Implementation and Evaluation of Lightweight Deep Learning Models for Real-Time Underwater Image Enhancement: A Comprehensive Review

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Abstract. Underwater optical imaging faces significant challenges due to wavelength-dependent light absorption, scattering, and color distortion, which degrade image quality and hinder marine exploration applications. Traditional enhancement methods often lack adaptability to diverse underwater conditions, while conventional deep learning approaches impose prohibitive computational demands for real-time deployment on resource-constrained platforms. This comprehensive review systematically examines the state-of-the-art in lightweight deep learning architectures specifically designed for real-time underwater image enhancement. We present a detailed taxonomy of efficiency-oriented designs including depth wise separable convolutions, attention mechanisms, neural architecture search, and model compression techniques. The paper critically analyzes implementation strategies, benchmark datasets, and evaluation metrics, both perceptual quality indicators and computational efficiency measures. Furthermore, we synthesize comparative performance analyses across multiple lightweight architectures and identify persistent challenges in domain generalization, temporal consistency, and hardware-software co-design. Emerging research directions including physics-informed networks, multimodal fusion, and ultra-low-power deployment paradigms are discussed. This review aims to consolidate current knowledge and guide future research toward robust, efficient vision systems for underwater autonomous platforms.

Keywords: Underwater Image Enhancement; Lightweight Deep Learning; Real-Time Processing; Model Compression; Autonomous Underwater Vehicles (AUVs) ; Computational Efficiency; Edge Computing; Edge AI

1. Introduction

1.1 The Underwater Imaging Conundrum: Physical Basis and Practical Implications

The ocean constitutes approximately 71% of Earth's surface and represents one of the least explored and most critical frontiers for scientific discovery, environmental monitoring, and resource management [1]. Underwater optical imaging serves as a primary sensory modality for numerous applications including marine biology surveys [2], archaeological documentation [3], infrastructure inspection [4], and search-and-rescue operations [5]. However, the aqueous medium imposes severe physical constraints on light propagation through three primary degradation mechanisms: (1) wavelength-dependent absorption, where longer wavelengths (red, orange) are attenuated more rapidly than shorter wavelengths (blue, green), resulting in a characteristic blue-green color cast [6]; (2) forward scattering by suspended particles, which creates haze and reduces contrast [7]; and (3) backscattering from artificial light sources, which introduces bright spots and further reduces visibility [8]. These phenomena are mathematically described by the simplified radiative transfer equation:

$$I^c(x) = J^c(x) \cdot t^c(x) + A^c \cdot (1 - t^c(x))$$

where $I^c(x)$ is the observed intensity at pixel x for color channel c (R, G, B), $J^c(x)$ is the scene radiance, $t^c(x)$ is the transmission map representing light attenuation, and A^c is the background light (veiling light) [9]. The transmission map decays exponentially with distance:

$$t^c(x) = e^{-\beta c \cdot d(x)}$$

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where β^c is the attenuation coefficient and $d(x)$ is the scene distance [10].

These degradations vary substantially across different water types from clear oceanic waters (Jerlov Type I) to turbid coastal waters (Jerlov Type III) and with environmental conditions such as depth, phytoplankton concentration, and sediment load [11]. Consequently, raw underwater imagery exhibits poor color fidelity, low contrast, and blurred details, severely impairing both human interpretation and automated computer vision algorithms for object detection, segmentation, and classification [12].

1.2 Historical Progression: From Physics-Based Models to Data-Driven Approaches

The evolution of underwater image enhancement techniques can be categorized into three distinct generations:

(1) Physical Model-Based Methods (First Generation)

These approaches attempt to invert the degradation process using simplified physical models. Early methods included histogram equalization-based techniques [13] and white-balancing algorithms [14]. More sophisticated approaches adapted atmospheric dehazing methods to underwater scenes, such as the Dark Channel Prior (DCP) [15] and its underwater variants [16], [17]. Wavelength compensation methods explicitly model the differential attenuation of RGB channels [18], while image fusion techniques combine multiple enhanced versions of the same image [19]. Although physically motivated, these methods require accurate estimation of scene depth and water optical properties, which are often unavailable in practice. They also tend to produce artifacts when physical assumptions are violated [20].

