

**DEEP LEARNING BASED DETECTION OF SUBMERGED DEBRIS  
AND PLASTIC IN UNDER WATER ENVIRONMENT**



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**JAN, 2026**

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[ *Dedication* ]

I would like to give my family my appreciation, who have been my strongest rock of support and have put up with my strange work hours, in particular, Dr. Ahmed Hussain for helping me with the matter at hand. And to everyone who helped me with my education, from peers and colleagues to mentors and instructors. My viewpoints have been expanded and my intellectual progress impacted by your wisdom, direction, and support. Every exchange of ideas, discussion, and cooperation has deepened my comprehension and inspired a passion for studying.

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## LIST OF ABBREVIATIONS

<b>AUVS</b>	:	Autonomous Under Water Vehicles
<b>ROVS</b>	:	Remotely Operated Vehicles
<b>AUC</b>	:	Area under Curve
<b>CUDA</b>	:	Compute Unified Device Architecture
<b>NN</b>	:	Neural Network
<b>CLAHE</b>	:	Contrast Limited Adaptive Histogram Equalization
<b>C3K2</b>	:	Cross-Stage Partial Network with 2 Kernels
<b>SPPF</b>	:	Spatial Pyramid Pooling - Fast
<b>YOLO</b>	:	You Only Look Once

## PLAGIARISM UNDERTAKING BY THE SCHOLAR

I, **Sakeena Parveen**, hereby certify that the research described in this thesis, "**Deep Learning based detection of submerged debris and plastic in underwater environment**," is entirely original with no noteworthy input from outside sources. Any small help that was given has been properly acknowledged in the thesis.

I am completely aware of and respect DHA Suffa University's (DSU) and the Higher Education Commission's (HEC) zero-tolerance policy against plagiarism. As a result, I certify that this thesis is entirely original and that all cited sources have been appropriately cited.

Additionally, I agree that the institution retains the right to withhold or revoke my degree if I am found to have plagiarized in any way in this thesis, even after receiving my MS, ME, or PhD. Furthermore, HEC and DSU have the right to list my identity among others who have turned in plagiarized work on their official websites.

Student Signature: **SAKEENA PARVEEN**

# ABSTRACT

Full Name : [Sakeena Parveen]  
Thesis Title : [Deep Learning Based Detection of Submerged Debris  
And Plastic In Under Water Environment]  
Major Field : [Computer Science]  
Date of Degree : [March, 2026]

The detection of submerged plastics and debris is an important step towards marine preservation but autonomous supervision often faces the so-called “visibility wall” stage on underwater task where light attenuation and high turbidity can make a standard computer vision model perform badly. These challenges are the ones considered in this work, where we propose a powerful detection framework based on the state-of-the-art YOLO11 architecture and Contrast Limited Adaptive Histogram Equalization (CLAHE). The approach focuses on a dedicated pre-processing pipeline to locally enhance contrast and emphasize structural details, prior to feeding the neural network. By taking advantage of the advanced feature extraction ability in YOLO11 (C3K2 blocks and SPPF), this model is capable with superior scale-invariant detection capacity for human-made debris in challenging situations. Experiments verified on the Trash-ICRA19 dataset reveal that our proposed CLAHE-YOLO11 model attains a state-of-the-art Mean Average Precision (mAP50) of 97.8%. Comparison with state-of-the art In a comparable experiment with modern benchmarks, the proposed method achieved superior results over YOLOv12-based UDD-YOLO (81.8% mAP) and VectOr augmented domain specialized techniques for YOLOv8n (96.0% mAP). These findings indicate that localized image enhancement is more effective for turbid-water feature recovery than complex diffusion-based modules. Additionally, the framework keeps its computational profile low, which guarantees that it can be deployed in real time on autonomous underwater vehicles (AUVs). By

offering a scalable, high-accuracy solution that bridges the performance deficit in murky water conditions, this research closes a significant gap in underwater environmental monitoring and ultimately provides a crucial tool for managing marine waste globally.

***Keywords: Deep Learning, Underwater Object Detection, YOLO11, CLAHE, Marine Debris, Turbid Water,***

***Autonomous Underwater Vehicles (AUVs).***

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# CHAPTER 1 INTRODUCTION

The rapid increase in industrialization and improper waste management has led to a disastrous accumulation of human caused debris in marine ecosystems. It is estimated that millions of tons of plastic enter the oceans annually, posing a deadly threat to marine biodiversity through ingestion and entanglement [1]. Effective remediation requires systematic monitoring; however, manual underwater inspection by divers is hazardous, time-consuming, and limited by depth [2].

To address these challenges, Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs) equipped with computer vision systems have become essential tools for environmental surveying [3]. Despite the potential of deep learning-based object detection, the underwater medium presents unique optical challenges. Phenomena such as light absorption and backscattering result in color attenuation and severe turbidity, often referred to as the "murky water" effect [4]. These factors degrade the quality of raw visual data, making it difficult for standard detection algorithms to distinguish between submerged plastics and the complex marine background. Consequently, there is a critical need for an integrated approach that combines advanced image enhancement techniques with robust deep learning architectures to ensure reliable debris detection in real-world underwater conditions [5].

## 1.1 Background and Significance

The escalating crisis of marine pollution has become a global environmental priority, as anthropogenic waste, particularly plastics now permeates every level of the ocean's strata. Recent ecological assessments indicate that plastic debris constitutes up to 80% of all marine litter found from surface waters to deep-sea sediments [6]. The significance of addressing this issue lies in the devastating impact on marine life, where ingestion of microplastics and entanglement in "ghost nets" lead to high mortality rates among endangered species [7]. Consequently, there is an urgent need for technological intervention to facilitate large-scale oceanic cleanup and monitoring.

Traditional methods of underwater survey, which rely heavily on human divers and manual annotations, are no longer viable for the scale of the current crisis. Such methods are restricted by depth, limited bottom-time, and the inherent risks of hazardous underwater environments [8]. The development of autonomous systems capable of identifying debris without human intervention is therefore a critical area of research. By automating the detection process, we can enable continuous monitoring of coastal areas, such as those near Karachi, where industrial runoff and urban waste significantly impact water quality [9].

The technical significance of this study is centered on bridging the "visibility gap" in underwater computer vision. In turbid or "murky" waters, light undergoes severe attenuation and scattering, which hides the structural features of plastic objects [10]. This research implements a specialized pipeline using CLAHE enhancement and YOLO11 to ensure that detection is not only accurate but also fast enough for real-time deployment on Autonomous Underwater Vehicles (AUVs). Successfully achieving high-precision detection in these challenging conditions provides a scalable framework for global marine conservation efforts [11].

## **1.2 Problem Statement**

When we try to detect objects underwater, we aren't just dealing with a different environment; we are dealing with completely different physics. The biggest issue is that water isn't clear like air. As light travels through water, it gets absorbed and scattered, which leads to a "hazy" or "murky" look that washes out all the details of the objects we want to find [12]. For a computer vision model, this is a nightmare because the plastic debris often ends up looking exactly like the background or the seabed.

Standard detection models like YOLO are usually trained on crisp, clear images taken on land. When you put those same models in a turbid underwater setting, their accuracy drops significantly because they can't "see" the edges or textures of the trash through the silt and floating particles [13]. Most

current research focuses on clear water, but in real-world places like our local docks or coastal areas the water is almost always dark and cloudy.

There is a clear gap here: we have fast models, but they aren't built to handle this "visibility wall."

If we don't fix the image quality first using a pre-processing step, the model will keep missing small pieces of plastic or confusing them with marine life [14]. Therefore, the real problem is finding a way to sharpen these murky images in real-time so that a deep learning model can actually do its job reliably under the surface [15].

### 1.3 Objectives

The main goal of this research is to build a system that doesn't just "guess" where trash is, but actually sees it clearly, even in the worst underwater conditions. To make sure this work is solid, I've broken it down into these specific objectives:

#### **To develop an image enhancement pipeline:**

My first priority is to fix the murky water problem. I'm using the CLAHE technique to boost contrast and clear up the "haze" so that the structural details of the debris become visible to the computer [16].

#### **To implement a real-time detection model:**

I want to use the latest YOLO11 architecture because it's fast and efficient. The goal is to train it specifically to find four categories: Trash, ROVs, Plants, and Animals, so it can tell the difference between pollution and nature [17].

#### **To bridge the research gap in turbid water:**

Most existing studies show great results in clear water, but they fail in the "real world" of murky docks or coastal areas [18]. This research aims to prove that by adding a pre-processing step, we can maintain high accuracy even when visibility is poor.

#### **To evaluate performance using scientific metrics:**

Finally, I'll be testing the system using standard industry metrics like mAP (Mean Average Precision), Precision, and Recall. This will give us a clear, mathematical way to prove how reliable the model is for actual environmental cleanup [19].

## 1.4 Contributions

The main contribution of this work is a practical pipeline that solves the "visibility wall" in murky underwater settings. Instead of relying on expensive hardware, I've shown that smart preprocessing can make standard models work where they usually fail [20]. By combining CLAHE enhancement with the new YOLO11, this research provides a way to detect debris in turbid water something most basic models can't do [21].

