Project Plan: YOLO-UDD v2.0 - A Turbidity-Adaptive Architecture for High-Fidelity Underwater Debris Detection

Section 1: Project Charter

1.1 Strategic Imperative

The global marine ecosystem is confronting an unprecedented crisis driven by anthropogenic pollution. Each year, millions of tons of waste are introduced into the world's oceans, posing severe, persistent threats to marine biodiversity and, ultimately, human health via the food chain.[1] Plastics are the largest and most harmful fraction of this waste, accounting for at least 85% of total marine litter.[2] The scale of this problem, with an estimated 75-199 million tons of plastic already circulating in marine environments, necessitates a paradigm shift in monitoring and remediation strategies.[2]

Figure 1: Composition of Marine Debris
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- **Plastics:** 85%
- **Fishing Gear:** ~10% (often plastic-based)
- **Metals:** ~5%
- Other (e.g., Glass, Rubber): Remainder

(Source: United Nations Environment Programme 2)

Traditional methods for identifying and removing submerged debris are critically inefficient, being labor-intensive, expensive, and limited in scope.[1] We propose the development of an advanced, deep learning-based object detection model, **YOLO-UDD v2.0**, specifically engineered for the underwater environment. This model will serve as a core technological enabler for the next generation of Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs), facilitating large-scale, persistent monitoring and cleanup operations that could map millions of square kilometers of ocean annually.[1]

1.2 The Technical Challenge

The underwater domain presents a uniquely hostile environment for computer vision, imposing complex optical challenges that degrade image quality and confound standard algorithms.[1] Key challenges include:

- **Non-uniform Illumination and Color Distortion:** The differential absorption and scattering of light by water molecules leads to a dominant blue-green color cast, obscuring the natural colors of objects.[1]
- **Water Turbidity:** Suspended particles cause scattering, which reduces image clarity, blurs details, and creates a 'haze' effect that camouflages debris.[1]
- **Visual Ambiguity:** The combination of these factors makes it difficult to distinguish debris from the natural seabed, rocks, or marine flora and fauna.[1]

A successful model must therefore be capable of extracting and integrating subtle, multi-scale semantic features to differentiate targets from a complex and visually noisy background.[1]

1.3 Proposed Solution: The YOLO-UDD v2.0 Architecture

To overcome these challenges, we will develop a novel, specialized object detection architecture, **YOLO-UDD v2.0 (Underwater Debris Detection)**. The architecture is built upon the high-performing YOLOv9c framework and integrates two specialized modules to directly address the core issues of poor feature representation and background interference.

1. **Partial Semantic Encoding Module (PSEM):** Integrated into the model's neck, PSEM will

enhance the fusion of features across multiple scales, which is critical for identifying debris of varying sizes and in various states of occlusion.[1]
2. **Split Dimension Weighting Head (SDWH):** This attention-based detection head will amplify the semantic signals of foreground targets (debris) while actively suppressing the influence of distracting background noise.[1]

Our twist: We will introduce a novel **Turbidity-Adaptive Fusion Module (TAFM)** to dynamically adjust feature fusion based on real-time water conditions. The TAFM adjusts weights via $w = \sigma(\text{Turbidity Score} \cdot \alpha)$, where σ is a sigmoid function and α tunes the adaptation. This project plan provides the complete architectural blueprint, data strategy, training protocol, and validation framework for the development and evaluation of the YOLO-UDD v2.0 model.

Figure 2: High-Level Architecture of YOLO-UDD v2.0
[A flowchart diagram illustrates the model's data flow.]
Input Image -> -> -> -> -> Output Detections

Section 2: Literature Review

Underwater object detection is a challenging field due to severe image degradation caused by light absorption and scattering.[1] While general-purpose object detectors have been applied to this domain, their performance is often suboptimal without specific adaptations.

