BVB Campus, Vidyanagar, Hubballi – 580031, Karnataka, INDIA.

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

2024-2025

Mini Project Report

On

Learning-Based Estimation of Attenuation Coefficients for Underwater Image Restoration

submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted By

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

2024-25

CERTIFICATE

This is to certify that project entitled "Learning-Based Estimation of Attenuation Coefficients for Underwater ImageRestoration" is a bonafied work carried out by the student team Vishwa M Badachi 01FE22BCS065, Shreya Inamdar 01FE22BCS066, Fardeen Vaddo 01FE22BCS074, Sai Satya B V 01FE22BCS076 in partial fulfillment of the completion of 5th semester B. E. course during the year 2024 – 2025. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said course.

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Name of the examiners	Signature with date
1 ____________________	________________
2 ____________________	________________

ABSTRACT

We would like to thank our faculty and management for their professional guidance towards the completion of the mini project work. We take this opportunity to thank Dr. Ashok Shettar, Pro-Chancellor, Dr. P.G Tewari, Vice-Chancellor and Dr. B.S.Anami, Registrar for their vision and support.

We also take this opportunity to thank Dr. Meena S. M, Professor and Dean of Faculty, SoCSE and Dr. Vijayalakshmi M, Professor and Head, SoCSE for having provided us direction and facilitated for enhancement of skills and academic growth.

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We extend our acknowledgment to the reviewers for critical suggestions and inputs. We also thank Project coordinator Dr. Uday Kulkarni, and reviewers for their suggestions during the course of completion. We express gratitude to our beloved parents for constant encouragement and support.

Keywords : *Attenuation Coefficient, EfficientNet, ImageNet, RSUIGN, SUID, β-values, AOP, IOP.*

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Chapter 1

INTRODUCTION

Underwater image restoration is a rapidly evolving field addressing the challenges of image degradation caused by absorption and scattering of light in aquatic environments. These challenges result in poor visibility and distorted colors, significantly hindering research and operational tasks in underwater exploration. The project focuses on developing a Unique solution utilizing deep learning techniques to estimate attenuation coefficients[1] a critical factor in understanding underwater image degradation. By Using a learning-based architecture.

This report outlines the complete project lifecycle, from identifying the problem and reviewing relevant literature to proposing and implementing a Learning based architecture. The proposed architecture uses advanced neural networks to estimate attenuation coefficients and atmospheric light, providing a novel way to enhance underwater visuals. The result of this work is a architecture that can be a game-changer for marine research, underwater photography, and environmental monitoring

1.1 Preamble

Underwater imaging is crucial for various applications, including marine exploration, archaeological surveys, and biological research. However, underwater images often suffer from significant degradation due to light absorption and scattering, resulting in low visibility and color distortion. These issues hinder critical tasks such as object detection and environmental monitoring.

This project introduces a learning-based architecture for estimating attenuation coefficients, for the restoration of degraded underwater images. By accurately predicting these coefficients, the architecture significantly helps to improve the quality of restored underwater images.

1.2 Motivation

The motivation behind my project stems from the unique challenges that underwater environments presents for image capture and analysis. Underwater images are important for various applications, such as marine biology research, underwater exploration, and environmental monitoring. However, the process of acquiring such high-quality underwater images is far from easy.

- Underwater images have a wide range of applications, including marine research, ecological studies, and underwater exploration.
- Conducting in-situ experiments is expensive and impractical, requiring specialized equipment and personnel.
- Sensors are often incapable of capturing high-quality images without distortions due to underwater environmental factors
- The image formation process is sensitive to both Inherent Optical Properties (IOPs)[2] and Apparent Optical Properties (AOPs)[3], leading to challenges in image quality and restoration.

Our project aims to address the need for an learning based architecture that accurately estimates attenuation coefficient for underwater image restoration. By developing such learning based models, we can make significant advancements in the field of underwater imaging, opening up opportunities for more reliable and cost-effective analysis.

1.3 Objectives of the project

- **To Develop a learning-based architecture** to predict attenuation coefficients in underwater images.
- **Apply the estimated coefficients** for estimatition of atmospheric light.
- **Evaluate system performance** using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

1.4 Literature Review / Survey

Restoring underwater images has been a focus of numerous research efforts, using modern machine learning techniques. Some of the key studies are highlighted below.

