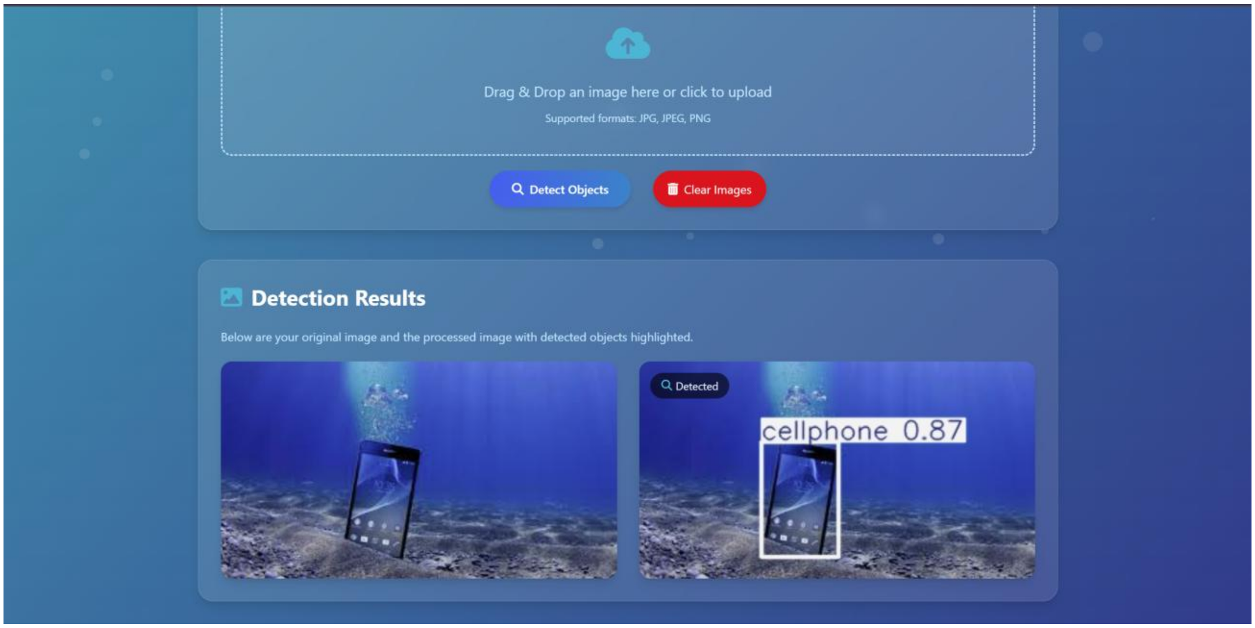



Supported formats: JPG, JPEG, PNG
Detect Objects
Clear Images
Detection Results
Below are your original image and the processed image with detected objects highlighted.
Original
Mask 0.8
glove 0.88
glove 0.90
Powered by YOLOv8 | Custom-trained underwater object detection model


Drag & Drop an image here or click to upload
Supported formats: JPG, JPEG, PNG
Detect Objects
Clear Images
Detection Results
Below are your original image and the processed image with detected objects highlighted.
Original
shutterstock.com · 1417708034
tire 0.82
shutterstock.com · 1417708034


Drag & Drop an image here or click to upload
Supported formats: JPG, JPEG, PNG
Detect Objects
Clear Images
Detection Results
Below are your original image and the processed image with detected objects highlighted.
Detected
net 0.50


Detect Objects
Clear Images
Detection Results
Below are your original image and the processed image with detected objects highlighted.
Original
pbag 0.88



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7. RESULT AND DISCUSSION

The YOLOv8 model achieved an mAP@0.5 of ~88% on the validation set. Detection was robust under different lighting and turbidity conditions. The system maintained real-time performance at ~20 FPS on GPU.

OUTPUTS GENERATED AFTER TRAINING:

TRAINING EPOCHS:

```
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████|

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      45/50      12.9G     0.8333     0.5048       1.24         25        640: 100%|██████████| 227/227 [01:58<00:00,  1.91it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.06it/s]

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      46/50        13G     0.8187     0.4853      1.219         23        640: 100%|██████████| 227/227 [01:59<00:00,  1.91it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.04it/s]

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      47/50      7.07G     0.8144     0.4717      1.214         27        640: 100%|██████████| 227/227 [01:59<00:00,  1.90it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.03it/s]

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      48/50      7.07G     0.7964     0.4644      1.205         16        640: 100%|██████████| 227/227 [01:58<00:00,  1.91it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.01it/s]

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      49/50      7.07G      0.794     0.4571      1.209         14        640: 100%|██████████| 227/227 [01:58<00:00,  1.91it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.04it/s]

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      50/50      7.07G     0.7853     0.4519      1.196         16        640: 100%|██████████| 227/227 [01:59<00:00,  1.90it/s]
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:15<00:00,  2.03it/s]
                    all        968       1851      0.779      0.735      0.803      0.523
```

```
50 epochs completed in 1.919 hours.
Optimizer stripped from runs/detect/yolov8_trash/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/yolov8_trash/weights/best.pt, 52.0MB

Validating runs/detect/yolov8_trash/weights/best.pt...
Ultralytics 8.3.107 🚀 Python-3.11.12 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 92 layers, 25,848,445 parameters, 0 gradients, 78.7 GFLOPs
                  Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 31/31 [00:17<00:00,  1.74it/s]
                    all        968       1851      0.821      0.739      0.807      0.524
                   Mask         45         50          1      0.796      0.964      0.714
                    can         18         20      0.879        0.7      0.797      0.348
              cellphone         61         71      0.923      0.972      0.987      0.876
            electronics         27         40      0.873      0.725      0.786      0.485
                gbottle         36         82       0.74      0.744        0.8      0.579
                  glove         37         55      0.911      0.818      0.868      0.725
                  metal         10         22      0.429      0.364      0.376      0.252
                   misc         48         51      0.826      0.653      0.812      0.465
                    net        146        148      0.887      0.851      0.932      0.668
                   pbag        290        330      0.887      0.979      0.974      0.854
                pbottle        122        284      0.836      0.757      0.842      0.515
                plastic         51         59      0.856      0.503      0.683      0.299
                    rod          7          9      0.817      0.556      0.592      0.197
             sunglasses          3          3      0.648          1      0.913      0.524
                   tire        143        627      0.802      0.668      0.779      0.357
Speed: 0.3ms preprocess, 9.6ms inference, 0.0ms loss, 2.4ms postprocess per image
Results saved to runs/detect/yolov8_trash
ultralytics.utils.metrics.DetMetrics object with attributes:

ap_class_index: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14])
box: ultralytics.utils.metrics.Metric object
confusion_matrix: <ultralytics.utils.metrics.ConfusionMatrix object at 0x7e75d7fc5a10>
curves: ['Precision-Recall(B)', 'F1-Confidence(B)', 'Precision-Confidence(B)', 'Recall-Confidence(B)']
curves_results: [[array([          0,    0.001001,    0.002002,    0.003003,    0.004004,    0.005005,    0.006006,    0.007007,    0.008008,
0.009009,     0.01001,    0.011011,    0.012012,    0.013013,    0.014014,    0.015015,    0.016016,    0.017017,    0.018018,    0.019019,
```