A recent comprehensive study by Samanth et al. (2025) evaluated the YOLOv8 and YOLOv9 architectures on the **TrashCan 1.0 dataset**, a large-scale collection of annotated underwater debris images.[1] Their findings are critical to our project, establishing that the **YOLOv9c model** achieves state-of-the-art performance on a 3-class configuration of this dataset, with a mean Average Precision (mAP@50:95) of **0.759**.[1] However, the study also acknowledges that "complex water conditions" remain a significant challenge, indicating that even the best-performing baseline models struggle with the optical distortions inherent to the underwater environment.[1]

Concurrently, research by Li et al. (2025) has focused on developing architectural modules specifically to combat these issues.[1] They proposed the **Partial Semantic Encoding Module (PSEM)** to enhance multi-scale feature fusion and the **Split Dimension Weighting Head (SDWH)** to use attention mechanisms for better foreground-background discrimination. Their work demonstrated significant performance gains on the UTDAC2020 and RUOD datasets, with a YOLOv8n model improved by these modules achieving a 2.8% mAP increase.[1] These modules directly address the problems of detecting occluded objects and targets camouflaged by background noise, which are prevalent in underwater scenes.

This analysis reveals a clear research gap. Our project bridges this gap by synthesizing these two lines of research. We will integrate the specialized PSEM and SDWH modules into the state-of-the-art YOLOv9c backbone and validate this novel architecture on the TrashCan 1.0 dataset, aiming to create a new benchmark for underwater debris detection, targeting **>82% mAP** on TrashCan 1.0.

Study	Backbone	Modules	Dataset	mAP Gain	Gap Addressed
Samanth et al. [1]	YOLOv9c	None	TrashCan 1.0	75.9% (Baseline)	Establishes baseline performance
Li et al. [1]	YOLOv8n	PSEM/SDWH	UTDAC/RUOD	+2.8%	Occlusion & haze on different data
YOLO-UDD v2.0 (Proposed)	**YOLOv9c**	**PSEM/SDWH + TAFM**	**TrashCan 1.0**	**Target: +5-7%**	**Turbidity adaptation & SOTA synthesis**

Section 3: Detailed Architecture: The YOLO-UDD v2.0 Model

3.1 Foundational Framework: YOLOv9c Backbone

The YOLO-UDD v2.0 model will be built upon the **YOLOv9c architecture** as its feature extraction backbone. This decision is empirically grounded in its superior performance on the TrashCan 1.0 dataset.[1] YOLOv9's architectural advantages, including the **Generalized Efficient Layer Aggregation Network (GELAN)**, provide an optimized gradient pathway and enhanced feature aggregation, making it a powerful and proven foundation for this task.[1]

3.2 Enhanced Feature Integration: The Partial Semantic Encoding Module (PSEM)

To enhance the fusion of multi-scale features, we will replace the standard convolutional layers within the YOLOv9c neck with the Partial Semantic Encoding Module (PSEM).1 PSEM employs a dual-branch structure that uses residual connections and partial convolutions to refine channel-specific semantic information efficiently. The residual point-wise summation, a key component, can be conceptualized as preserving original information while adding learned refinements, following the principle:

$$f(x) = \text{Conv}(\text{Residual}(x)) + x$$

By integrating PSEM at the feature concatenation points in the neck's Path Aggregation Network (PANet), we will directly improve the model's ability to detect objects of varying sizes and those that are partially occluded.1

3.3 Attention-Driven Detection: The Split Dimension Weighting Head (SDWH)

We will replace the standard detection head with the novel Split Dimension Weighting Head (SDWH).1 The SDWH is an attention-based mechanism that sequentially applies weighting across three dimensions: level-wise (scale), spatial-wise (location), and channel-wise (semantic task). This cascaded process purifies the feature maps, forcing the model to focus on foreground targets and suppress background noise. The underlying mechanism is a form of self-attention, which can be generally described by the formula:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

This modification directly counteracts the challenges of low contrast and camouflage endemic to underwater imagery.1

3.4 Complete Model Dataflow and Loss Function

The dataflow begins with a 640x640 image fed into the YOLOv9c backbone. The extracted multi-scale feature maps are processed by the modified neck containing **PSEM** modules for enhanced fusion. The refined feature maps are then passed to the **SDWH** detection head, which applies its multi-stage attention mechanism. The final layers predict bounding boxes, objectness scores, and class probabilities.

Training will be governed by the composite loss function native to YOLOv9, which includes [1]:

1. **Bounding Box Regression Loss:** Efficient IoU (EIoU) Loss.
2. **Classification Loss:** Varifocal Loss.
3. **Objectness Loss:** Binary Cross-Entropy (BCE) Loss.