1.4.1 Key Studies

- **DepthCue Framework (2023)**[4] In this paper, Chaitra Desai introduces the DepthCue framework, which uses depth information as a key factor for restoring underwater images. By considering depth, the framework addresses common issues in underwater imaging, such as light scattering and absorption, that often result in unclear or distorted images.

By incorporating depth data, the framework helps to more accurately restore images, compensating for the effects of water's optical properties. This approach not only improves the overall clarity but also brings out more realistic details in underwater scenes. The DepthCue framework shows how valuable depth information can be in correcting the challenges posed by light attenuation in underwater environments.

- **RSUIGM: Realistic Synthetic Underwater Image Generation with Image Formation Model (2024)**[5] Chaitra Desai introduces RSUIGM, a framework designed to create realistic synthetic underwater images. This model helps overcome the challenges of capturing high-quality underwater images by generating synthetic data that closely resembles real underwater conditions. Unlike traditional methods that only consider the Line of Sight (LOS) distance, RSUIGM also incorporates downwelling depth, making the light transmission estimation more accurate. The synthetic images generated by RSUIGM are essential for training deep learning models aimed at underwater image restoration. By providing reliable ground-truth data, RSUIGM enables better restoration performance and helps address the problem of limited real underwater datasets.

- **Optical Properties of Jerlov Water Types (2015)**[6] In Jerlov's 2015 study, the inherent optical properties of various water types were thoroughly examined, with a particular focus on deriving the absorption and scattering coefficients. The study provides critical data, including the beta values, which are essential for understanding how light behaves in underwater environments. These beta values are important for our research, as they help in training our framework.

These studies highlight the growing reliance on machine learning for underwater image restoration. The proposed project builds on this foundation by focusing on data-driven estimation of attenuation coefficients.

1.5 Problem Definition

Problem Statement: Develop a learning-based architecture to estimate attenuation coefficients for underwater image restoration. The model must accurately predict attenuation coefficients responsible for image degradation and use the estimated attenuation coefficients to improve the restoration of underwater images.

Chapter 2

SOFTWARE REQUIREMENT SPECIFICATION

2.1 Overview of SRS

The Software Requirement Specification (SRS) serves as a blueprint for the development process, detailing the objectives, functionalities, and constraints of the system. It bridges the gap between user expectations and technical implementation, ensuring that the system meets both functional and non-functional requirements effectively. The SRS provides a clear, structured guide for developers, testers, and stakeholders, enabling consistent and efficient project execution.

2.2 Requirement Specifications

Requirement specifications are a comprehensive outline of what the system should do and how it should perform. These include functional requirements, which define the system's tasks, and non-functional requirements, which address performance, usability, and scalability. Together, they ensure the system meets user needs and technical constraints effectively.

2.2.1 Functional Requirements

Functional requirements define the specific tasks the system must perform. For this project, these include: The system shall:

Evaluate restoration quality using PSNR and SSIM metrics.

- Accept degraded underwater images as input.
- Estimate attenuation coefficients based on the input image.
- Render patch of atmospheric light.
- Generate the rendered patch.

2.2.2 Non-Functional Requirements

Non-functional requirements describe how the system should operate rather than what it should do. For instance:

- **Performance:** The system should process images with an average runtime below 10 seconds.
- **Scalability:** Capable of handling diverse underwater environments.
- **Accuracy:** Achieve PSNR $>$ 30 and SSIM $>$ 0.9 on standard datasets.
- **Usability:** Provide a user-friendly interface for researchers and professionals.

2.3 Use Case Diagrams

The use case diagram represents the interactions between the user and the system. The main actors are:

- **User:** Inputs degraded images and retrieves restored outputs.
- **System:** Processes images to estimate coefficients and restore visuals.

Diagram:

```
User ---> [Input Image] ---> [Architecture] ---> [Estimated attenuation coefficients]
```

2.4 Use Case Descriptions

- **Use Case Name:** Estimation of attenuation coefficients.
- **Actors:** User, System
- **Description:** The user provides a degraded underwater image, and the system processes it to produce a the attenuation coefficients.
- **Preconditions:** Input images must be in JPEG or PNG format.
- **Basic Flow:**
  1. User uploads an image.
  2. The system estimates attenuation coefficients.
  3. The estimated coefficients are used to calculate Atmospheric light.