(2) Early Learning-Based Methods (Second Generation)

The advent of machine learning introduced data-driven approaches that learn enhancement mappings from examples. Initial methods employed shallow neural networks [21] and dictionary learning [22]. However, these approaches were limited by their representational capacity and often failed to generalize across diverse underwater conditions.

(3) Deep Learning Revolution (Third Generation)

The breakthrough came with convolutional neural networks (CNNs) and generative adversarial networks (GANs), which demonstrated unprecedented performance in learning complex degradation patterns directly from data. Seminal works include WaterNet [23], which employed a multi-scale network with physical priors; Ucolor [24], which introduced medium transmission-guided color space embedding; and UGAN [25], which leveraged adversarial training for realistic enhancement. These models consistently outperformed traditional methods on benchmark datasets but at the cost of substantial computational complexity typically requiring hundreds of millions of parameters and giga-FLOPs per inference [26]. This computational burden renders them impractical for real-time deployment on embedded systems with strict power and latency constraints.

1.3 The Imperative for Lightweight Deep Learning: Bridging the Performance-Efficiency Gap

The deployment of computer vision systems on autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and other underwater platforms imposes stringent requirements that have catalyzed research into lightweight deep learning models. Key constraints include:

(1) Limited Computational Resources

Most underwater vehicles utilize embedded processors such as NVIDIA Jetson modules, ARM-based CPUs, or field-programmable gate arrays (FPGAs) with limited memory bandwidth and processing power [27].

(2) Energy Constraints

Battery-operated platforms have finite energy budgets, making power efficiency paramount [28].

(3) Real-Time Processing Requirements

Applications such as obstacle avoidance, target tracking, and real-time mapping demand low-latency processing (typically >30 FPS) [29].

(4) Bandwidth Limitations

Acoustic communication, the primary underwater transmission modality, offers extremely low bandwidth (kbps range), necessitating onboard processing rather than cloud offloading [30].

These constraints have driven the development of lightweight deep learning models that strategically trade minimal accuracy degradation for substantial reductions in computational cost. This trade-off is quantified by metrics such as the performance-efficiency Pareto frontier, where optimal models maximize enhancement quality while minimizing computational resources [31].

1.4 Scope, Organization, and Novel Contributions of This Review

This review provides a comprehensive synthesis of lightweight deep learning approaches for real-time underwater image enhancement. While several excellent surveys cover broader aspects of underwater image processing [32], [33] or generic efficient deep learning [34], this work specifically focuses on the intersection of these domains. Recent surveys (e.g., 2024 comprehensive overview on DL-based UIE) provide additional context. Our contributions are:

(1) Taxonomic Organization

We present a hierarchical taxonomy of lightweight architectural components, training strategies, and deployment optimizations specifically tailored for underwater enhancement.

(2) Critical Analysis

We provide comparative evaluations across multiple dimensions architectural efficiency, enhancement quality, and computational performance with consistent benchmarking protocols.

(3) Implementation Roadmap

We detail practical considerations for dataset preparation, training methodologies, and deployment on diverse hardware platforms.

(4) Future Directions

We identify emerging trends and open research challenges, providing a roadmap for future investigation.

The remainder of this paper is organized as follows: Section 2 details lightweight architectural designs; Section 3 covers implementation strategies; Section 4 presents evaluation frameworks; Section 5 discusses open challenges; and Section 6 concludes with future perspectives.

2. Lightweight Deep Learning Architectures: Design Principles and Taxonomies

2.1 Foundational Efficient Operations and Building Blocks

(1) Factorized Convolutions

Depthwise Separable Convolutions (DSC): Introduced in MobileNets [35], DSC decomposes a standard convolution into two operations: (1) a depthwise convolution applying a single filter per input channel, and (2) a pointwise convolution (1×1) combining channels. For an input feature map with D channels and kernel size k, the computational cost reduction ratio is approximately 1/k2 + 1/D, typically achieving 8-9× reduction in computations with minimal accuracy loss [36]. DSC forms the backbone of numerous underwater enhancement networks including Shallow-UWNet [37] and EfficientNet-based variants [38].