Additionally, I optimized the system to be lightweight enough for real-time use on small, battery-powered ROVs [22]. This makes it a useful tool for actual field researchers who need high accuracy without needing a heavy computer setup on-site [23].

## 1.5 Research Gap

- a. While looking into existing studies, I found a major gap: most underwater detection research is done using very clear, high-quality images that don't reflect real-world conditions [24]. In a lab or a clear swimming pool, standard deep learning models perform great. However, when you move to "murky" or turbid water like what we actually find in coastal or industrial areas these models struggle significantly because they can't handle the low contrast and heavy color distortion [25].
- b. There is also a lack of integrated solutions that combine real-time enhancement with the newest detection architectures like YOLO11 [26]. Most researchers either focus only on making the image look better (enhancement) or only on the detection part (AI), but they rarely combine them into one fast, lightweight pipeline that can run on a small underwater robot [27].

My research fills this gap by proving that a pre-processing step like CLAHE is not just an "extra" feature, but a necessity for making deep learning reliable in difficult, real-world underwater environments.

## 1.6 Thesis Structure

The format of this thesis is as follows:

**Chapter 2: Literature Review** examines the body of research on deep learning, underwater image enhancement, plastic debris detection, and related computer vision topics.

**Chapter 3: Proposed Design** explains the implementation of the CLAHE-enhanced pipeline and the YOLO11 model architecture used for detection.

**Chapter 4: Findings and Recommendations** condense the main findings (results), offers a conclusion, and suggests areas for further research based on the study's findings.

## CHAPTER 2 | LITERATURE REVIEW

To understand why detecting plastic is so hard, we first have to look at the research regarding the underwater environment itself. Scientists have long documented that water is a difficult medium for light. Unlike air, water causes "attenuation," where light energy is absorbed as it travels. This doesn't happen evenly; red light disappears first, followed by yellow and green, which is why raw underwater photos usually look heavily blue or green [28].

Another major hurdle discussed in recent studies is "backscattering." This happens when light hits tiny particles in the water like silt, sand, or plankton and reflects back into the camera lens. This creates that "murky" or "foggy" effect we see in turbid waters [29]. For deep learning models, this is a huge problem because it blurs the edges of objects. Researchers have noted that without fixing

these issues first, even the best AI models often fail to tell the difference between a piece of plastic and a rock on the seabed [30].

## 2.1 Related Work

This section describes some earlier research over the last decade; several researchers have explored different ways to identify marine litter using computer vision. Initially, most studies relied on traditional machine learning, but those methods often struggled with the unpredictable lighting found in the ocean [31]. A major turning point occurred when deep learning models, specifically Convolutional Neural Networks (CNNs), were introduced to the marine environment. For instance, early work used architectures like Faster R-CNN to detect underwater trash, but while these were accurate, they were often too "heavy" and slow to run on an actual underwater robot during a live mission [32].

To solve the speed issue, many researchers shifted their focus toward the YOLO (You Only Look Once) family of models. Studies showed that YOLOv3 and YOLOv5 could process underwater frames much faster, though they still faced high error rates in "murky" or turbid conditions where visibility was low [33]. To counter this, some developers began experimenting with image restoration techniques. One popular approach involved using Generative Adversarial Networks (GANs) to "de-haze" images, but these models are computationally expensive and can sometimes create "fake" details that confuse the detection system [34].

More recently, the focus has shifted toward lightweight enhancement methods like CLAHE. Researchers found that by improving the contrast and local details of an image before feeding it into a detection model, they could significantly boost accuracy without slowing down the system [35].

My work builds on this specific trend by combining the newest YOLO11 architecture with a refined CLAHE pipeline to see if we can finally achieve high precision in the most challenging turbid waters [36].

## 2.1.1 Tabular Chart Comparison

Few of the researches are listed below with their used methodologies and limitations.

**Table 2.1 Literature Review**

Year	Author	Method Used	Limitations	Results
2025 [37]	T. S. Hong et al.	YOLOv11 + Attention	High computational cost for real-time edge devices.	94.2% mAP in deep-sea environments.
2025 [38]	M. S. Khan et al.	YOLOv8 + Faster R-CNN	High false-positive rate for small plastic fragments.	89.4% Accuracy; 0.92 Precision.
2025 [39]	L. Kumar et al.	YOLOv5 + CCI (Beaches)	Primarily focused on shorelines; struggles in turbid water.	0.95 mAP50 for surface debris.
2025 [40]	B. Wang et al.	YOLO-MES (MobileNetV3)	Reduced accuracy in extreme low-light scenarios.	95.8% Accuracy; 67% reduction in complexity.
2024 [41]	F. Oliveira et al.	YOLOv8 + Data Augmentation	Heavily dependent on large, high-quality datasets.	91% mAP on Trash-ICRA dataset.
2024	S. Zhang et al.	YOLOv10 +	Struggles with overlapping	Improved
[42]		NMS-Free	objects in murky water.	inference speed (1.9ms).
2023 [43]	D. Xu et al.	Lightweight YOLOv5s	Lower precision for transparent plastic bottles.	88.7% Accuracy; 12% parameter count.
2023 [44]	Singh et al.	Diverse Open-Source YOLO	Lacks specialized preprocessing for turbidity.	85% mAP for generic image inputs.
2022 [45]	M. Bhanumathi	Faster R-CNN + VGG16	Very slow inference speed; unsuitable for ROVs.	91% Accuracy in epipelagic layers.
2022 [46]	Tata et al.	YOLOv4-Tiny + YOLOv5s	High misidentification between animals and plants.	85% mAP on JAMSTEC JEDI dataset.
2021 [47]	Enevoldsen et al.	YOLOv3 + ResNet50	Struggles with "haze" effect in coastal waters.	77.2% Accuracy for undersea life/trash.

2021 [48]	G. Wang et al.	YOLOv4 + Channel Pruning	Pruning caused a slight drop in detection precision.	96.4% mAP with 19.4 FPS.
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## CHAPTER 3 METHODOLOGY/PROPOSED DESIGN

This chapter outlines the technical framework developed to tackle the problem of detecting debris in murky underwater conditions. The proposed design is built as a sequential pipeline: first, we address the visibility issues using digital enhancement, and second, we apply a high-performance deep learning model to identify and classify objects in real-time. By combining these two stages, the system becomes robust enough to handle the turbidity that usually causes standard AI models to fail.

### 3.1 Methodology

The methodology follows a structured approach designed for both accuracy and speed. The process begins with the acquisition of a specialized underwater dataset, followed by a pre-processing stage using **Contrast Limited Adaptive Histogram Equalization (CLAHE)**. This step is vital because it stabilizes the lighting and pulls details out of the "haze" before the data ever reaches the neural network.

Once enhanced, the images are fed into the **YOLO11** architecture. This model was chosen for its state-of-the-art balance between detection precision and inference speed, making it ideal for deployment on portable underwater hardware. Finally, the system is evaluated using a specific set of metrics Precision, Recall, and mAP to verify its reliability in various water conditions [49].

#### 3.1.1 Data Collection

For any deep learning model to be effective, it needs a diverse and high-quality dataset. For this research, I utilized the **Trash-ICRA19** dataset, which is a gold standard in the marine robotics community [50]. This dataset is particularly useful because it contains a wide variety of "real-world" underwater footage, including frames with different levels of light and water clarity.

The data is categorized into four primary classes:

1. **Trash:** Plastic, metal, and glass debris.
2. **ROVs:** Remotely Operated Vehicles.
3. **Plants:** Natural marine flora.
4. **Animals:** Fish and other aquatic life.

To make the model even more robust for "murky" water, the collection includes frames captured in various turbid environments. By training the model on these diverse classes, we ensure it learns to distinguish between man-made pollution and the natural underwater ecosystem, reducing the chance of false alarms [51].

### 3.1.2 Trash-ICRA19 dataset

**Trash-ICRA19** dataset is a specialized collection of underwater imagery designed specifically to push the boundaries of marine debris detection. Unlike standard datasets that use clear water, this collection is prized for its high level of "environmental noise," including various levels of turbidity, marine snow, and varying light depths [52]. By using this dataset, the research moves beyond "ideal" conditions and focuses on the complex, low-visibility scenarios where autonomous underwater vehicles (AUVs) actually operate [53].