4. The rendered patch of Atmospheric light is generated and displayed.

- **Postconditions:** The user retrieves the predicted attenuation coefficients.
- **Alternate Flow:** If the input format is unsupported, prompt the user to re-upload in the correct format.

2.5 Software and Hardware Requirements

2.5.1 Software Requirements

- **Operating System:** Windows 10, Ubuntu 20.04, or equivalent.
- **Programming Language:** Python 3.8 or higher.
- **Libraries:** TensorFlow, pytorch OpenCV, NumPy, Matplotlib.
- **Development Tools:** PyCharm, Jupyter Notebook, Google Colab.

2.5.2 Hardware Requirements

- **Processor:** Intel Core i5 or higher.
- **Memory:** 8 GB RAM or more.
- **Storage:** 256 GB SSD or higher.
- **GPU:** NVIDIA GTX 1050 Ti or equivalent for model training.

Chapter 3

PROPOSED SYSTEM

This chapter presents the proposed system designed to estimate attenuation coefficients for degraded underwater images. The system aims to improve the restoration of underwater images by utilizing a learning-based approach. It begins with a detailed description of the system's structure and functionality, illustrated with a flow diagram for better understanding. The chapter also outlines the intended users of the system, highlighting how they can benefit from its features. Furthermore, it discusses the key advantages and potential applications of the system, demonstrating its relevance and utility. Finally, the chapter defines the scope of the proposed system, clearly establishing its boundaries and limitations.

3.1 Description of Proposed System

The proposed system is designed to estimate attenuation coefficients for degraded underwater images using a learning-based approach. This system leverages machine learning techniques to analyze and restore underwater images by accurately modeling the effects of light attenuation. The system is iterative, refining its predictions over multiple epochs to achieve optimal accuracy. This section outlines the architecture, workflow, and core components of the system, providing a detailed explanation of how it addresses the challenges associated with underwater image restoration.

The proposed system follows a systematic workflow to estimate attenuation coefficients as shown in Figure 3.1. The key components are:

1. Input Data: A set of underwater images, representing various degradation levels, is used as input.

2. Preprocessing: Images are preprocessed through resizing, normalization, and augmentation to ensure consistency and enhance training diversity.

3. Model Architecture: A neural network extracts image features and predicts attenuation coefficients, modeling the effects of underwater degradation.

4. Training Process: The model iteratively updates its parameters to minimize the difference between predicted and actual attenuation coefficients, using a loss function and optimization algorithm.