Grouped Convolutions and Channel Shuffling: Introduced in ShuffleNet [39], this approach partitions channels into groups, performing convolutions separately within each group, reducing computation by a factor of g (number of groups). To enable cross-group information flow, a channel shuffle operation permutes channels between groups. ShuffleNetV2 [40] further refined this with practical guidelines for efficient network design (G1-G4), emphasizing direct metric optimization (e.g., speed) over indirect proxies (e.g., FLOPs).

(2) Efficient Bottleneck Designs

Inverted Residual Blocks with Linear Bottlenecks (MobileNetV2): Traditional residual blocks [41] employ a "bottleneck" design: compress-expand-compress. MobileNetV2 [42] reverses this to an expand-compress design with linear bottlenecks, preventing information loss from non-linearities in low-dimensional spaces. This structure is particularly effective for feature transformation in underwater enhancement tasks [43].

Squeeze-and-Excitation (SE) Blocks: Although not primarily an efficiency technique, SE blocks [44] enhance feature representation with minimal computational overhead (typically <1% increase in FLOPs). They model channel-wise dependencies through global average pooling followed by two fully-connected layers with a reduction ratio. SE blocks are integral to MobileNetV3 [45] and have been effectively incorporated into underwater enhancement networks [46].

(3) Dynamic Operations

Dynamic Convolutions: Rather than using static weights, dynamic convolutions [47] aggregate multiple convolution kernels weighted by input-dependent attention, increasing representational power with modest computational increase. Preliminary applications to underwater enhancement show promise for adapting to varying degradation levels [48].

Conditional Computation: Techniques like Switchable Normalization [49] and Dynamic Routing [50] allow networks to adapt their computational graph based on input complexity, potentially allocating more resources to challenging regions (e.g., heavily degraded areas).

2.2 Attention Mechanisms for Efficient Feature Enhancement

Attention mechanisms enable selective focus on informative features while suppressing irrelevant ones---particularly valuable for underwater enhancement where degradation is non-uniform.

Channel Attention Mechanisms: Beyond SE blocks, Efficient Channel Attention (ECA) [51] removes dimensionality reduction to maintain performance while lowering complexity. ECA-Net has been adapted for underwater enhancement in models like ECA-integrated variants (e.g., similar to ECA-UWNet [52]), demonstrating improved color restoration with negligible overhead.

Spatial Attention: Convolutional Block Attention Module (CBAM) [53] sequentially applies channel and spatial attention, with the latter computed via average and max pooling followed by a convolution. Lightweight variants use depthwise convolutions for spatial attention computation [54].

Pixel-Attention (PA): Computes an attention map at pixel-level granularity, allowing fine-grained adjustment. Pixel-aware models (e.g., inspired by PA-URLNet [55]) combine pixel attention with a lightweight U-Net structure, achieving state-of-the-art performance with only 0.9M parameters. For recent examples, see Ghost-UNet (2024).

Non-Local Attention in Efficient Forms: Traditional non-local attention [56] is computationally expensive (O(N^2)). Efficient variants like Criss-Cross Attention [57] and Global Context (GC) blocks [58] approximate global dependencies with reduced complexity. A^2-Net [59] introduces double attention for both position and channel, showing promise for underwater applications.

2.3 Neural Architecture Search (NAS) and Automated Design

NAS automates network architecture discovery under specific constraints, potentially uncovering novel efficient designs for underwater enhancement.

Differentiable Architecture Search (DARTS): Formulates architecture search as a continuous optimization problem [60], enabling efficient search for optimal operations (e.g., separable conv, dilated conv, skip connections) for underwater enhancement tasks [61].

EfficientNet and Compound Scaling: EfficientNet [62] uses NAS to discover a baseline architecture (EfficientNet-B0) and applies compound scaling to uniformly scale depth, width, and resolution. The EfficientNet-B0/B1 variants have been successfully adapted for underwater enhancement with modifications to handle color distortion [38], [63].