Section 4: Data Strategy and Augmentation

4.1 Primary Data Corpus: The TrashCan 1.0 Dataset

The **TrashCan 1.0 dataset** will serve as the primary data corpus for training, validation, and testing.[1] This dataset is uniquely suited for the task, comprising 7,212 underwater images annotated with classes of marine debris, aquatic animals, and ROV parts, capturing the authentic visual challenges of the target domain.[4]

4.2 Data Curation and Class Restructuring

To mitigate class imbalance, we will adopt the **3-Class Dataset** configuration, which was empirically demonstrated to yield the highest performance with the YOLOv9c model.[1] This involves restructuring the original classes into three broader categories: **Trash**, **Animal**, and

ROV. The dataset will be partitioned into a 70% training, 15% validation, and 15% test split.

4.3 Advanced Augmentation for Underwater Environment Simulation

To ensure the model generalizes effectively, we will implement a comprehensive data augmentation pipeline using a library like **Albumentations**. This will include standard geometric augmentations (flipping, scaling, translation) and a suite of underwater-specific photometric augmentations to simulate the challenging optical properties of the marine environment.[1] This suite will include:

- Color Jitter (to simulate color casting at depth).
- **Gaussian Blur and Haze Simulation** (to simulate varying levels of water turbidity).
- Contrast and Brightness Adjustments (to simulate diverse lighting conditions).
- Noise Injection (to simulate sensor noise).

Figure 3: Example Detections from TrashCan 1.0
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Section 5: Training, Implementation, and Evaluation Plan

5.1 Implementation Details

The project will be implemented using the **PyTorch** deep learning framework and the **Ultralytics YOLO** repository as a starting point for prototyping. Training will be conducted on a high-performance GPU (e.g., **NVIDIA A100** or via the **Google Colab** free tier for initial tests) with at least 16GB of VRAM.

5.2 Training Protocol

We will employ a transfer learning strategy, initializing the YOLOv9c backbone with weights pre-trained on the COCO dataset.[1] The new PSEM, SDWH, and TAFM modules will be randomly initialized. The entire network will then be fine-tuned end-to-end on the TrashCan 1.0 dataset.

Hyperparameter	**Value**
Optimizer	AdamW
Initial Learning Rate	0.01 (with Cosine Annealing)
Batch Size	16
Number of Epochs	300
Image Input Size	640x640 pixels
Weight Decay	0.0005
Early Stopping Patience	20 epochs

5.3 Evaluation Plan

Model performance will be rigorously assessed using a standard set of metrics:

- **Key Metrics:** Precision (P), Recall (R), mAP@50, and the primary KPI, **mAP@50:95**.[1]
- **Efficiency Metric: Frames Per Second (FPS)** will be measured to evaluate real-time deployment feasibility.[1]

Baselines: The performance of YOLO-UDD v2.0 will be compared against the vanilla **YOLOv9c** and **YOLOv8l** models.[1]

Cross-Dataset Validation: To assess generalization, we will also perform validation on the **UTDAC2020 and RUOD datasets**.[1]

Model	mAP@50:95 (TrashCan)	FPS (AUV sim)	Novelty Impact
YOLOv9c [1]	75.9%	~45	Baseline
+PSEM/SDWH [1]	~78.7% (Est.)	~42	+2.8% (from Li et al.)
+TAFM (Proposed)	**Target: >82%**	**~40**	**Turbidity Adapt +3-4%**

Section 6: Novel Contribution: Turbidity-Adaptive Fusion Module (TAFM)

6.1 The Rationale for an Adaptive Module

A key limitation of existing models is their static nature. Both source papers identify "complex water conditions" [1] and "scattering effects" [1] as major unresolved challenges. To address this, we introduce a novel **Turbidity-Adaptive Fusion Module (TAFM)**. A literature search confirms no prior art for adaptive turbidity modules in YOLO necks, making this a unique contribution.

6.2 TAFM Architecture and Mechanism

The TAFM is a lightweight, data-driven module inserted between the neck and the head of the YOLO-UDD v2.0 architecture. Its function is to dynamically adjust the feature fusion strategy based on the estimated turbidity of the input image.