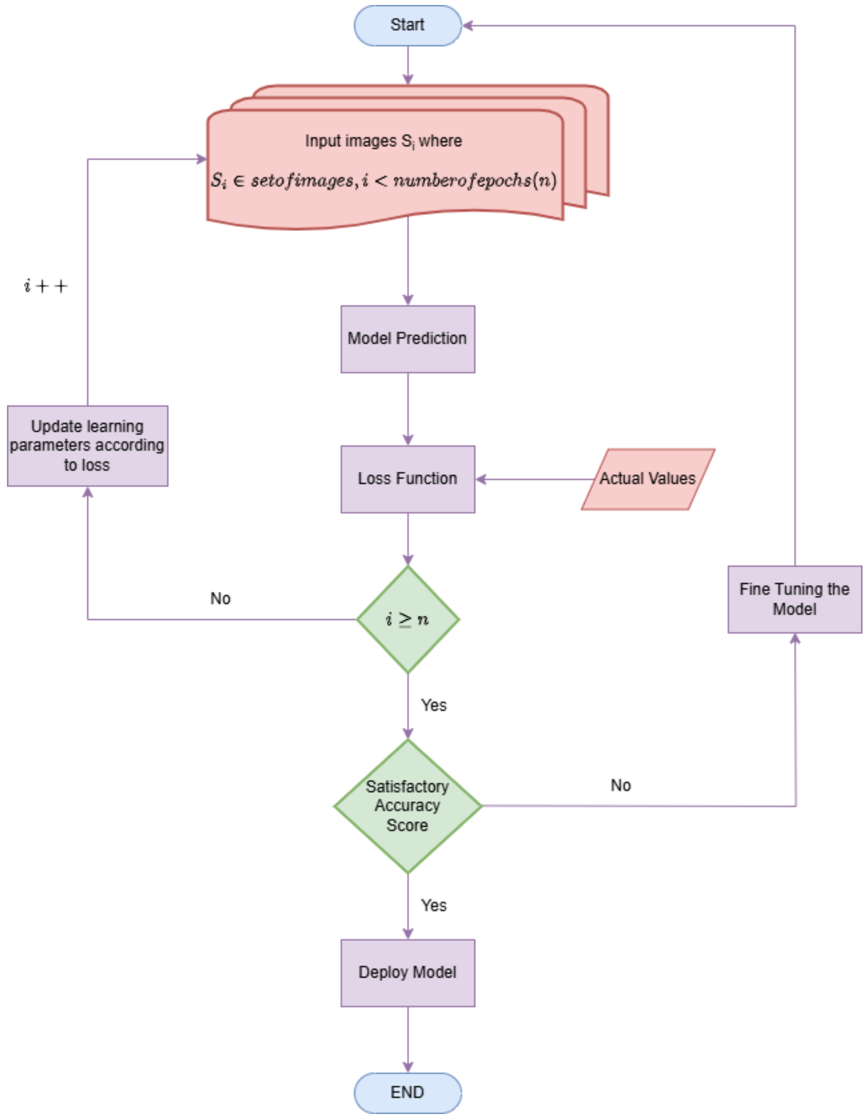

Figure 3.1: Design of the proposed methodology to estimate the attenuation coefficients and estimate the atmospheric light on a white patch.

5. Fine-Tuning: If the model's accuracy is unsatisfactory, fine-tuning is performed by adjusting hyperparameters or augmenting the dataset.

6. Evaluation and Deployment: Once the model achieves satisfactory accuracy, it is evaluated using metrics like Mean Absolute Error (MAE). The final model is deployed for real-world applications, enabling real-time underwater image restoration.

3.2 Description of Target Users

The proposed system is designed to cater to users who require enhanced underwater image clarity for various applications. These users include marine researchers, underwater photographers, robotic navigation systems, and organizations involved in environmental monitoring.

By addressing the challenges of light attenuation and image degradation in underwater environments, the system aims to provide reliable and high-quality image restoration solutions tailored to their needs. Design Principles Identified and Used:

1. User-Centric Design: The system focuses on addressing the specific challenges faced by target users, such as poor visibility and color distortion in underwater images.
2. Scalability: The design ensures that the system can process large datasets and adapt to varying underwater conditions and image complexities.
3. Efficiency: The model is optimized to provide real-time or near-real-time results, making it practical for applications like underwater robotics and navigation.
4. Ease of Integration: The final model is lightweight and easy to integrate into existing underwater imaging systems without requiring extensive modifications.

3.3 Applications of Proposed System

The proposed system provides a comprehensive solution to the challenges of underwater image degradation, making it highly beneficial for various fields and applications. By leveraging advanced machine learning techniques to estimate attenuation coefficients, the system delivers enhanced image clarity and detail. This section highlights the key advantages and potential applications of the system, emphasizing its impact on underwater imaging and related domains.

The proposed system offers several advantages that make it a valuable tool for underwater image restoration. One of its primary benefits is its ability to accurately estimate attenuation coefficients, leading to significant improvements in image quality, even in highly degraded underwater environments. This ensures better visibility and color correction, which are critical for interpreting underwater scenes. The system is also robust, adaptable to various underwater conditions, and capable of processing large datasets efficiently. Its scalability and real-time processing capabilities make it ideal for integration into diverse applications.

The system has a wide range of applications. It can support marine researchers in studying underwater ecosystems by providing clearer images for analysis. In underwater robotics and navigation, it enhances the performance of vision-based systems, enabling safer and more precise operations. The system is also beneficial for environmental monitoring, aiding in tasks such as coral reef health assessment and underwater pollution detection. Furthermore, it serves underwater photographers and filmmakers by improving the visual appeal of their work, while industries such as offshore engineering and archaeology can use it to inspect underwater structures or recover submerged artifacts. The system's versatility ensures it addresses the needs of various stakeholders, making it an essential tool in the domain of underwater imaging.