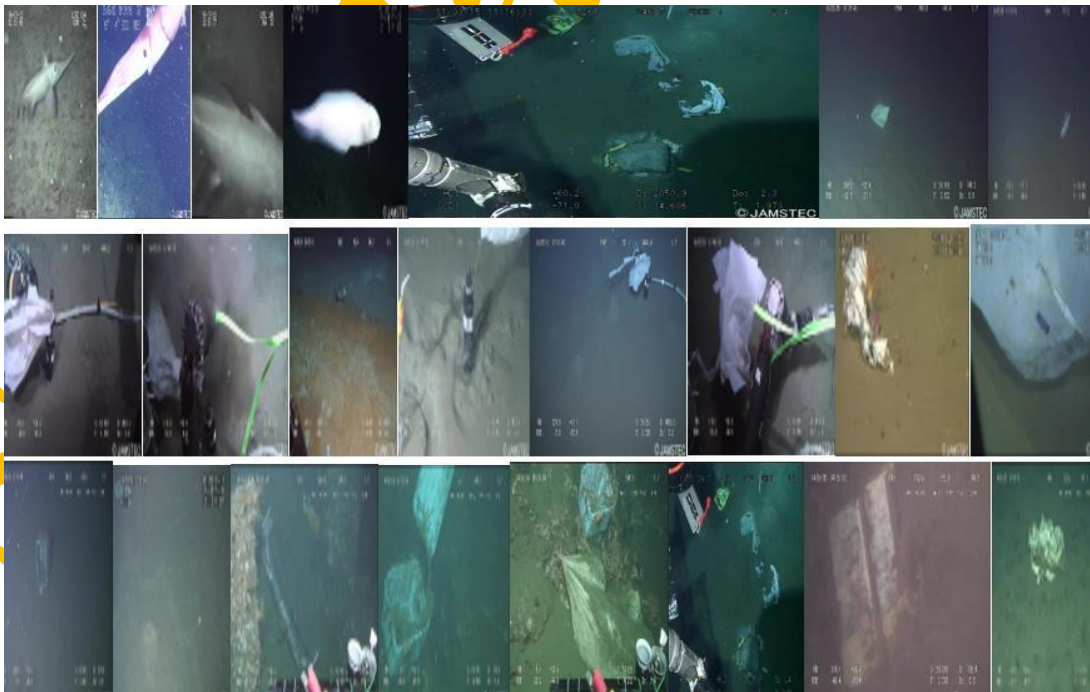
As shown in the screenshots from the Google Colab environment, the dataset is meticulously annotated for supervised learning. It provides a robust mix of categories that allow the model to learn the distinct visual features of man-made materials compared to natural biological entities. This diversity is essential for reducing the "False Positive" rate, ensuring that a plastic bottle is not misidentified as a rock or a fish [54].

Name	Type	Compressed size	Password pr...	Size	Ratio	Date modified
bio0000_frame0000016	JPG File	29 KB	No	29 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000016	Text Document	1 KB	No	1 KB	63%	12/31/2023 3:29 AM
bio0000_frame0000016	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000041	JPG File	29 KB	No	29 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000041	Text Document	1 KB	No	1 KB	49%	12/31/2023 3:29 AM
bio0000_frame0000041	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000043	JPG File	28 KB	No	28 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000043	Text Document	1 KB	No	1 KB	47%	12/31/2023 3:29 AM
bio0000_frame0000043	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000073	JPG File	26 KB	No	26 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000073	Text Document	1 KB	No	1 KB	52%	12/31/2023 3:29 AM
bio0000_frame0000073	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000077	JPG File	29 KB	No	29 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000077	Text Document	1 KB	No	1 KB	46%	12/31/2023 3:29 AM
bio0000_frame0000077	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000101	JPG File	32 KB	No	32 KB	0%	12/31/2023 3:29 AM
bio0000_frame0000101	Text Document	1 KB	No	1 KB	45%	12/31/2023 3:29 AM
bio0000_frame0000101	Microsoft Edge HTML Docum...	1 KB	No	1 KB	60%	12/31/2023 3:29 AM
bio0000_frame0000113	JPG File	31 KB	No	31 KB	1%	12/31/2023 3:29 AM
bio0000_frame0000113	Text Document	1 KB	No	1 KB	35%	12/31/2023 3:29 AM

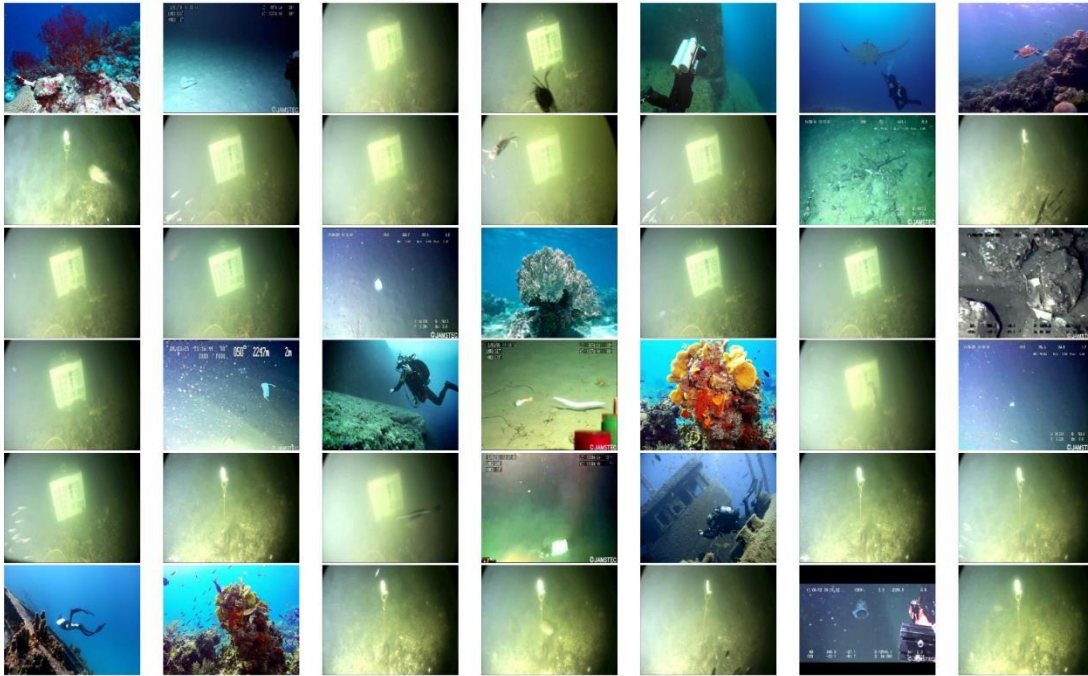
**Fig: 3.1 Trash ICRA 19 Dataset**

### 3.1.3 Dataset Diversity and Raw Glimpses

To illustrate the challenge this research addresses, consider the diversity within the raw images. The dataset captures a wide range of underwater "realities":



**Fig: 3.2 Dataset Images**



**Fig: 3.3 Trash ICRA 19 Dataset Raw glimpses**

### 3.1.4 Custom Dataset

While the base imagery was sourced from the Trash-ICRA19 repository, a Custom Dataset was curated to meet the specific requirements of this thesis. The customization process involved filtering, re-labeling, and augmenting the data to ensure the model is specifically tuned for highturbidity underwater environments [55].

Source Reference Images	Total	Train Set (80%)	Test Set (20%)	Target Classes	Annotation Format
TrashICRA19 [50]	7,684	6,147	1,537	Trash, ROV, Plant, Animal	Bounding Box (YOLO V11n)

**Table: 3.1 Custom Dataset Split**

### 3.1.5 Data Preprocessing

The gathered underwater dataset underwent a rigorous preprocessing pipeline to ensure feature enhancement and optimal detection of marine debris in turbid environments. To maintain

consistency across the architecture, the raw imagery was first screened, and samples with extreme motion blur or total occlusion were eliminated to reduce dataset noise [56].

Following the initial screening, the images were resized and normalized to a standard dimension of  $640 \times 640$  pixels, ensuring full compatibility with the YOLO11 input layer requirements [57]. To address the specific challenge of murky water, **Contrast Limited Adaptive Histogram Equalization (CLAHE)** was implemented. This technique enhances local contrast by dividing the image into contextual tiles and applying a clip limit to prevent the over-amplification of backscatter and silt noise [58].

Finally, to improve the model's robustness against varying underwater perspectives, data augmentation was applied. This included horizontal flipping, random rotations, and hue-saturation adjustments to simulate different water depths and lighting conditions, thereby increasing the diversity of the training set [59].