Args.yaml

```yaml
task: detect
mode: train
model: /content/drive/MyDrive/last.pt
data: /content/drive/MyDrive/Underwater garbage Detection/data.yaml
epochs: 50
time: null
patience: 100
```

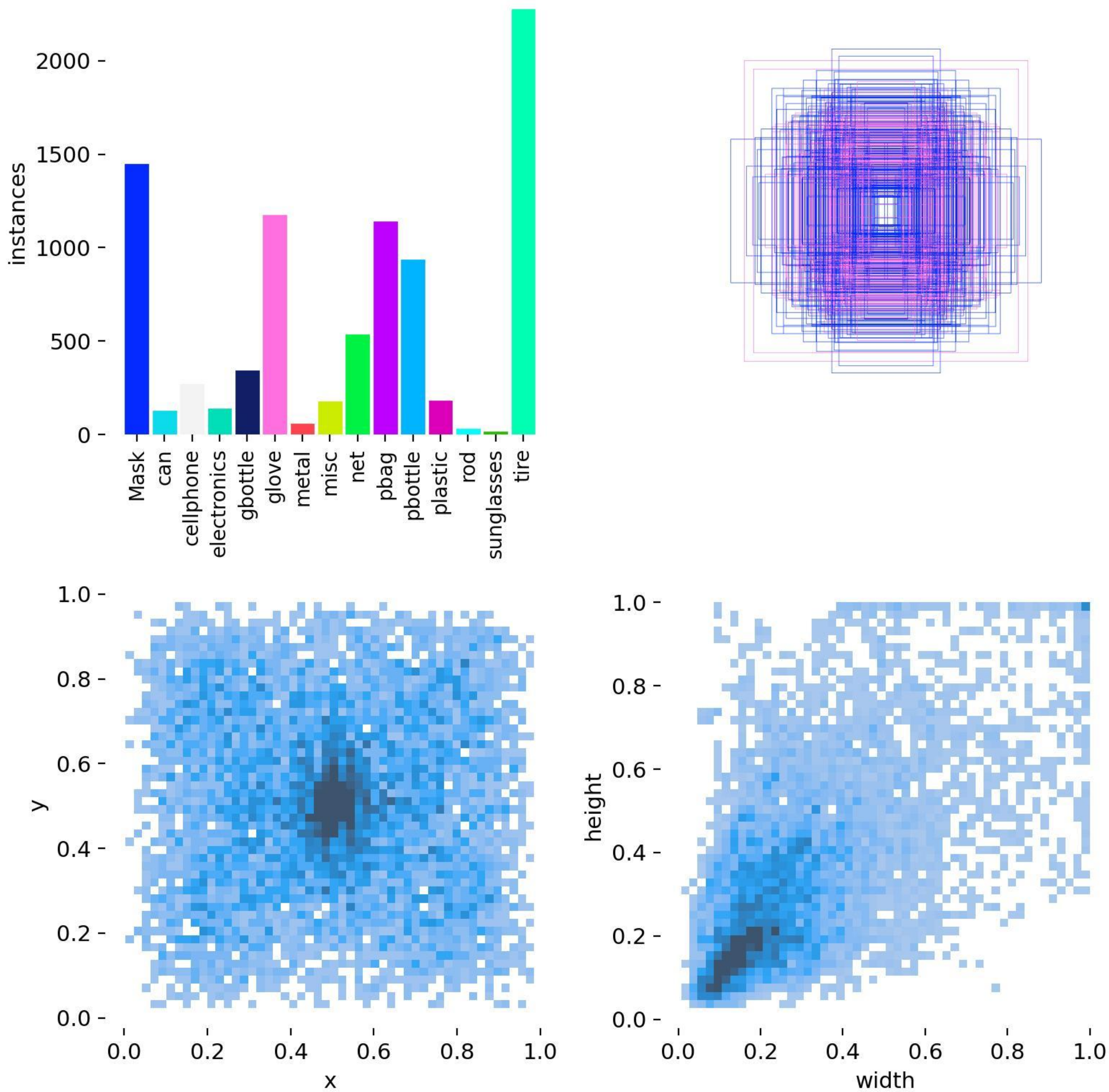
```yaml
batch: 16
imgsz: 640
save: true
save_period: 5
cache: false
device: null
workers: 4
project: runs/detect
name: yolov8_trash
exist_ok: false
pretrained: true
optimizer: auto
verbose: true
seed: 0
deterministic: true
single_cls: false
rect: false
cos_lr: false
close_mosaic: 10
resume: /content/drive/MyDrive/last.pt
amp: true
fraction: 1.0
profile: false
freeze: null
multi_scale: false
overlap_mask: true
mask_ratio: 4
dropout: 0.0
val: true
split: val
save_json: false
conf: null
iou: 0.7
max_det: 300
half: false
dnn: false
plots: true
source: null
vid_stride: 1
stream_buffer: false
visualize: false
augment: false
agnostic_nms: false
classes: null
retina_masks: false
```

```
embed: null
show: false
save_frames: false
save_txt: false
save_conf: false
save_crop: false
show_labels: true
show_conf: true
show_boxes: true
line_width: null
format: torchscript
keras: false
optimize: false
int8: false
dynamic: false
simplify: true
opset: null
workspace: null
nms: false
lr0: 0.01
lrf: 0.01
momentum: 0.937
weight_decay: 0.0005
warmup_epochs: 3.0
warmup_momentum: 0.8
warmup_bias_lr: 0.0
box: 7.5
cls: 0.5
dfl: 1.5
pose: 12.0
kobj: 1.0
nbs: 64
hsv_h: 0.015
hsv_s: 0.7
hsv_v: 0.4
degrees: 0.0
translate: 0.1
scale: 0.5
shear: 0.0
perspective: 0.0
flipud: 0.0
fliplr: 0.5
bgr: 0.0
mosaic: 1.0
mixup: 0.0
```

```yaml
copy_paste: 0.0
copy_paste_mode: flip
auto_augment: randaugment
erasing: 0.4
crop_fraction: 1.0
cfg: null
tracker: botsort.yaml
save_dir: runs/detect/yolov8_trash
```