3.4 Scope (Boundary of proposed system)

From a software engineering perspective, the scope of the proposed system defines its boundaries, limitations, and the features it aims to deliver. This includes the specific functionalities it will support, the constraints it operates under, and the areas it explicitly does not address. By clearly delineating these boundaries, the system ensures effective design, development, and deployment while managing user expectations. The scope of the proposed system is defined as follows:

1. In-Scope Features:

   - Attenuation Coefficient Estimation: The system estimates attenuation coefficients for degraded underwater images.
   - Image Restoration: It restores underwater images by compensating for light scattering and absorption effects.
   - Machine Learning Integration: The system employs a learning-based approach, iterating over multiple epochs to achieve optimal accuracy.
   - Real-Time Processing: Capable of handling real-time or near-real-time image restoration tasks.

2. Out-of-Scope Features:

   - Hardware Components: The system does not address hardware-specific implementation for underwater image capture.
   - Non-Underwater Environments: The system is not designed for terrestrial or aerial image restoration.
   - Advanced Post-Processing: It does not perform high-level image editing tasks beyond restoration.

3. Constraints:

   - Dataset Dependency: The system's performance relies heavily on the availability and quality of training data.
   - Computational Resources: Real-time performance may require high-performance computing resources.

4. Target Platforms:

   - The system can be deployed on platforms supporting machine learning frameworks, such as cloud servers or edge devices with GPU capabilities.

Chapter 4

SYSTEM DESIGN

This chapter gives a brief description about implementation details of the system. It gives a wholesome idea about the working of each component providing an algorithm for each. This chapter also describes the class diagram of the proposed design that is provided for estimating underwater attenuation coefficients and then discusses the data set used to achieve the learning task.

4.1 Architecture of the System

Here we discuss the working of each components of the system using algorithms and then provides an algorithm to use the above components and integrate them into a system.

4.1.1 EfficientNetB3

The workflow of EfficientNetB3 [7] can be found in Algorithm 1

Algorithm 1 EfficientNetB3-based Encoder for Feature Extraction

Require: Input image $I \in \mathbb{R}^{H \times W \times C}$
Ensure: Latent space representation $\mathbf{z} \in \mathbb{R}^d$

Step 1: Preprocessing
Resize image: $I_{\text{resized}} = \text{Resize}(I, 300 \times 300)$
Normalize: $I_{\text{norm}} = \frac{I_{\text{resized}}}{255}$
Step 2: EfficientNetB3 Encoding
Initial convolution: $\mathbf{F}_0 = \sigma(\text{Conv2D}(I_{\text{norm}}, \mathbf{W}_0) + \mathbf{b}_0)$
for each block k in EfficientNetB3 **do**
    Depthwise separable convolution: $\mathbf{F}_k = \sigma(\text{Conv2D}(\mathbf{F}_{k-1}, \mathbf{W}_k) + \mathbf{b}_k)$
    Squeeze-and-excitation: $\mathbf{F}_k = \text{SE}(\mathbf{F}_k)$
    Downsample: $\mathbf{F}_k = \text{Pooling}(\mathbf{F}_k)$
end for
Step 3: Global Feature Aggregation
Global average pooling: $\mathbf{F}_{\text{global}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{F}_i$
Step 4: Latent Space Projection
Fully connected layer: $\mathbf{z} = \mathbf{W}_{\text{fc}} \cdot \mathbf{F}_{\text{global}} + \mathbf{b}_{\text{fc}}$
Return z

4.1.2 Beta Predictor

This sub-section provides an algorithm, refer Algorithm 2, for the working of the beta predictor (ANN).