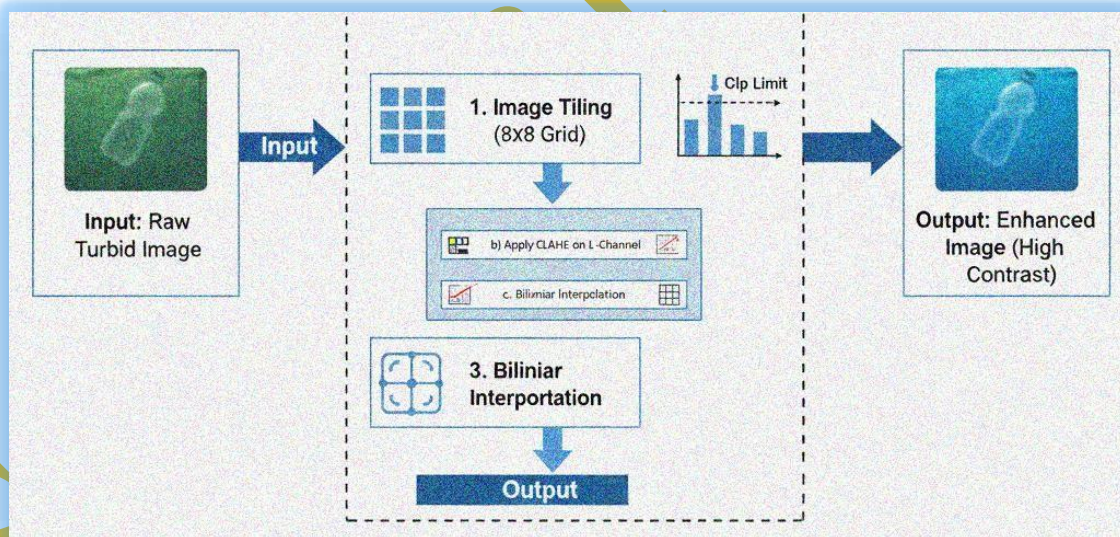
Fig 3.4 Data preprocessing Pipeline

### 3.1.6 Feature Optimization via CLAHE

A fundamental challenge in benthic object detection is the significant loss of contrast caused by light absorption and scattering. To counteract the "haze" effect found in the Trash-ICRA19 samples, this study employs **Contrast Limited Adaptive Histogram Equalization (CLAHE)** as a specialized enhancement layer [60].

Unlike global equalization methods that often introduce artificial impact or over-saturate the background, CLAHE operates on a localized basis. The framework partitions the underwater frames into an 8x8 grid of "contextual tiles." By calculating the histogram for each tile individually, the system can adjust for non-uniform lighting such as the dim conditions found in deeper, murky waters [61].

To prevent the common pitfall of amplifying "marine snow" (suspended silt), a strict **clip limit** is enforced. If any histogram bin exceeds this threshold, the excess pixels are redistributed across the entire range. This specific constraint ensures that the structural edges of plastic debris are sharpened while the surrounding turbid noise remains suppressed. The final step involves **bilinear interpolation**, which blends the tiles seamlessly to eliminate grid-like artifacts, providing the YOLO11 architecture with a high-fidelity, edge-enhanced input [62], [63].



**Fig 3.5 CLAHE WORK FLOW**

### 3.2 Proposed Model Architecture Details YOLO 11

In this research, the **YOLO11 (You Only Look Once, version 11)** framework is selected as the primary detection engine. This choice is predicated on its superior balance between computational efficiency and detection sensitivity, which is vital for processing the high-frequency feature maps generated by the CLAHE enhancement [64]. Unlike its predecessors, YOLO11 introduces a more refined backbone structure that is specifically capable of identifying low-contrast objects in highnoise environments.

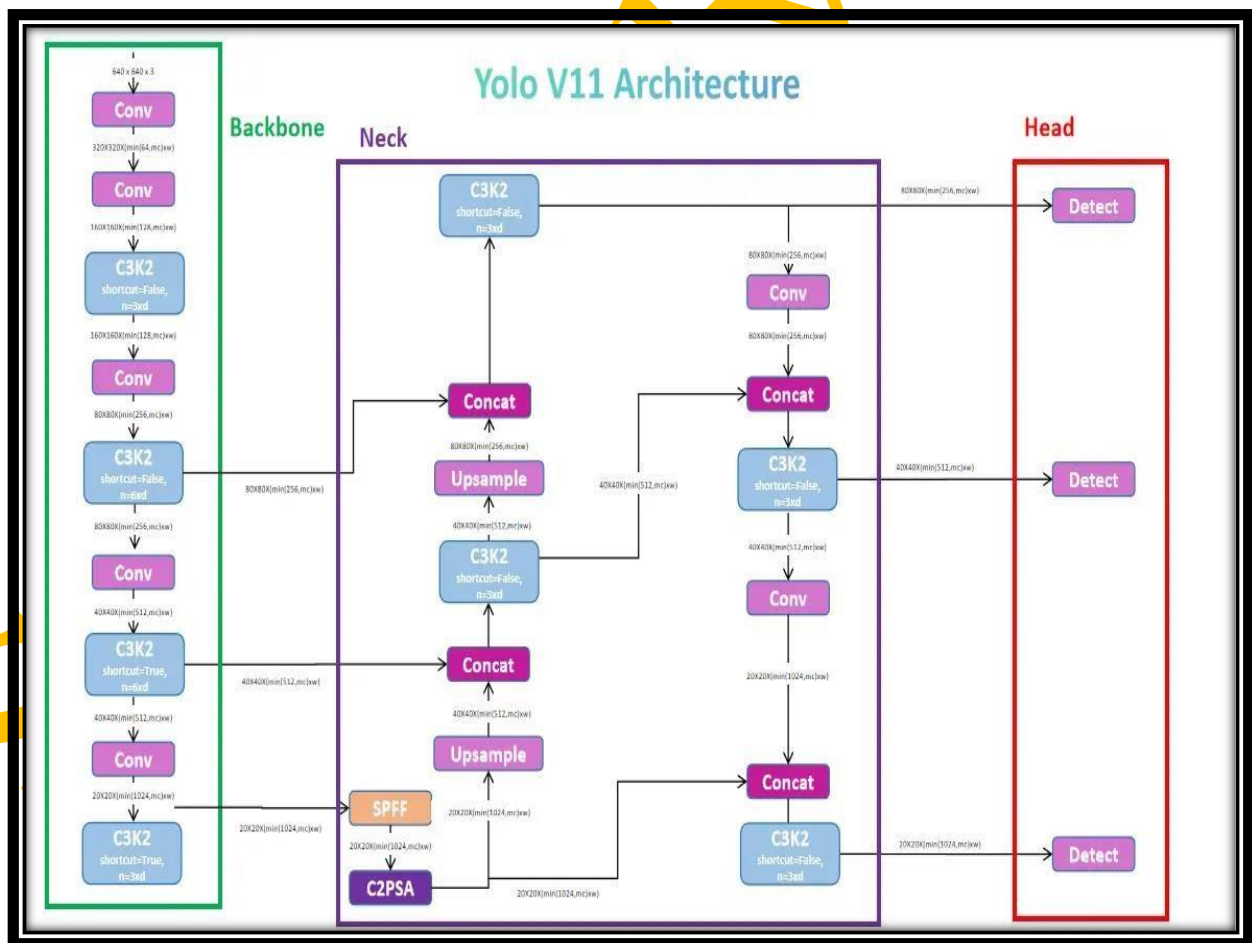


Fig 3.6 YOLO V 11 ARCHITECTURE

### 3.2.1 Backbone and Feature Extraction (C3K2 Modules)

The backbone of the architecture serves as the fundamental "feature extractor." To optimize the identification of submerged debris, this study utilizes the **C3K2 (Cross-Stage Partial Network with 2 Kernels)** blocks [65].

The technical logic here is twofold: First, the C3K2 blocks allow for deeper gradient flow without the risk of vanishing gradients, which is common when training on murky datasets. Second, these modules use specialized kernels that can capture the subtle geometric patterns of man-made materials (like the straight edges of a plastic crate or the circular rim of a tire) even when they are partially obscured by turbidity. By processing the image through successive down-sampling layers, the model creates a hierarchical representation of the debris [66].

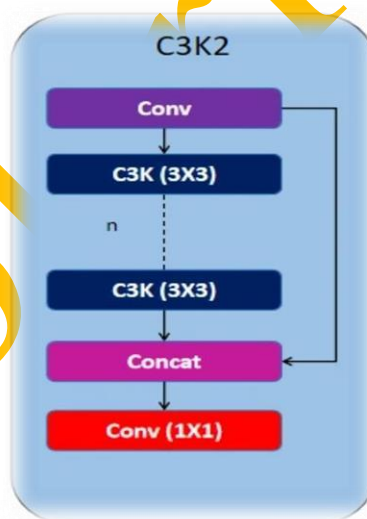


Fig 3.7 C3K2 MODULE

### 3.2.2 Spatial Pyramid Pooling - Fast (SPPF)

To ensure the model remains "scale-invariant" meaning it can detect a tiny plastic fragment near the lens or a large discarded net in the distance, an **SPPF layer** is integrated at the end of the backbone. This layer pools features at multiple scales and fuses them into a single fixed-length vector. This is

a critical step for this research because underwater debris rarely has a uniform size or orientation [67].