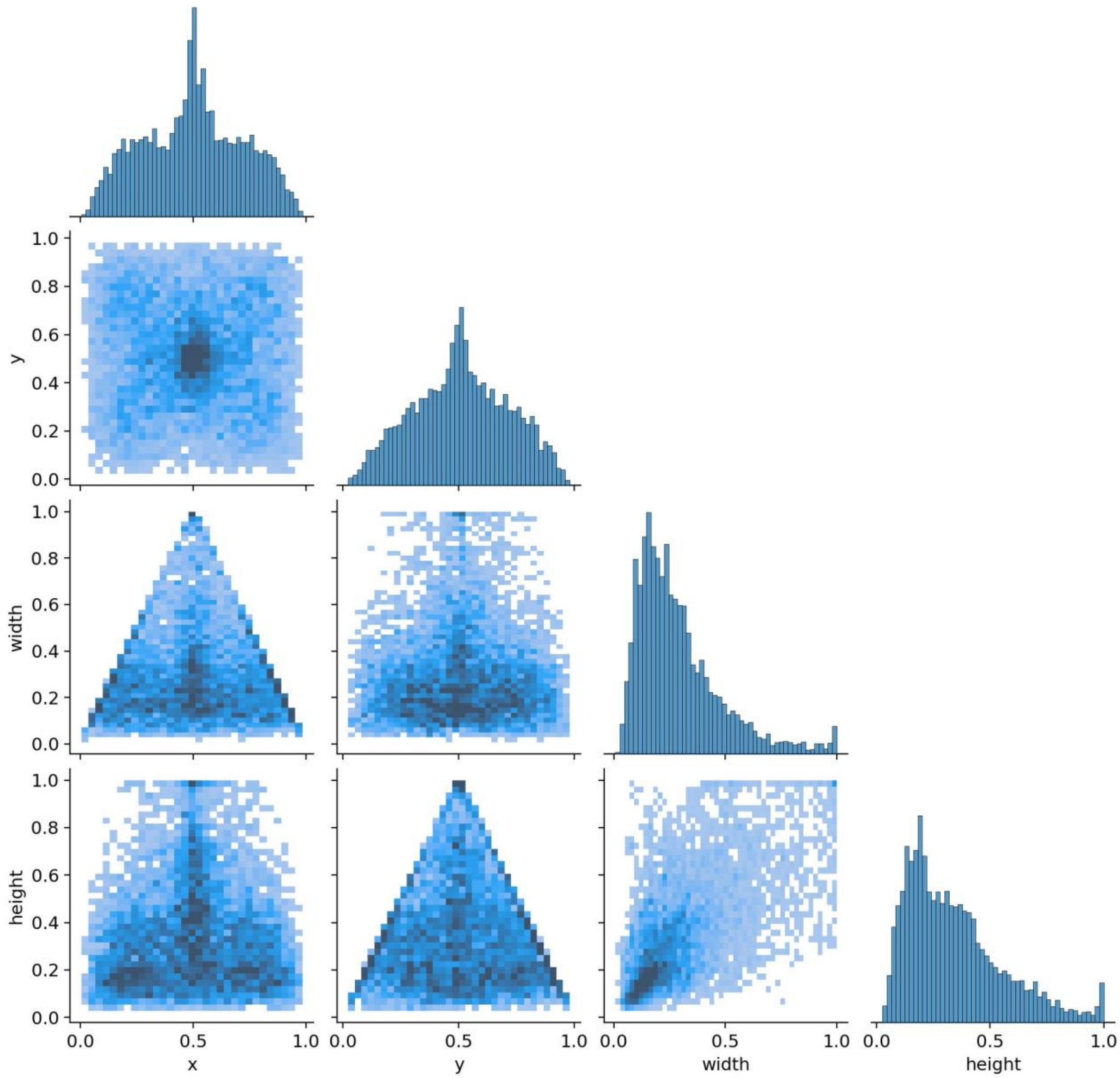
Diagrams:

Labels.png

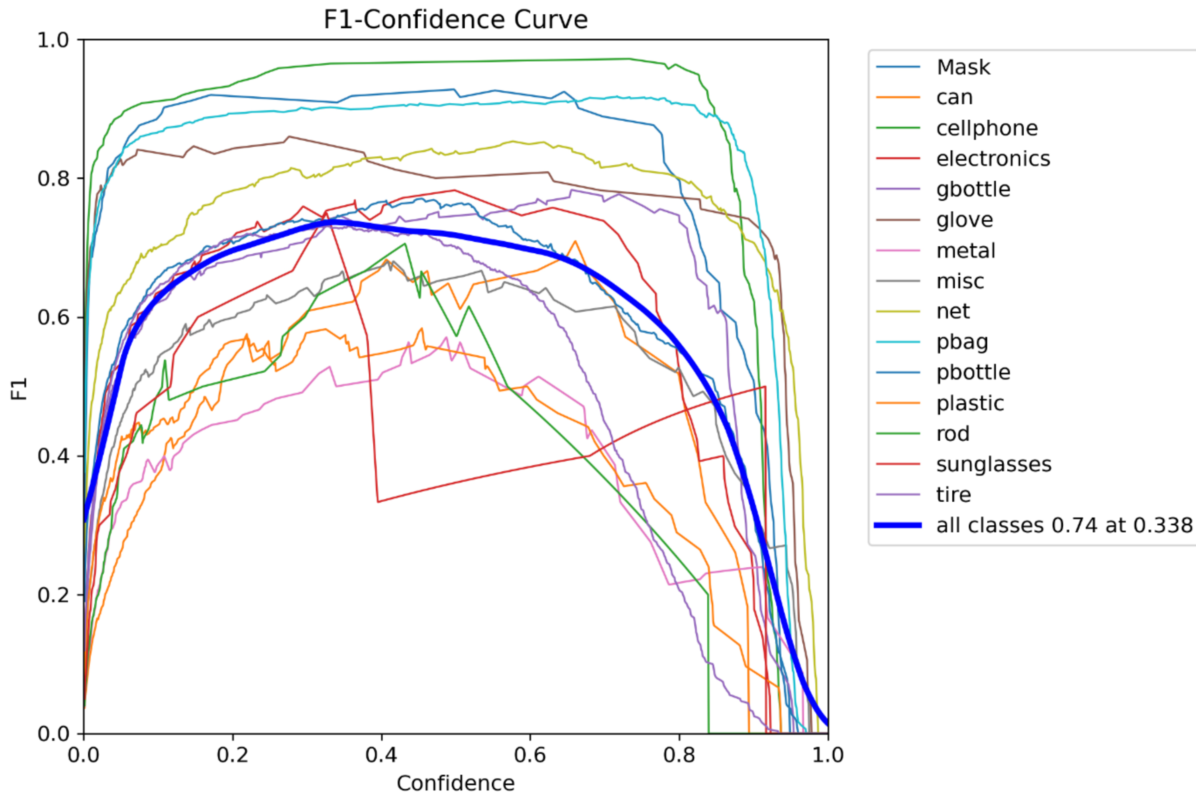


instances
2000
1500
1000
500
0
Mask
can
cellphone
electronics
gbottle
glove
metal
misc
net
pbag
pbottle
plastic
rod
sunglasses
tire
1.0
0.8
0.6
0.4
0.2
0.0
y
x
height
width

