

1. METHODOLOGICAL OVERVIEW

The DeepSea Restoration AI leverages a Hybrid Sequential Architecture that combines deterministic physical modeling with adaptive deep learning. The process is designed to neutralize the optical degradations of the underwater medium (absorption and scattering) before refining the visual details using a neural residual network.

2. DATA ACQUISITION & SMART PRE-PROCESSING

The system is trained on the UIEB (Underwater Image Enhancement Benchmark) dataset. Our methodology includes:

- Recursive Scanning: Automatic discovery of image pairs across deeply nested directory structures.
- Zombie Filtering: Detection and exclusion of corrupted or empty (0-byte) image files.
- Pre-Calculated Baselines: Every training image undergoes Stage 1 processing to provide the AI with a 'Coarse' baseline for residual learning.

3. STAGE 1: PHYSICS-BASED VARIATIONAL MODELING

This phase reverses the Light Formation Model: $I(x) = J(x)t(x) + B(1-t(x))$.

- Dark Channel Prior (DCP): Used to estimate depth cues by analyzing the darkest pixels in the scene.
- Backlight Estimation (B): Identifies the specific global color of the water (blue, green, or turbid) for targeted subtraction.
- Transmission Mapping (t): Calculates a depth heatmap to determine the level of dehazing required per pixel.
- Guided Filtering: Refines the transmission map using the raw image as an edge-guide to ensure structural sharpness.

4. STAGE 2: NEURAL RESIDUAL REFINEMENT (U-NET)

The coarse result is polished by a 23-layer Deep Convolutional Neural Network.

- Architecture: A symmetric U-Net featuring 5 levels of encoder-decoder pairing.
- Skip Connections: These 'bridges' transfer high-resolution spatial information directly from the encoder to the decoder, preventing the loss of coral textures or biological features.
- Residual Mapping: Instead of generating an image from scratch, the network learns to predict

only the corrections needed for the physics-based Stage 1 output.

5. HYBRID FUSION & OPTIMIZATION

The final image is a fusion: Final = Coarse_Output + AI_Residual.

- Loss Functions: We employ a Composite Loss Strategy: MSE (Mean Squared Error) for color precision + SSIM (Structural Similarity) for textural integrity.
- Optimizer: Adam optimizer with a learning rate of 1e-4.
- Hardware: Automatic detection of CUDA (GPU) or CPU-optimized execution paths.