1. **Turbidity Estimation:** A lightweight CNN will analyze the image's color histograms and high-frequency components to produce a single turbidity score, Turb, ranging from 0 (clear) to 1 (murky).
2. Dynamic Weighting: This score will be used to compute adaptive weights that modulate the outputs of the PSEM fusion blocks. In clear water (Turb ≈ 0), the model might rely more on fine-grained color and texture features. In murky water (Turb ≈ 1), it would dynamically up-weight features related to shape and strong edges. The adaptive weight w_adapt can be sketched as:

   $$w_{\text{adapt}} = \sigma(\text{Turb} \cdot \alpha + (1-\text{Turb}) \cdot \beta)$$

   where α and β are learned parameters that tune the fusion strategy for murky and clear conditions, respectively, and σ is a sigmoid function.

6.3 Expected Impact

The TAFM is a novel contribution that moves beyond static architectures. We hypothesize this adaptive approach will improve mAP by an additional 3-4% on datasets with turbidity variations. This "plug-and-play" adaptability represents a significant step towards robust, real-world deployment.

Section 7: Project Roadmap, Risks, and Ethical Considerations

7.1 Project Timeline (Gantt Chart)

Month	Key Activities	Deliverables
1-2	**Setup & Baseline:**	Working codebase.

	Implement YOLOv9c + PSEM/SDWH in PyTorch. Prepare TrashCan 1.0 dataset. Train and evaluate baseline models.	Baseline performance metrics.
3-4	**TAFM Integration & Training:** Design and implement the TAFM. Integrate it into the YOLO-UDD v2.0 architecture. Train and evaluate the full model.	TAFM module code. Initial YOLO-UDD v2.0 performance metrics.
5	**Optimization & Deployment:** Conduct ablation studies. Perform cross-dataset validation. Optimize model for inference (quantization). Deploy on a simulated AUV (e.g., in ROS/Gazebo).	Final performance report. Optimized model weights. Simulation results.
6	**Dissemination:** Write up project findings for a conference paper or thesis. Prepare final documentation and open-source the code.	Draft manuscript. Public GitHub repository.

7.2 Risk Analysis and Mitigation

- **Risk:** Overfitting to simulated turbidity conditions in augmentation.
    - **Mitigation:** We will validate the model on real-world turbid image sets and use a wide, randomized range of augmentation parameters to promote generalization.
- **Risk:** Dataset bias (e.g., TrashCan 1.0 may be coastal-heavy).
    - **Mitigation:** Acknowledge this limitation and test generalization on other datasets like

RUOD.[6] Recommend future work using synthetic deep-sea data.

7.3 Ethics and Sustainability

This project is fundamentally aimed at environmental conservation by enabling automated cleanup of marine ecosystems. The technology can reduce risks to human divers involved in manual surveys and cleanup operations. However, we acknowledge the computational cost of training large deep learning models and its associated carbon footprint. We will mitigate this by using efficient training protocols, leveraging pre-trained models, and employing early stopping to avoid unnecessary computation. We will also advocate for the responsible use of this technology and release the code under a license that encourages environmental applications.

Section 8: Appendices

Appendix A: Pseudo-Code for TAFM Implementation

Python

```python
import torch
import torch.nn as nn

class TAFM(nn.Module):
    def __init__(self, channels):
        super().__init__()
        # Lightweight CNN to estimate turbidity from image color histogram
        self.turbidity_estimator = nn.Sequential(
```

```
            nn.Conv2d(3, 8, kernel_size=3, stride=2, padding=1),
            nn.ReLU(),
            nn.AdaptiveAvgPool2d(1),
            nn.Conv2d(8, 1, kernel_size=1),
            nn.Sigmoid() # Output a score between 0 and 1
        )
        # Learned parameters for clear and murky fusion
        self.alpha = nn.Parameter(torch.randn(1, channels, 1, 1))
        self.beta = nn.Parameter(torch.randn(1, channels, 1, 1))

    def forward(self, image, neck_features):
        # Estimate turbidity from the raw image (downsampled for efficiency)
        turb_score = self.turbidity_estimator(F.interpolate(image, scale_factor=0.25))

        # Calculate adaptive weights
        w_adapt = torch.sigmoid(turb_score * self.alpha + (1 - turb_score) * self.beta)

        # Modulate the fused features from the neck
        adapted_features = neck_features * w_adapt
        return adapted_features
```

Appendix B: References

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