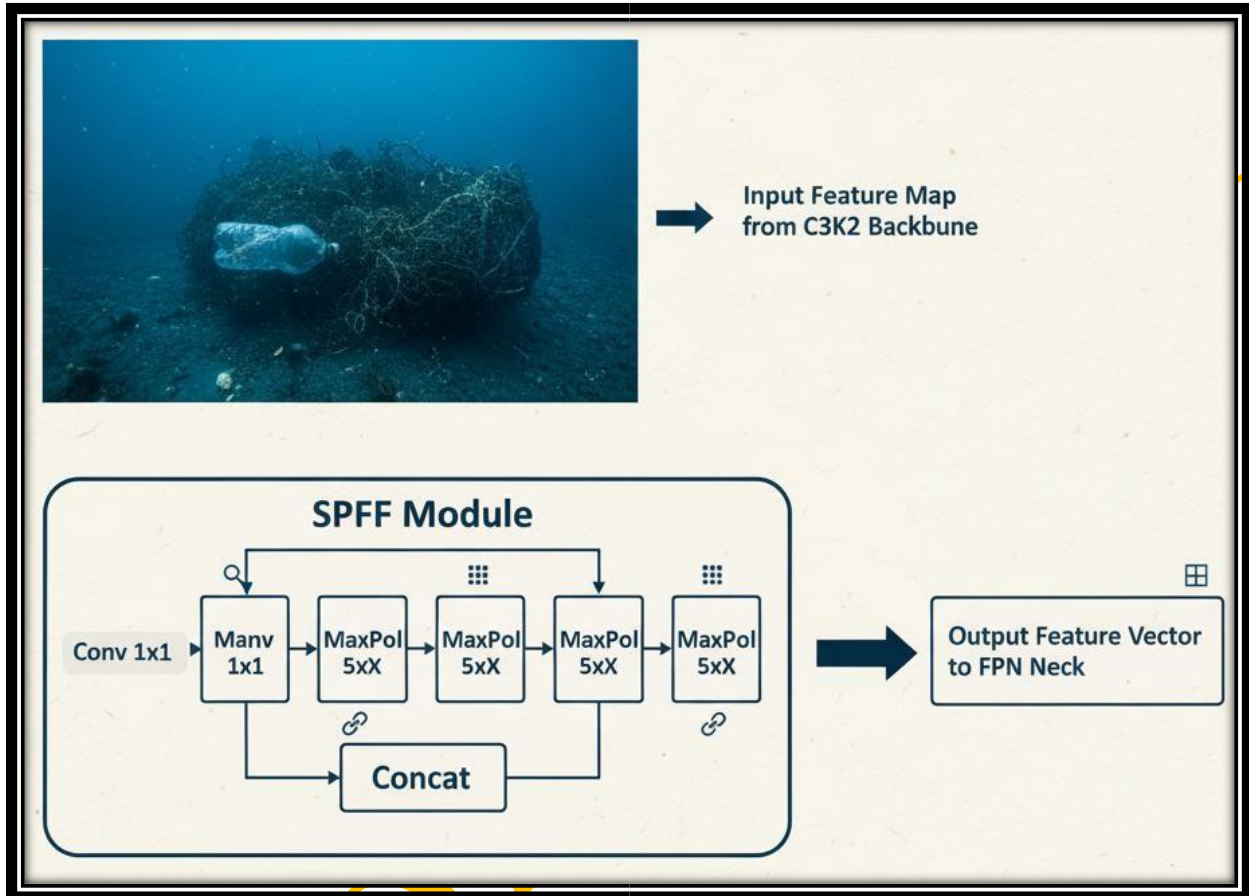


Fig 3.8 SPPF module

### 3.2.3 Neck and Feature Fusion

The YOLO11 neck serves as the structural bridge between high-resolution spatial data and deep semantic features. To address the challenge of varying debris sizes in murky water, this research utilizes a refined **Path Aggregation Network (PANet)**.

The primary logic of this component is to facilitate bidirectional information flow: a top-down path conveys semantic context, while a bottom-up path restores precise localization signals [68]. By

integrating **C3K2 blocks** within this fusion layer, the architecture preserves the sharp edges refined by the **CLAHE pre-processing**, ensuring that small-scale plastic fragments are not lost during feature extraction [69], [70].