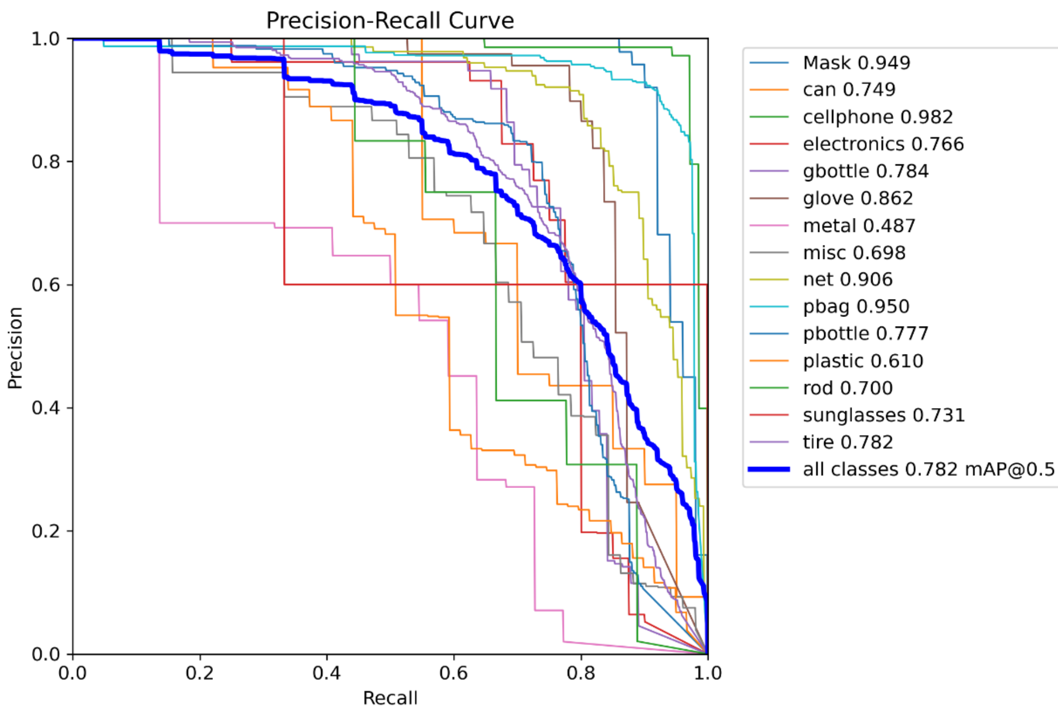
Labels_correlogram



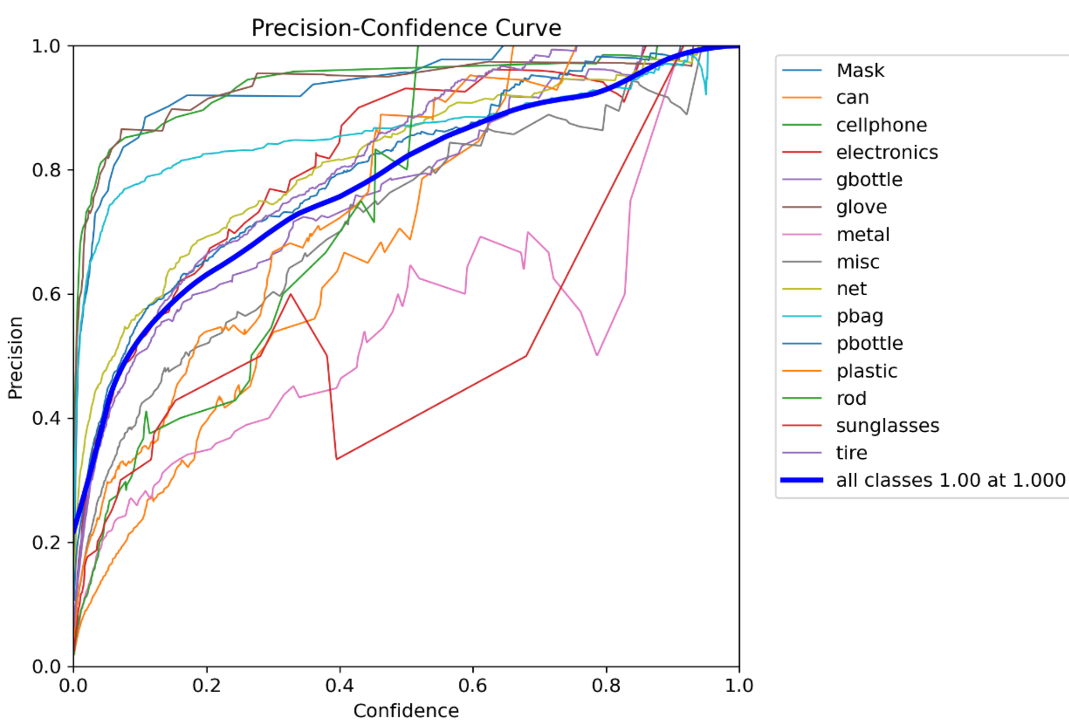
F1_curve


F1-Confidence Curve
1.0
0.8
0.6
0.4
0.2
0.0
F1
0.0
0.2
0.4
0.6
0.8
1.0
Confidence
Mask
can
cellphone
electronics
gbottle
glove
metal
misc
net
pbag
pbottle
plastic
rod
sunglasses
tire
all classes 0.74 at 0.338