Hardware-Aware NAS (HW-NAS): Extends NAS to directly optimize for hardware-specific metrics like latency or energy consumption. ProxylessNAS [64] and FBNet [65] search directly on target devices. HW-NAS for underwater enhancement remains largely unexplored but holds significant potential for specialized deployment [66].

One-Shot NAS and Weight Sharing: Methods like ENAS [67] and Single Path One-Shot NAS [68] enable rapid architecture evaluation through weight sharing, potentially accelerating the discovery of optimal underwater enhancement networks.

2.4 Model Compression and Acceleration Techniques

(1) Knowledge Distillation (KD)

KD transfers knowledge from a large, accurate teacher model to a compact student model [69]. For underwater enhancement:

- Response-based KD: The student mimics the teacher's output distribution [70]. Lightweight GAN [71] uses this approach to distill a full-sized GAN into a MobileNetV2-based generator.

- Feature-based KD: The student matches intermediate feature representations [72]. Hint-based distillation [73] has been applied to preserve both low-level texture and high-level semantic information in underwater enhancement [74].
- Relation-based KD: Captures relationships between different layers or data samples [75]. This approach could help maintain structural relationships in enhanced underwater images.

(2) Pruning Strategies

Structured Pruning: Removes entire filters or channels [76]. Network Slimming [77] uses L1 regularization on scaling factors in batch normalization layers to identify unimportant channels. Applied to underwater enhancement networks, this can reduce parameters by 40-60% with <1 dB PSNR drop [78].

Unstructured Pruning: Removes individual weights [79], requiring specialized hardware for acceleration. Iterative Magnitude Pruning [80] with rewinding has shown effectiveness for compression of enhancement networks [81].

Neuron Importance Score Propagation (NISP): Propagates importance scores from output to input to identify redundant neurons [82], potentially useful for task-specific pruning of enhancement networks.

(3) Quantization Techniques

Post-Training Quantization (PTQ): Converts a pre-trained FP32 model to lower precision (e.g., INT8) with minimal calibration data [83]. TensorRT and OpenVINO provide robust PTQ implementations that have been applied to underwater enhancement models for deployment on Jetson platforms [84].

Quantization-Aware Training (QAT): Simulates quantization during training to improve accuracy [85]. QAT is particularly important for GAN-based enhancement models which are sensitive to precision reduction [86].

Mixed-Precision Quantization: Allocates different bit-widths to different layers based on sensitivity [87]. For underwater enhancement, convolutional layers might be quantized to INT8 while attention mechanisms retain FP16 precision [88].

Binary/Ternary Networks: Extreme quantization to 1-2 bits [89], though currently challenging for enhancement tasks requiring precise color reproduction.

2.5. Hybrid and Specialized Architectures

Multi-Branch Networks with Heterogeneous Design: CondenseNet [90] connects layers with dense connections but learns to prune these connections during training. Adapted for underwater enhancement (e.g., similar to Condense-UWNet [91]), it achieves efficient information flow with reduced redundancy. Recent examples include Rep-UWnet (2024), a lightweight fully connected convolutional network with dense blocks for underwater enhancement.

Recurrent Designs for Sequential Enhancement: For video enhancement, lightweight recurrent units like ConvGRU [92] or IndRNN [93] can maintain temporal consistency with manageable computational increase.

Transformer-Based Lightweight Designs: Vision Transformers (ViTs) [94] show strong generalization but high computational cost. Efficient variants like MobileViT [95], LeViT [96], and PoolFormer [97] combine convolutional inductive biases with transformer global modeling, offering promising directions for underwater enhancement [98]. Hybrid transformer models (2025) integrate these for improved results.

Updated with 2025 models: DNnet uses PBP structures for 4K real-time on edge devices; Zero-UAE for parameter-free adaptive enhancement.

3. Implementation Pipeline: From Data to Deployment

3.1 Datasets: Curated Collections and Synthesis Methods

(1) Real-World Paired Datasets

UIEB (Underwater Image Enhancement Benchmark) [23]: Contains 890 real underwater images with corresponding high-quality reference images generated via multiple enhancement methods followed by manual selection. It serves as the primary benchmark but has limitations in diversity of water types and degradation patterns.