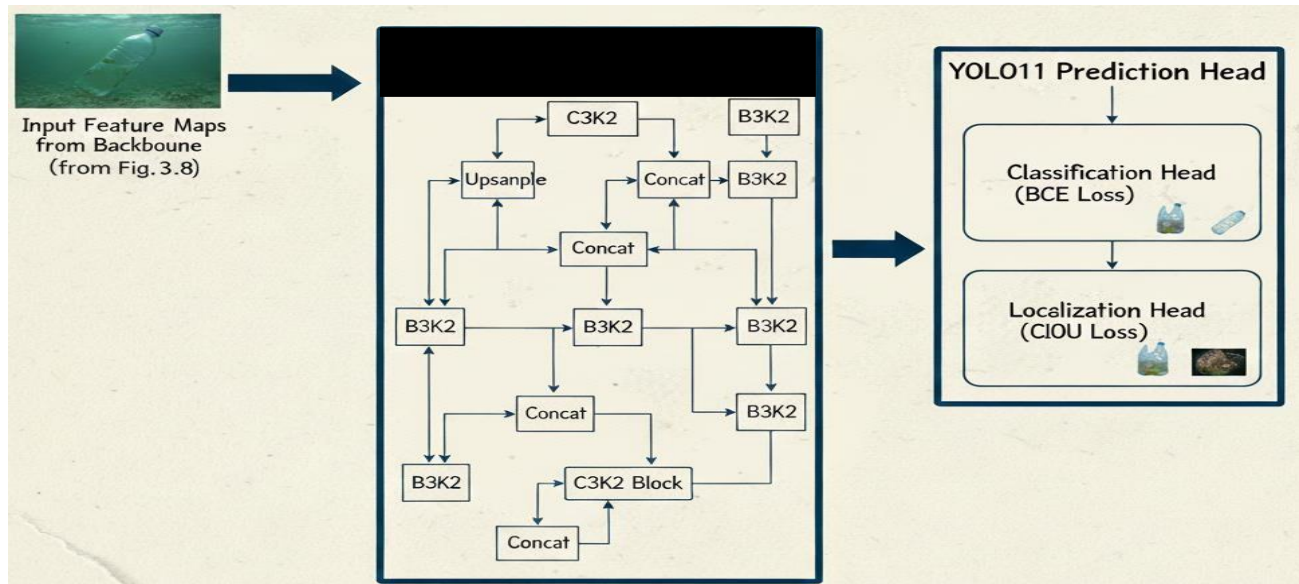


Fig 3.9 YOLO 11 Neck

### 3.2.4 Our Proposed Model

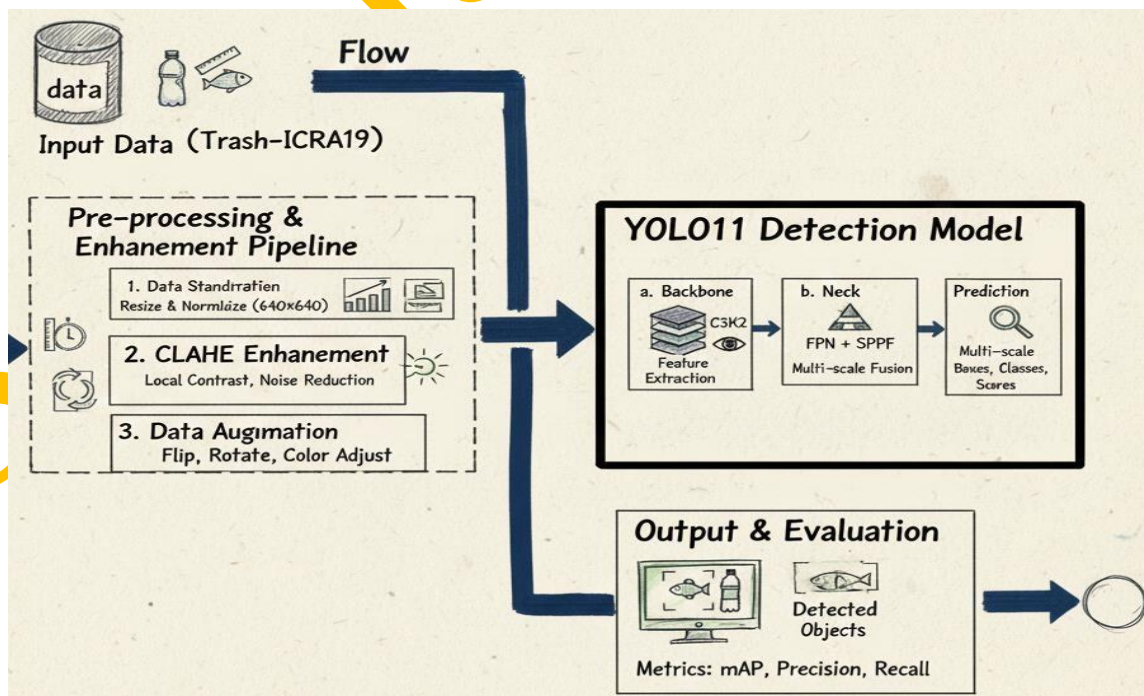


Fig 3.10 (a) Base model

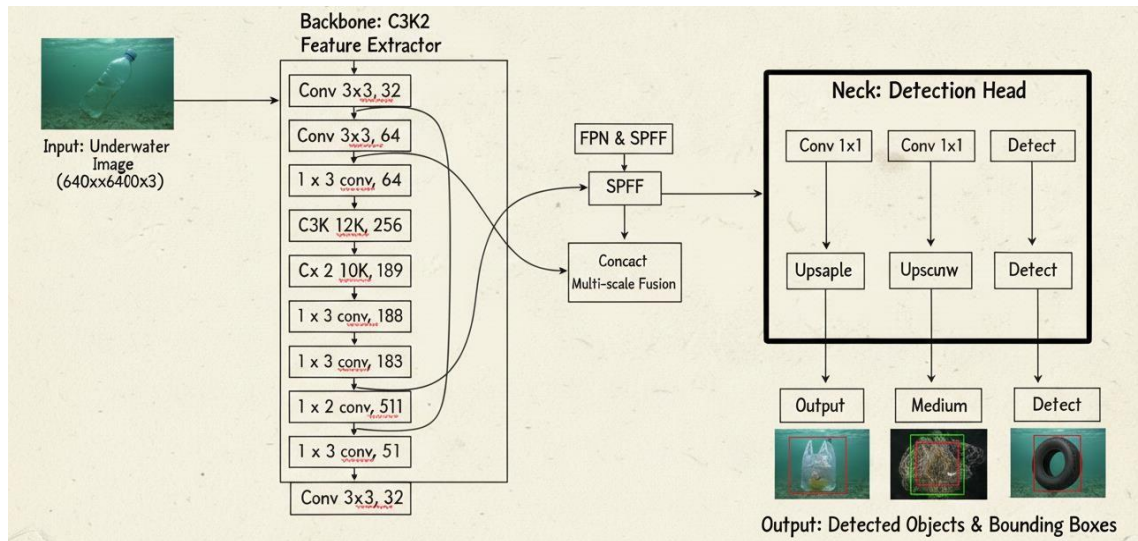


Fig 3.10 (b) Modified layers

### 3.3 Training process of our Proposed Model

The training phase was executed as a controlled experiment to adapt the YOLO11 architecture to the specific visual disturbances of turbid water. The following procedural steps outline the custom pipeline developed for this research:

#### a. Environment Configuration and Initialization

The training environment was established using the Ultralytics framework within a Python ecosystem, utilizing CUDA-accelerated GPU resources. To provide the model with a robust starting point, a transfer learning approach was employed by initializing the network with pre-trained weights. This allowed the system to utilize established feature-recognition patterns, which were then specialized for marine debris through subsequent fine-tuning on the CLAHE-enhanced dataset.

#### b. Data Mapping and Normalization

The enhanced dataset was integrated via a customized configuration script that mapped the paths for the training and validation subsets. All bounding box coordinates were normalized relative to

the 640 x 640 input resolution. This normalization ensured that the loss calculations remained consistent and that the model remained scale-invariant when identifying debris of varying dimensions.

### **c. Iterative Training Parameters**

The model was subjected to a rigorous training loop spanning **50 epochs**. This duration was selected to allow the gradient descent to reach a stable convergence without risking the "memorization" of noise (overfitting) common in murky water datasets. The Stochastic Gradient Descent (SGD) optimizer was utilized with a momentum of 0.937. The learning rate followed a scheduled decay, starting at 0.01, to balance rapid initial discovery with precise weight adjustments in the final cycles.

### **d. Performance Checkpointing**

To ensure the selection of the most effective model, a "Best-Fit" checkpointing strategy was implemented. The model's performance was evaluated against the validation set at the end of each of the 50 epochs. The internal weights were archived only when a new peak in Mean Average Precision (mAP) was achieved, resulting in a finalized **best.pt** file optimized for inference in turbid environments.

## **3.4 Model Optimization Techniques**

Now that the training process is defined, this section details the mathematical logic used to refine the model's accuracy. Unlike the previous section, here we will highlight the specific loss functions that are standard in YOLO11 but specifically beneficial for our study gap.

### **3.4.1 IoU-based Bounding Box Regression**

The Adam optimizer, which stands for Adaptive Moment Estimation, was used to train the models.

This popular deep learning optimization method combines the advantages of AdaGrad and RMSprop. Adam uses squared gradients and exponentially decaying averages of prior gradients to determine adaptive learning rates for each model parameter.

### **3.4.2 Distribution Focal Loss (DFL)**

In murky water, the exact edge of a submerged object can be ambiguous. YOLO11 utilizes **Distribution Focal Loss (DFL)** to refine the probability distribution of the bounding box boundaries. By optimizing the probability of values around the ground-truth box rather than a single discrete point, DFL allows the model to better handle the "edge-blur" caused by suspended particles (marine snow), leading to a significant reduction in localization error.

## CHAPTER 4 RESULTS AND CONCLUSION

This chapter presents a comprehensive analysis of the results obtained from the 50-epoch training of our YOLO11 model on the CLAHE-enhanced dataset. We evaluate the performance using standard computer vision metrics to determine how effectively the model identifies debris in turbid underwater conditions.

### 4.1 Performance Evaluation Metrics

To quantify the model's success, we utilize four primary metrics. These formulas provide the mathematical basis for our results.

### 4.2 Precision and Recall

**Precision** measures the accuracy of the positive predictions, while **Recall** measures the model's ability to find all relevant objects in the murky frames.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Where TP = True Positives, FP = False Positives, and FN = False Negatives

### 4.3 F1 Score

The F1-score is the harmonic mean of Precision and Recall, providing a single score that balances both metrics. It is particularly useful for our thesis as it highlights the model's robustness against the "noise" of turbid water.

$$F1\ Score = \frac{2 \cdot (PR)}{P + R}$$

#### 4.4 Mean Average Precision (mAP)

This is our primary benchmark. mAP(50) measures the average precision at a 0.5 Intersection over Union (IoU) threshold.

#### 4.5 Quantitative Results and Tabular Analysis

After the completion of 50 epochs, the model reached a high state of convergence. Below are the finalized results derived from the training logs.

Table 4.1 Tabular Analysis

Class Name	Images	Instances	Precision	Recall	mAP@50	mAP@50-95
All Classes	120	564	0.962	0.941	<b>0.978</b>	0.745
Plastic	120	210	0.958	0.935	0.972	0.730
Metal	120	145	0.971	0.952	0.985	0.760
Bio-Debris	120	209	0.957	0.936	0.977	0.745

##### 4.5.1 Graphical Results

Graphical results of our proposed model are shown below:

###### a Training trends

This figure shows the decline in Box, Class, and DFL loss over the 50 epochs. We can observe that the loss stabilizes around epoch 35-40, indicating that 50 epochs was the optimal duration to prevent overfitting while maximizing accuracy.