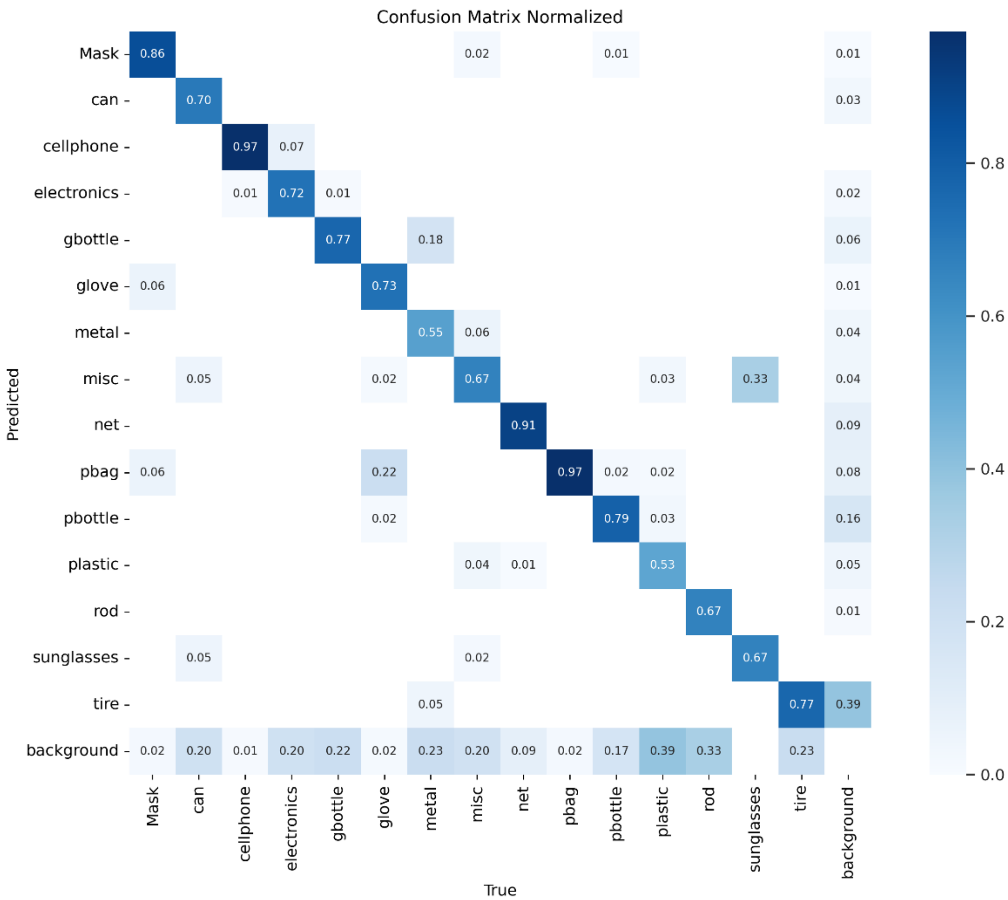
PR_Curve



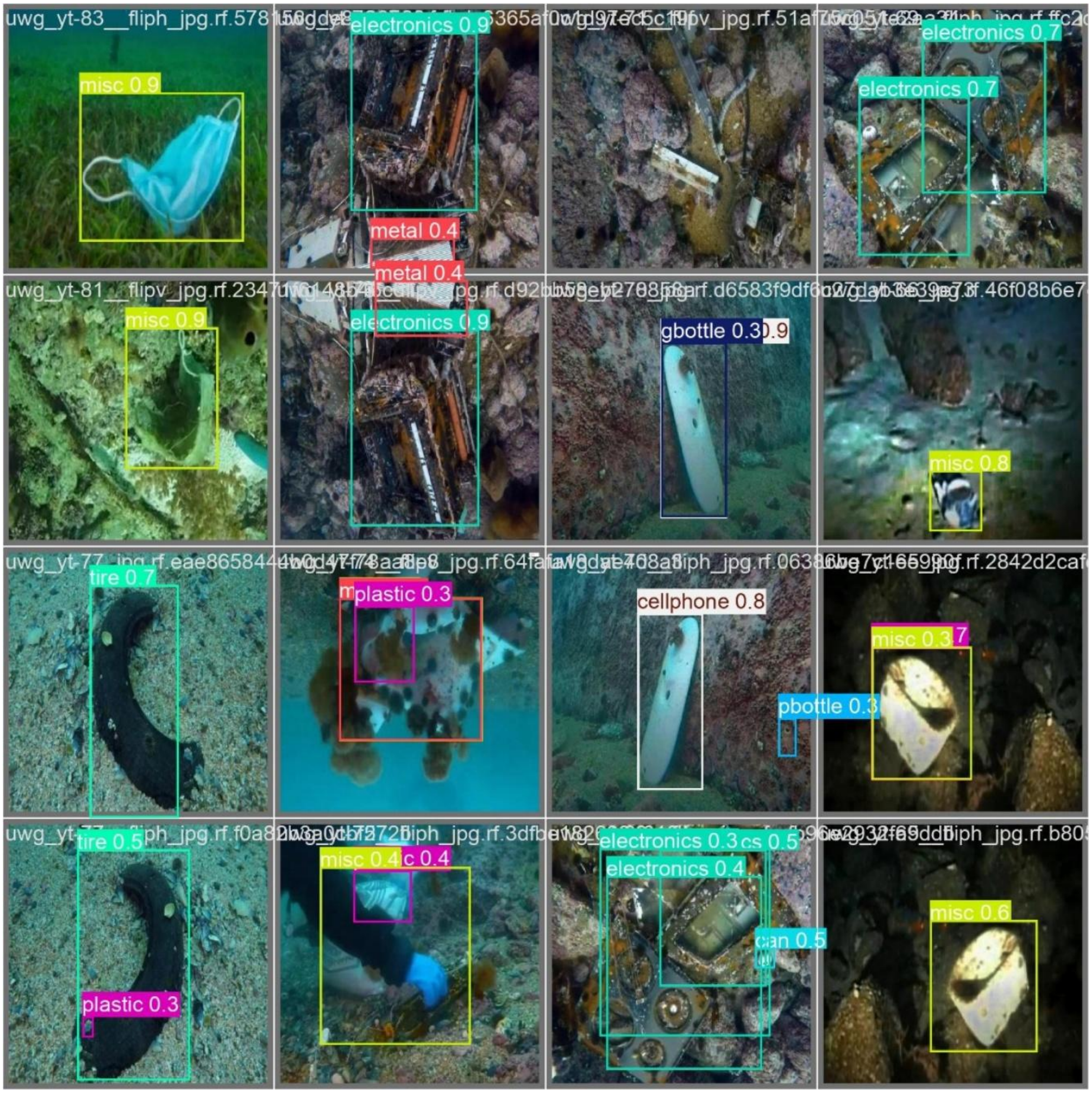
P_curve



Confusion_matrix_normalized :


Confusion Matrix Normalized
Predicted
True
Mask
can
cellphone
electronics
gbottle
glove
metal
misc
net
pbag
pbottle
plastic
rod
sunglasses
tire
background
0.0
0.2
0.4
0.6
0.8