EUVP (Enhancement of Underwater Visual Perception) [99]: Provides 11,670 paired and 8,133 unpaired images across different cameras and environments, facilitating both supervised and unsupervised learning. Includes challenging scenarios like extremely turbid conditions.

SUIM (Semantic Underwater Imagery) [100]: While primarily for segmentation, provides 1,525 images with segmentation masks that can be used for multi-task enhancement approaches.

U45 (Underwater Image Enhancement Benchmark with 45 Images) [101]: A recently introduced test dataset with 45 challenging images from diverse underwater environments (e.g., color casts, low contrast, haze effects) and no reference images, used for non-reference evaluation. Recent additions: LSUI (2023+, ~5,000 pairs for large-scale training).

(2) Synthetic Datasets and Generation Methods

Physics-Based Synthesis: Using radiative transfer models like Jaffe-McGlamery [102] or simplified formulations [103] to simulate attenuation and scattering. Parameters (attenuation coefficients, particle concentrations) can be varied to create diverse training samples [104].

GAN-Based Synthesis: WaterGAN [25] and its variants [105] use cycle-consistent adversarial networks to generate paired underwater-terrestrial image pairs without explicit physical modeling.

Style Transfer Approaches: Using neural style transfer [106] or AdaIN [107] to impose underwater degradation characteristics on clear terrestrial images.

Hybrid Approaches: Combining physical models with data-driven corrections to bridge the sim-to-real gap [108]. Recent: Diffusion models like UW-DDPM (2025 variants) for generating realistic synthetic data.

(3) Domain-Specific Considerations

Water Type Variations: Jerlov water classification [11] provides a framework for categorizing training data and evaluating cross-domain generalization.

Depth Stratification: Organizing datasets by depth brackets (0-5m, 5-15m, 15-30m, 30m+) to enable depth-aware enhancement models [109].

Illumination Conditions: Separate handling of natural illumination vs. artificial lighting scenarios [110].

3.2 Training Methodologies and Optimization Strategies

(1) Loss Function Design

A well-designed loss function is critical for training lightweight models effectively:

Pixel-Level Fidelity Losses:

- L1 Loss (Mean Absolute Error): Preferred over L2 for sharper results [111].
- Charbonnier Loss: Robust to outliers [112].

Structural Similarity Losses:

- SSIM Loss: Emphasizes structural preservation [113].
- MS-SSIM Loss: Multi-scale extension capturing structural information at different resolutions [114].

Perceptual and Style Losses:

- Perceptual Loss (VGG-based): $\Sigma_j \|\varphi_j(I) - \varphi_j(\hat{I})\|^2$, where φ_j denotes feature maps from the j-th layer of a pre-trained VGG network [115].
- Style Loss: Gram matrix matching for texture preservation [116].
- LPIPS (Learned Perceptual Image Patch Similarity): Uses a network trained on human perceptual judgments [117].

Color-Specific Losses:

- Color Constancy Loss: Based on the Gray World assumption [118]: $\Sigma_c(1/N\ \Sigma_x I^c(x) - \mu)^2$, where μ is the average intensity.
- Histogram Matching Loss: Encourages similarity in color distribution [119].

Adversarial Loss (for GAN-based approaches):

- Standard GAN Loss: $E[\log D(I)] + E[\log(1 - D(G(\hat{I})))]$ [120].
- LSGAN Loss: Uses least squares for training stability [121].
- Wasserstein GAN with Gradient Penalty (WGAN-GP): Improves training stability [122].

Total Variation (TV) Loss: Encourages spatial smoothness, reducing artifacts [123].

Composite Loss Formulation: Typically, a weighted combination:

$$L = \lambda_1 L_1 + \lambda_2 L_{SSIM} + \lambda_3 L_{perc} + ...,$$

with λ determined through ablation studies [124].

(2) Training Strategies and Regularization

Progressive Learning: Starting with easier samples (less degraded images) and gradually introducing more challenging cases [125].

Curriculum Learning: Organizing training data in a meaningful order based on degradation severity [126].

Multi-Task Learning: Jointly learning enhancement with related tasks like segmentation [100] or depth estimation [127] to improve generalization.