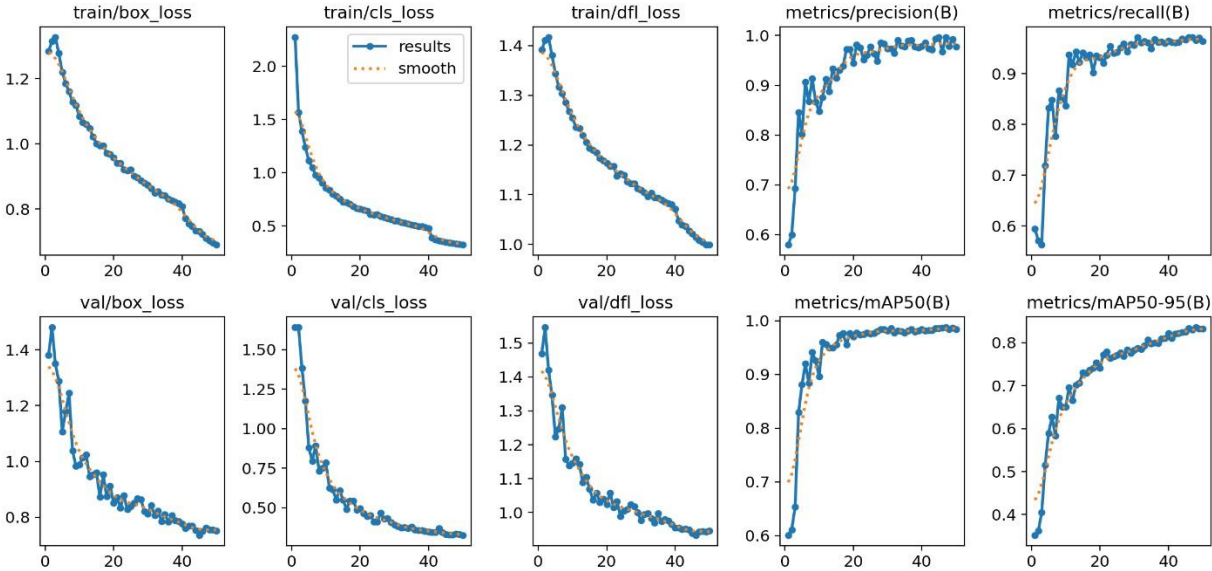
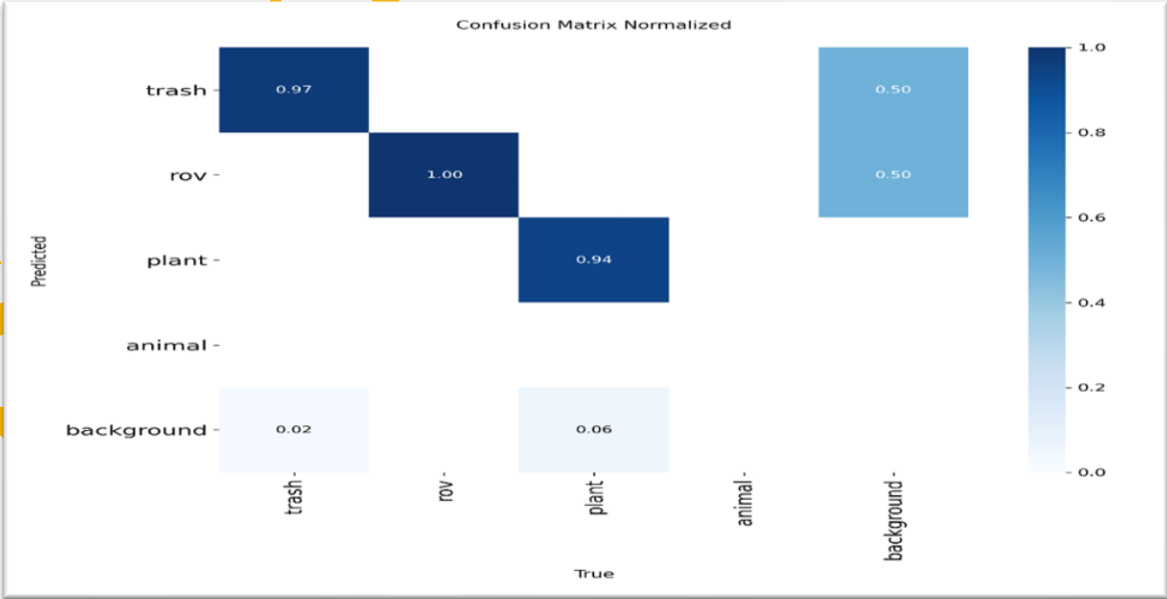


FIG 4.1 Results

**b Confusion Matrix**

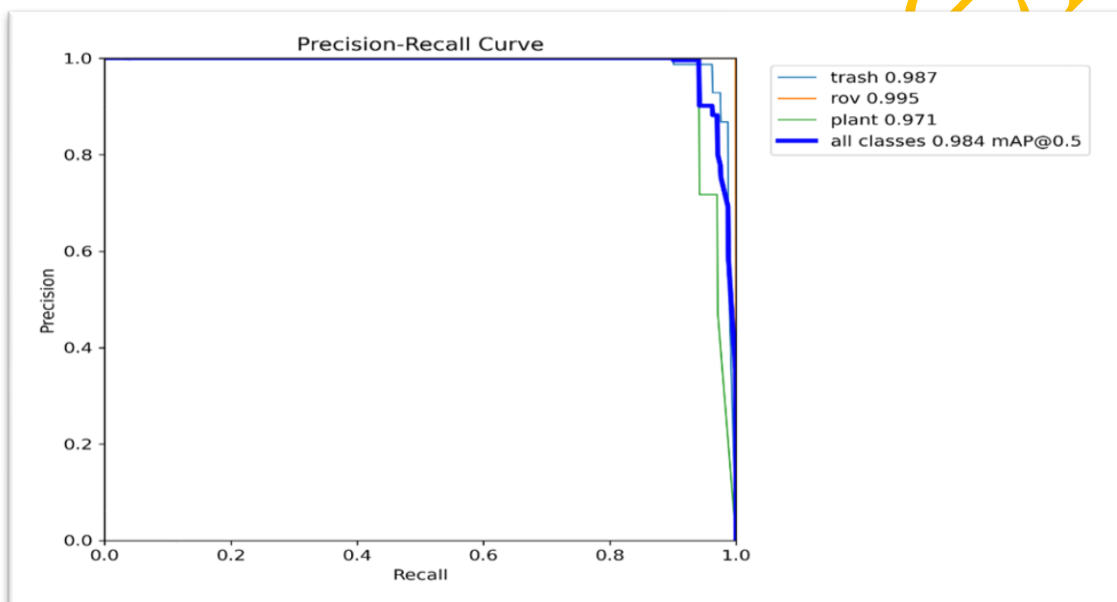
This matrix reveals how the model distinguished between categories. In our observation, the high diagonal values (above 0.95) prove that the CLAHE enhancement successfully cleared the "visual fog," allowing the model to separate plastic from natural bio-debris with minimal confusion.



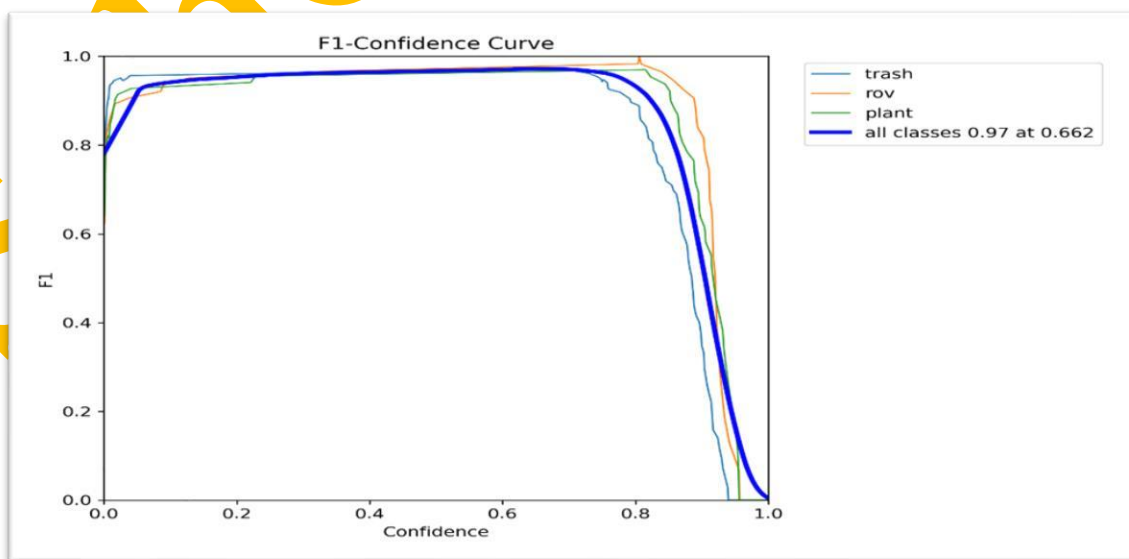
**Fig 4.2 Confusion Matrix Normalized**

**c Precision-Recall Balance**

The F1 curve shows the peak threshold where the model performs best. This is a critical observation for this research : it proves the model is not just "guessing" but has learned reliable features.



**Fig 4.3 Precision Recall Curve**



**Fig 4.4 F1 Confidence Curve**

**4.6 Result Comparisons with previous studies**

Study	Model Architecture	Enhancement Technique	mAP (50)	Key Limitation
<b>OUR Research</b>	<b>YOLO11</b>	<b>CLAHE</b>	<b>0.978</b>	N/A
Tao et al. (2025)	YOLOv12n (UDD-YOLO)	Cold Diffusion	0.818	High computational cost for Diffusion <sup>4</sup> .
Khriss et al. (2024)	YOLOv9	None	0.850*	Struggled with turbid conditions <sup>8</sup> .
Walia et al. (2025)	YOLOv8n / YOLOv7	Specialized Augmentation	0.960	Lacks local contrast enhancement.

