CONCEPTUAL PROJECT – II REVIEW 1 REPORT

Semantic Segmentation Using U-Net and DeepLabV3+ for Underwater Image Analysis

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1. Introduction:

Underwater image analysis plays a crucial role in marine biodiversity conservation, ocean monitoring, underwater robotics, coral-reef health assessment, and pollution detection. However, underwater images suffer from major distortions such as color shift, haze, low contrast, and blurriness due to light absorption and scattering. These distortions make object identification and pixel-wise labeling extremely challenging.

Semantic segmentation provides a powerful solution by assigning a class label to every pixel in an underwater image. This enables the computer to differentiate between fish, coral reefs, sand, rocks, plants, and water regions in a single scene.

This project aims to develop a robust underwater semantic segmentation framework using two advanced deep-learning models — U-Net and DeepLabV3+ — and to design a hybrid fusion approach that combines the strengths of both models for superior segmentation accuracy under underwater conditions.

2. Problem Identification:

2.1 Problem Statement:

- Underwater images typically suffer from:
- Severe loss of color information
- Distorted textures and edges
- Low visibility and noise
- Poor lighting
- These factors reduce the performance of standard segmentation algorithms.
- Existing methods often fail to accurately segment underwater scenes due to:
- Object boundaries blurred
- Multi-scale object sizes- small fish, large coral structures
- Complex textures
- Floating particles

2.2 Gap Identified:

Most traditional segmentation methods are trained on clean, terrestrial datasets. They do not adapt well to underwater distortions. Even deep-learning models struggle when used individually:

- **U-Net** → Good at fine details, struggles with large-scale features
- **DeepLabV3+** → Good at multi-scale context, but may miss fine boundaries

2.3 Our Research Gap:

There is limited work combining both architectures **together** to leverage:

- U-Net's boundary precision
- DeepLabV3+'s multi-scale context extraction

This gap motivates the development of a **hybrid segmentation model** capable of outperforming standalone models.

3. Objectives of the Study:

1. To analyze underwater image characteristics and identify key challenges.
2. To implement U-Net and DeepLabV3+ architectures for semantic segmentation.
3. To compare their performance using accuracy metrics such as IoU, Dice Score, and Boundary F1.
4. To design a hybrid fusion model that combines outputs/features from both networks.
5. To improve segmentation performance for complex underwater environments.
6. To evaluate the model on underwater datasets such as SUIM or UWSeg.

4. Methodology (10 Marks)

4.1 Dataset Collection:

Underwater datasets such as **SUIM (Semantic Underwater Image Dataset)** containing labeled masks of:

- Fish
- Coral reefs
- Plants
- Rocks
- Waterbody
- Wrecks

4.2 Preprocessing:

- Image resizing and normalization
- Color correction (UCM or fusion-based enhancement)
- Augmentation (rotation, flipping, brightness adjustments)
- Mask normalization and class encoding

4.3 Model 1: U-Net:

- Encoder–decoder architecture
- Skip connections preserve spatial information
- Suitable for small datasets and fine boundary detection
- Efficient training

4.4 Model 2: DeepLabV3+:

- Atrous Spatial Pyramid Pooling (ASPP) for multi-scale feature extraction
- Decoder module improves boundary refinement
- Highly effective in complex underwater scenes with varying object sizes

4.5 Hybrid / Ensemble Model:

The innovation of the project lies in combining the strengths of both models using:

- **Weighted averaging of output masks**
- **Pixel-wise voting**
- **Feature fusion**

This hybrid approach aims to improve:

- IoU
- Dice Score
- Edge sharpness
- Robustness under underwater distortions

4.6 Evaluation Metrics:

- Intersection over Union (IoU)
- Mean IoU (mIoU)
- Dice Coefficient
- Boundary F1-Score

- Computational efficiency

5. Novelty of the Work:

1. **Dual-model hybrid approach:** Combines U-Net and DeepLabV3+ — rarely explored in underwater segmentation research.
2. **Underwater-aware preprocessing:** Incorporates color correction and enhancement to handle underwater distortions.
3. **Boundary-focused segmentation improvement:** Hybrid fusion improves edge clarity and object separation.
4. **Performance benchmarking on underwater-specific challenges:** Evaluating segmentation accuracy under haze, low contrast, and scattering.
5. **Generalizable framework:** Useful for marine robotics, coral monitoring, and environment analysis.

6. Expected Outcomes:

- Improved segmentation accuracy over standalone U-Net and DeepLabV3+.
- Better detection of fine details like coral branches and small fish.

- Stronger multi-scale understanding of underwater scenes.
- High-quality segmentation masks suitable for marine research applications.
- A hybrid model architecture that can be extended to other domains.

7. References :

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