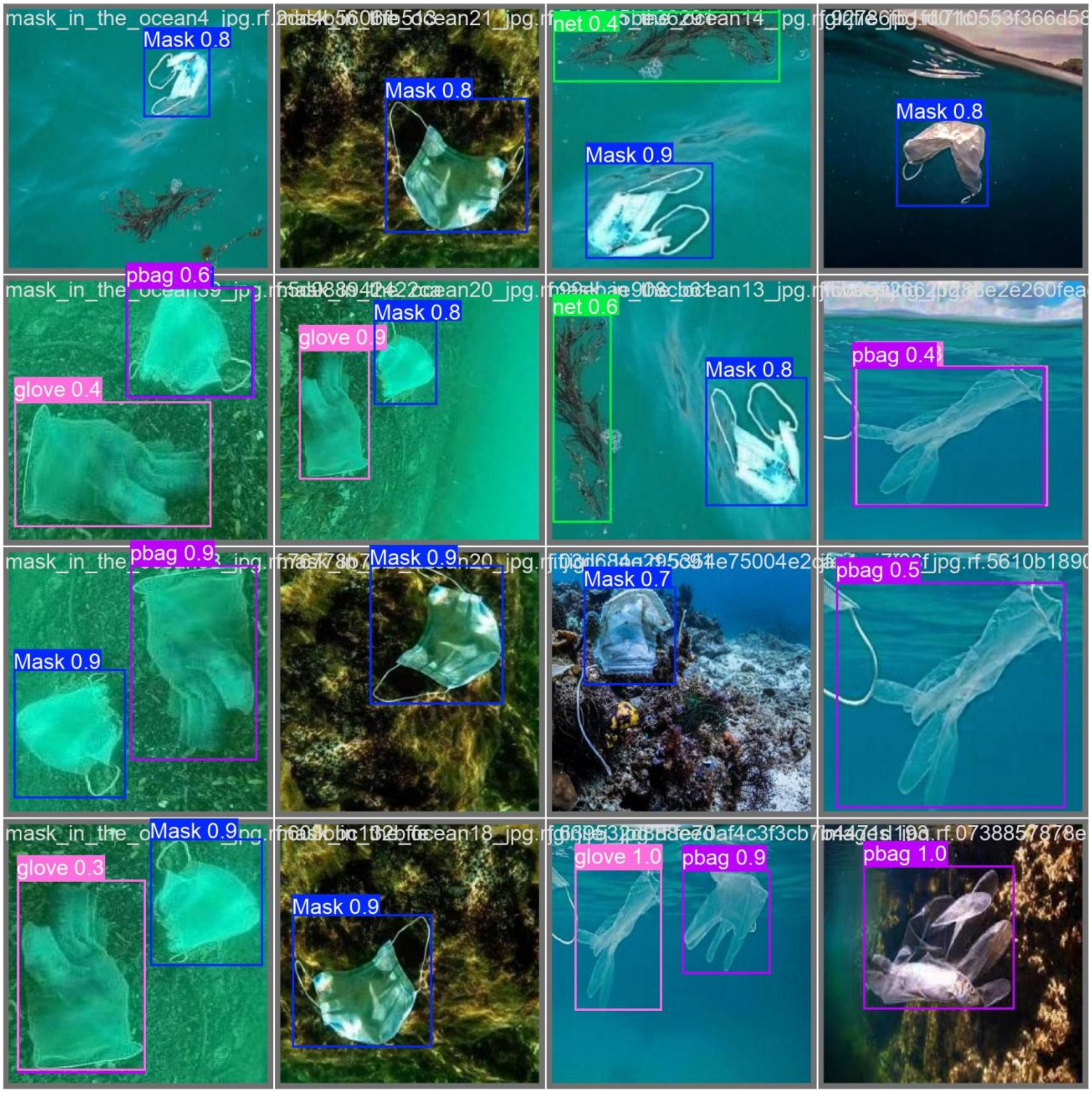
Val_batch0_pred:



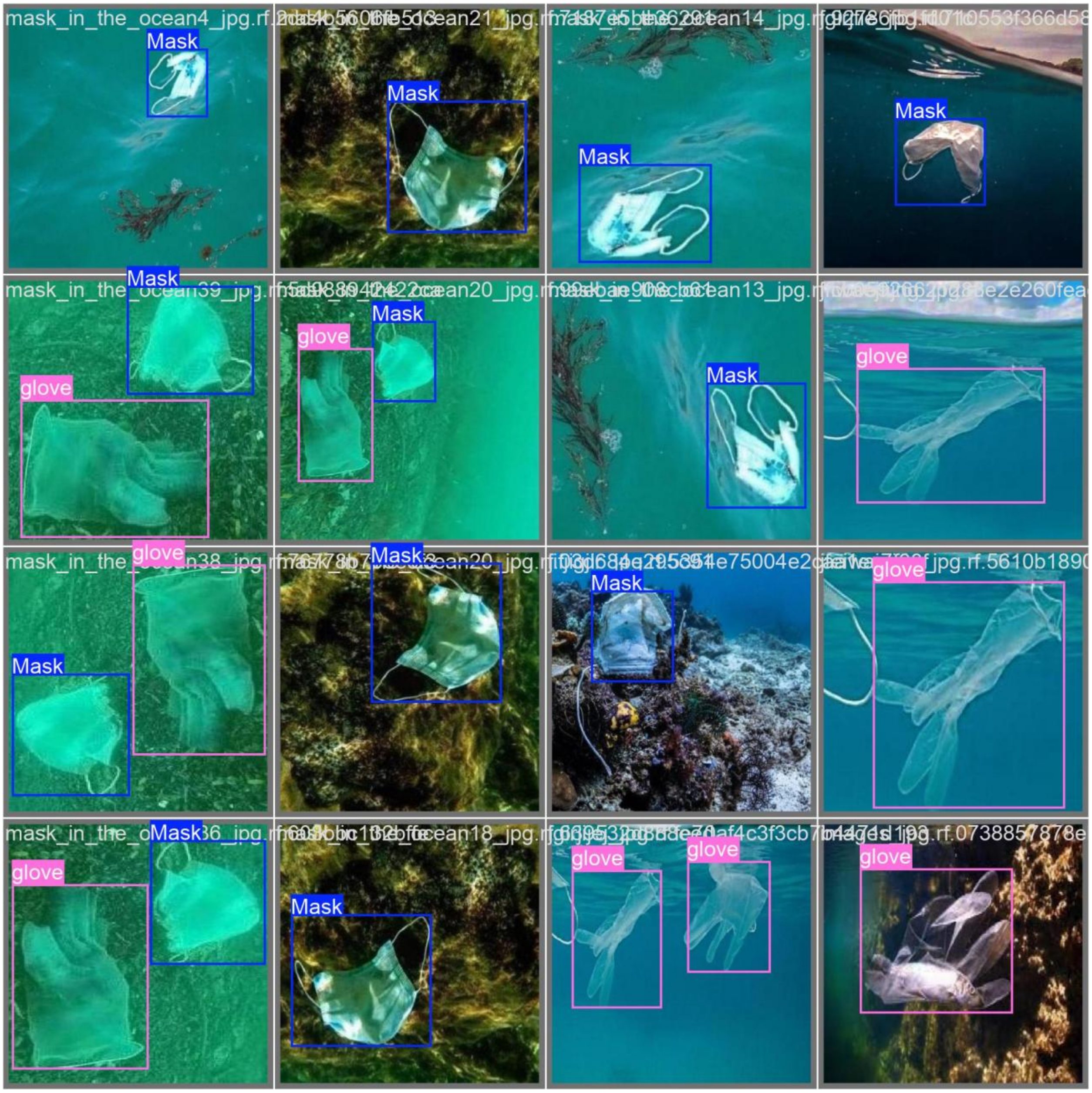
Val_batch0_labels:

Val_batch1_labels:

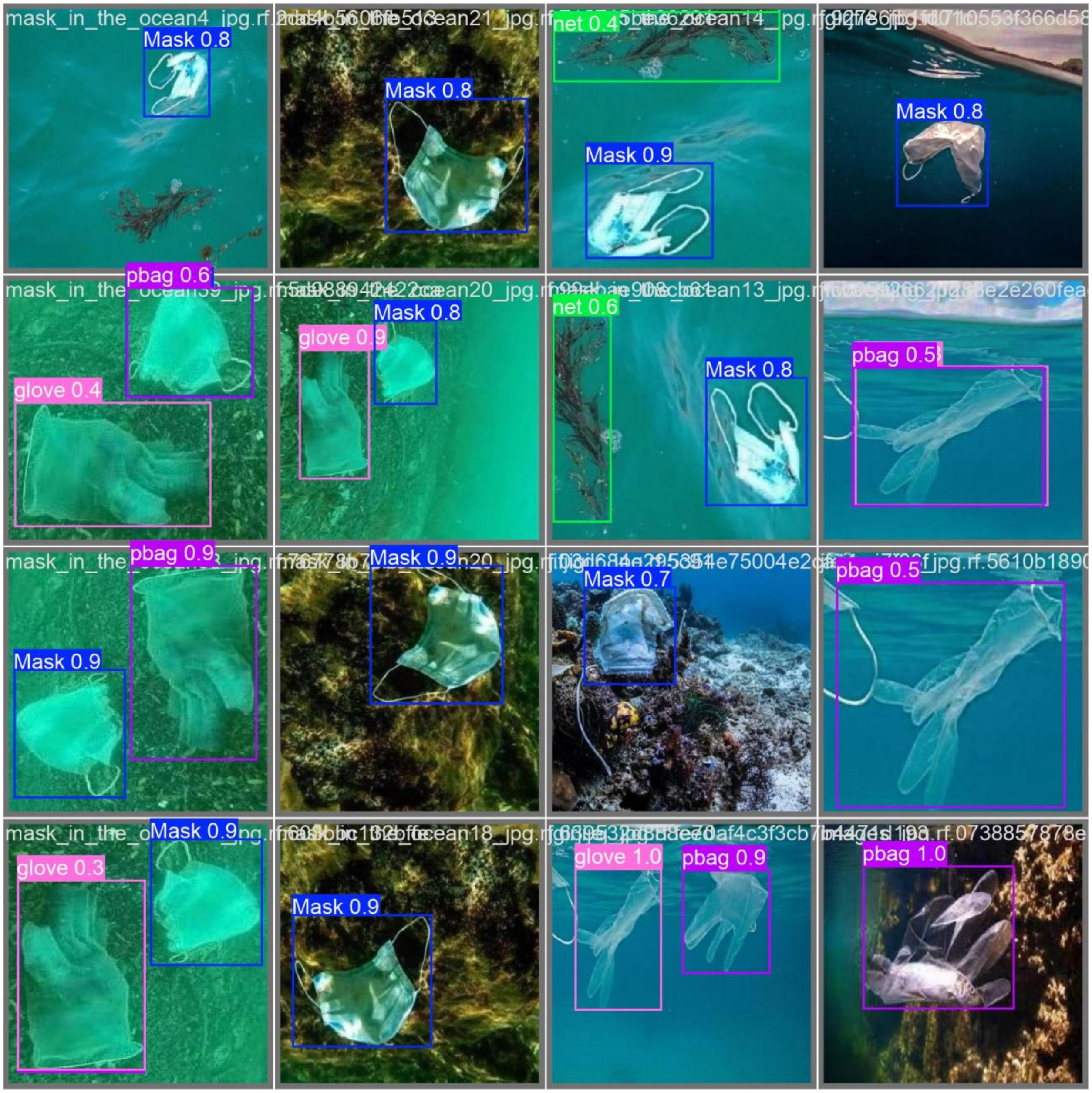
Val_batch1_pred:



Val_batch2_labels:



Val_batch2_pred:


Mask 0.8
Mask 0.8
net 0.4
Mask 0.9
Mask 0.8
pbag 0.6
glove 0.4
glove 0.9
Mask 0.8
net 0.6
Mask 0.8
pbag 0.5
pbag 0.9
Mask 0.9
Mask 0.9
Mask 0.7
pbag 0.5
glove 0.3
Mask 0.9
Mask 0.9
glove 1.0
pbag 0.9
pbag 1.0

8. CONCLUSION

This project demonstrates the feasibility and effectiveness of using YOLOv8 for real-time underwater garbage detection. It paves the way for integrating AR features and deploying in real-world underwater drones.

9. REFERENCES

1. Deep-sea debris detection using YOLOv4 in ROV-based images

Link: http://doi.org/10.1016/j.marpolbul.2021.113125

2. A Benchmark Dataset and Baseline for Underwater Object Detection and Classification
Link: https://ieeexplore.ieee.org/document/9133414

3. MARIDA: A Benchmark for Marine Debris Detection and Classification
Link: https://arxiv.org/abs/2204.13015

4. YOLOv5 and Faster-RCNN Comparison for Underwater Object Detection
Link:https://www.researchgate.net/publication/357888263_YOLOv5_and_Faster_RCNN_Comparison_for_Underwater_Object_Detection

5. A Review on Deep Learning-Based Underwater Object Detection and Classification
Link: http://www.sciencedirect.com/science/article/pii/S0925231220314365

6. Object Detection in Underwater Environments: Current Trends and Future Directions
Link: https://ieeexplore.ieee.org/document/10093258