Self-Supervised and Semi-Supervised Approaches: Leveraging unpaired or weakly labeled data, particularly important given the scarcity of high-quality paired underwater data [128].

Meta-Learning for Fast Adaptation: Learning to quickly adapt to new water conditions with few examples [129].

(3) Optimization Techniques

Adaptive Optimizers: AdamW [130] with carefully tuned weight decay often outperforms SGD for enhancement tasks.

Learning Rate Scheduling: Cosine annealing [131] or warm restarts [132] to escape local minima.

Gradient Clipping: Particularly important for GAN-based approaches to prevent training instability [133].

3.3 Deployment Challenges and Optimization

(1) Target Hardware Platforms

NVIDIA Jetson Series: Nano, TX2, Xavier, Orin Utilizing TensorRT for optimized inference [134].

Intel Platforms: Movidius Neural Compute Stick, OpenVINO toolkit [135].Qualcomm Snapdragon: DSP acceleration via SNPE [136].FPGA Platforms: Xilinx/AMD FPGAs with HLS or FINN framework for extreme efficiency [137].Microcontrollers (MCUs): ARM Cortex-M series with CMSIS-NN [138] for ultra-low-power applications.

(2) Software Optimization Techniques

Operator Fusion: Combining consecutive operations (Conv+BN+ReLU) into a single kernel [139]. Winograd Convolution: Reducing computational complexity for 3×3 convolutions [140]. Memory Layout Optimization: NHWC vs. NCHW formats for different hardware [141].Kernel Auto-Tuning: Using tools like AutoTVM [142] to find optimal implementations for specific hardware.

(3) Real-Time System Integration

Pipeline Optimization: Overlapping data loading, preprocessing, inference, and postprocessing [143]. Dynamic Resolution Adjustment: Adapting input resolution based on scene complexity or available computational budget [144]. Frame Skipping and Keyframe Selection: For video processing when full frame-rate processing is unsustainable [145].

Energy Efficiency Considerations

Dynamic Voltage and Frequency Scaling (DVFS): Adjusting processor frequency based on workload [146].

Power-Aware Scheduling: Prioritizing low-power modes for idle components based on [28].

4. Evaluation Frameworks

Metrics include PSNR/SSIM for quality, FLOPs/latency for efficiency. Use datasets like UIEB for fair comparison.

5. Open Challenges

Persistent issues: Domain generalization across water types; temporal consistency in video; hardware-software co-design for extreme underwater conditions. Emerging: Sim-to-real gaps in synthetic data; ethical considerations in marine data privacy.

Table 1 High and Low Settings of Predictor Variables

Model	Parameters (M)	FLOPs (G)	PSNR (UIEB)	SSIM (UIEB)	Latency (ms, Jetson)	Year
Shallow-UWNet [37]	0.5	1.2	22.5	0.85	15	2021
LU2Net	0.8	2.0	23.8	0.88	12	2024
Rep-UWnet	1.1	1.5	24.2	0.89	10	2024
DNnet	0.7	3.5	25.1	0.91	8 (4K)	2025
Zero-UAE	0.6	1.8	24.5	0.90	11	2025

6. Conclusion and Future Perspectives

This review has examined lightweight deep learning models for real-time underwater image enhancement, addressing the critical need to balance high-quality restoration with the computational constraints of underwater platforms like AUVs and ROVs. We presented a taxonomy of efficiency-focused designs including depth wise separable convolutions, attention mechanisms, neural architecture search, and compression techniques alongside practical insights into datasets, training strategies, and edge deployment. Comparative analyses show that recent models (e.g., Shallow-UWNet, LU2Net, Rep-UWnet, DNnet) achieve strong performance-efficiency trade-offs, enabling low-latency processing suitable for real-world marine applications.

Key challenges persist in domain generalization, temporal consistency for video, and hardware-software co-optimization. Looking forward, promising directions include physics-informed networks, multimodal fusion, diffusion-based generative enhancement, and advanced lightweight transformers. These advances will support more robust, energy-efficient vision systems, advancing ocean exploration, environmental monitoring, and autonomous underwater robotics. Continued focus on standardized benchmarks and cross-domain evaluation will accelerate progress in this vital field.

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