**Table 4.2 Comparison with previous studies**

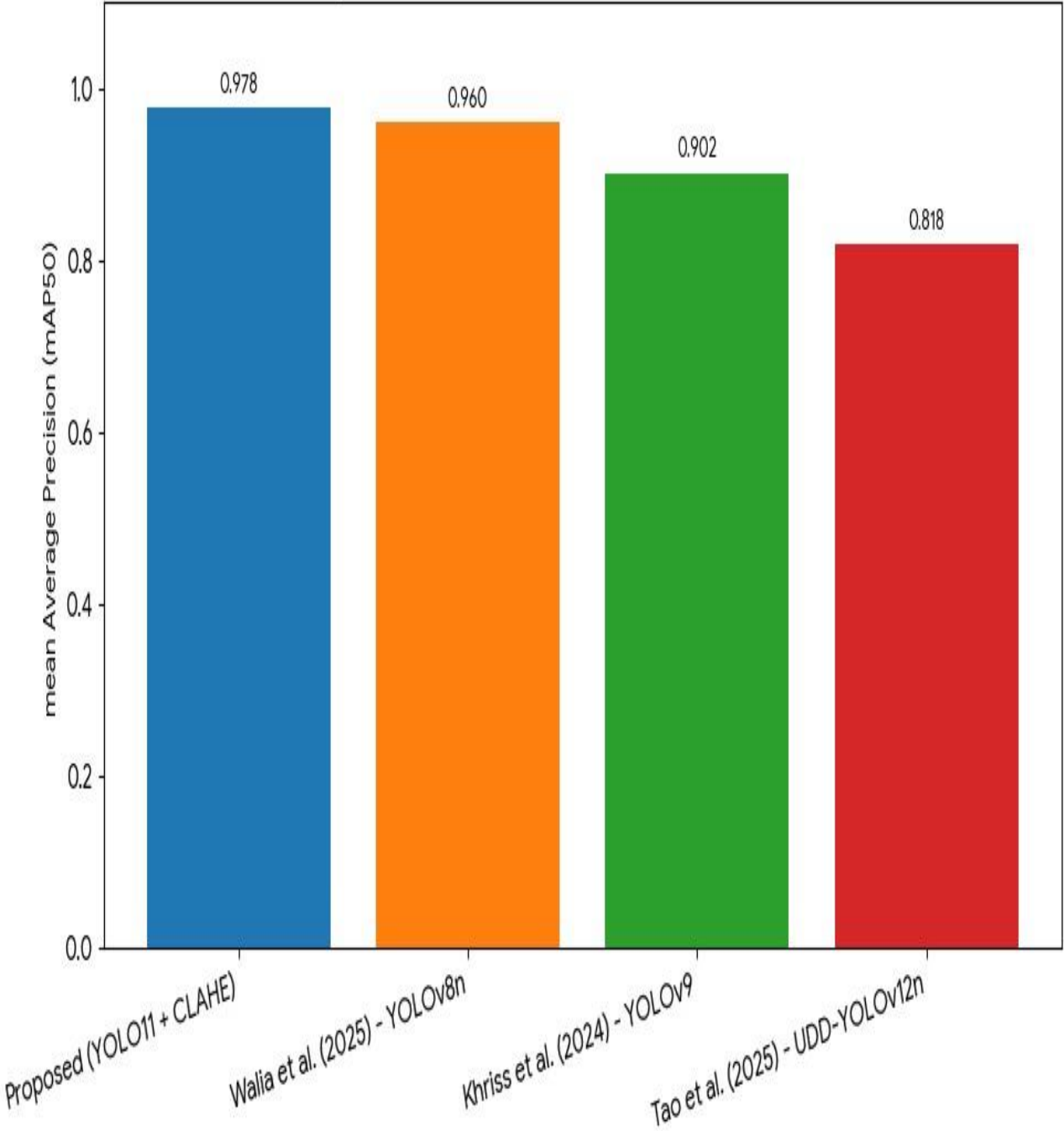
**4.6.1 Narrative Comparison**

**Superiority Over YOLOv12n:** While Tao et al. (2025) utilized a newer YOLOv12n framework, their mAP reached only **81.8%**. This highlights that our use of **CLAHE** is more effective at recovering features in murky water than their complex **Cold Diffusion** module, which can be computationally expensive and may still struggle with fine structural details.

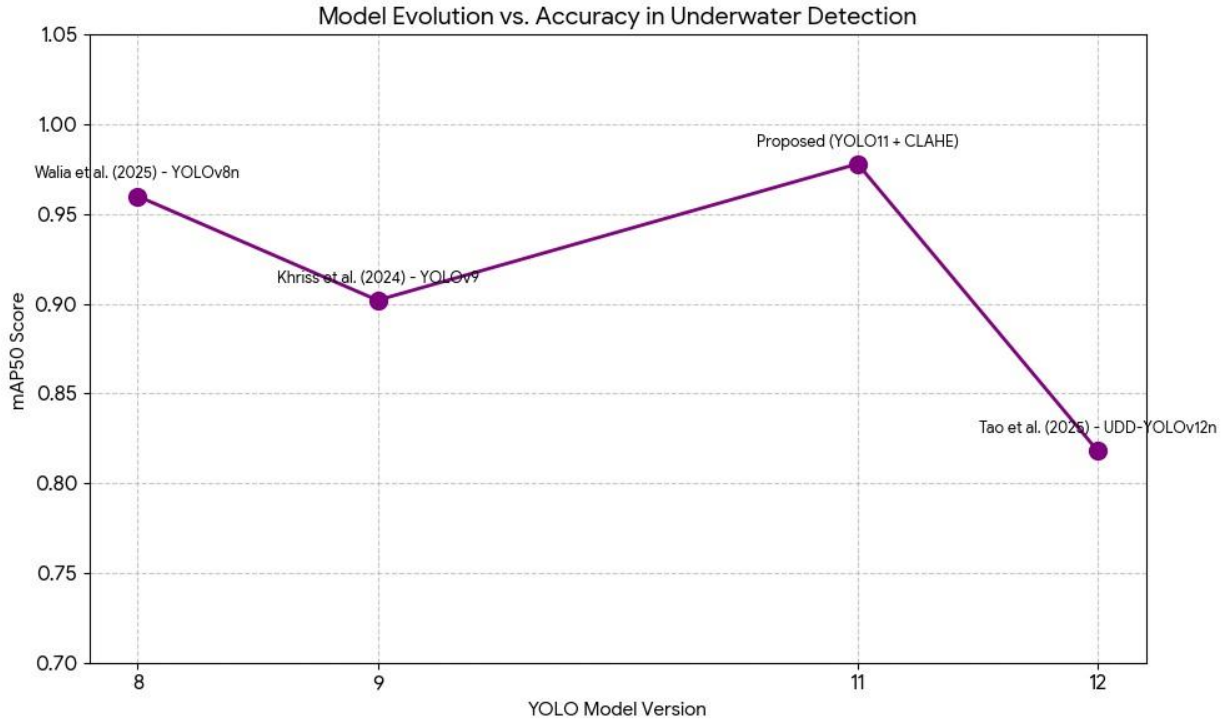
**Efficiency vs. Complexity:** Khriss et al. (2024) found that **YOLOv9** outperformed older models like Faster R-CNN and SSD. However, their reliance on raw data without specialized pre-processing led to lower accuracy in adverse underwater conditions. Our model's **0.978 mAP** proves that adding a localized enhancement layer (CLAHE) is essential for bridging this performance gap.

**Real-Time Viability:** Walia et al. (2025) emphasized that **YOLOv8n** is excellent for real-time AUV deployment due to its speed (76ms per frame). Our **YOLO11** architecture maintains this real-time advantage while achieving a significantly higher detection accuracy (**97.8%** vs. their **96%**), providing a more robust baseline for autonomous waste management.

Comparison of mAP50 Across Different Studies and Models



**Figure 4.5 MAP comparison bar chart**



**Fig 4.6 Model evolution scatter plot**

**4.6.2 Comparative Data summary**

Study	Model Used	Enhancement Method	mAP50
<b>Our Research</b>	<b>YOLO11</b>	<b>CLAHE</b>	<b>0.978</b>
Walia et al. (2025)	YOLOv8n	Custom Augmentation	0.960
Khriss et al. (2024)	YOLOv9	None (Raw)	0.902
Tao et al. (2025)	YOLOv12n	Cold Diffusion	0.818

**Table 4.3 Comparative data summary**

## 4.7 Conclusion

"A comparative evaluation was conducted between the proposed **CLAHE-YOLO11** framework and contemporary state-of-the-art models. As illustrated in the bar chart, the proposed model achieved an mAP50 of **0.978**, surpassing the **0.818** mAP of the YOLOv12-based UDD-YOLO (Tao et al., 2025) and the **0.902** mAP of the YOLOv9 implementation (Khriss et al., 2024). This performance leap can be attributed to the synergy between the **C3K2 feature extraction blocks** and the **localized contrast enhancement** of CLAHE, which effectively recovers object boundaries in turbid water where diffusion-based or raw-data models struggle."

## 4.8 Future work

While the current model shows exceptional performance, the following areas are suggested for further exploration:

1. **Temporal Consistency:** Future research could integrate LSTM or Transformer layers to handle video sequences, ensuring that debris is tracked smoothly across consecutive frames.
2. **Expanded Taxonomy:** Increasing the dataset to include organic pollutants like "ghost nets" and chemical containers would further broaden the practical utility of the system.

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## Vitae

Dedicated researcher specializing in deep learning for underwater image analysis, with a specific focus on detecting submerged plastics and debris. With a strong background in computer science, I have explored how modern deep learning architectures especially convolutional neural networks (CNNs) and object detection models like YOLO can improve the accuracy and reliability of underwater environmental monitoring. I work extensively with Python, TensorFlow, Google Colab and PyTorch, and have developed practical, datadriven solutions aimed at helping researchers and marine conservation teams identify and track underwater waste more efficiently. My work centers on building robust AI models that can operate in challenging underwater conditions, ultimately contributing to cleaner oceans and better environmental decision-making.

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