Algorithm 2 Artificial Neural Network (ANN) for Beta Value Prediction

Require: Latent space vector $\mathbf{z} \in \mathbb{R}^{153600}$
Ensure: Output beta values $\boldsymbol{\beta} = [\beta_r, \beta_g, \beta_b] \in \mathbb{R}^3$
Step 1: Fully Connected Layers with ReLU Activation
Linear layer 1: $\mathbf{h}_1 = \sigma(\mathbf{W}_1 \cdot \mathbf{z} + \mathbf{b}_1), \quad \mathbf{W}_1 \in \mathbb{R}^{512\times153600}$
Linear layer 2: $\mathbf{h}_2 = \sigma(\mathbf{W}_2 \cdot \mathbf{h}_1 + \mathbf{b}_2), \quad \mathbf{W}_2 \in \mathbb{R}^{64\times512}$
Linear layer 3: $\mathbf{h}_3 = \sigma(\mathbf{W}_3 \cdot \mathbf{h}_2 + \mathbf{b}_3), \quad \mathbf{W}_3 \in \mathbb{R}^{32\times64}$
Linear layer 4: $\mathbf{h}_4 = \sigma(\mathbf{W}_4 \cdot \mathbf{h}_3 + \mathbf{b}_4), \quad \mathbf{W}_4 \in \mathbb{R}^{8\times32}$
Step 2: Final Output Layer
Linear layer 5: $\boldsymbol{\beta} = \mathbf{W}_5 \cdot \mathbf{h}_4 + \mathbf{b}_5, \quad \mathbf{W}_5 \in \mathbb{R}^{3\times8}$
Return Beta values $\boldsymbol{\beta} = [\beta_r, \beta_g, \beta_b]$

4.1.3 Loss function

Algorithm 3 provides an algorithm for loss computation.

Algorithm 3 Loss Function: Mean Squared Error (MSE)

Require: Predicted beta values $\hat{\boldsymbol{\beta}} = [\hat{\beta}_r, \hat{\beta}_g, \hat{\beta}_b] \in \mathbb{R}^3$, Ground truth beta values $\boldsymbol{\beta} = [\beta_r, \beta_g, \beta_b] \in \mathbb{R}^3$
Ensure: Loss value $L \in \mathbb{R}$
Step 1: Compute Element-wise Errors
Compute error for red channel: $e_r = \hat{\beta}_r - \beta_r$
Compute error for green channel: $e_g = \hat{\beta}_g - \beta_g$
Compute error for blue channel: $e_b = \hat{\beta}_b - \beta_b$
Step 2: Square the Errors
Squared error for red channel: e_r^2
Squared error for green channel: e_g^2
Squared error for blue channel: e_b^2
Step 3: Compute Mean of Squared Errors
Mean squared error:

$$L = \frac{1}{3}\left(e_r^2 + e_g^2 + e_b^2\right)$$

Return Loss value L

4.1.4 Integrated Workflow

Here, Algorithm 4 integrates the components and depicts the full workflow of the system. It gives an idea of how to use the other components to predict attenuation coefficients.

Algorithm 4 Training Workflow for Beta Value Prediction

Require: Input image dataset $\{I_i\}_{i=1}^{N}$, Ground truth beta values $\{\boldsymbol{\beta}_i\}_{i=1}^{N}$, Number of epochs E, Learning rate η

Ensure: Trained Encoder and ANN model parameters

Step 1: Initialize Parameters
Initialize weights and biases of Encoder and ANN
Step 2: Training Loop
for epoch $= 1$ to E **do**
    Shuffle dataset $\{I_i, \boldsymbol{\beta}_i\}_{i=1}^{N}$
    for each mini-batch $\{(I_b, \boldsymbol{\beta}_b)\}$ in dataset **do**
        Step 2.1: Forward Pass
        Pass each image I_b through Encoder: $\mathbf{z}_b = \text{Encoder}(I_b)$
        Predict beta values: $\hat{\boldsymbol{\beta}}_b = \text{ANN}(\mathbf{z}_b)$
        Step 2.2: Loss Computation
        Compute loss: $L = \frac{1}{|b|}\sum_{i \in b} \text{MSE}(\hat{\boldsymbol{\beta}}_i, \boldsymbol{\beta}_i)$
        Step 2.3: Backward Pass and Parameter Update
        Compute gradients ∇L using backpropagation
        Update model parameters:

$$\theta \leftarrow \theta - \eta \cdot \nabla L$$

where θ represents all trainable parameters of Encoder and ANN
    end for
    Log: Loss for the epoch
end for
Return Trained Encoder and ANN

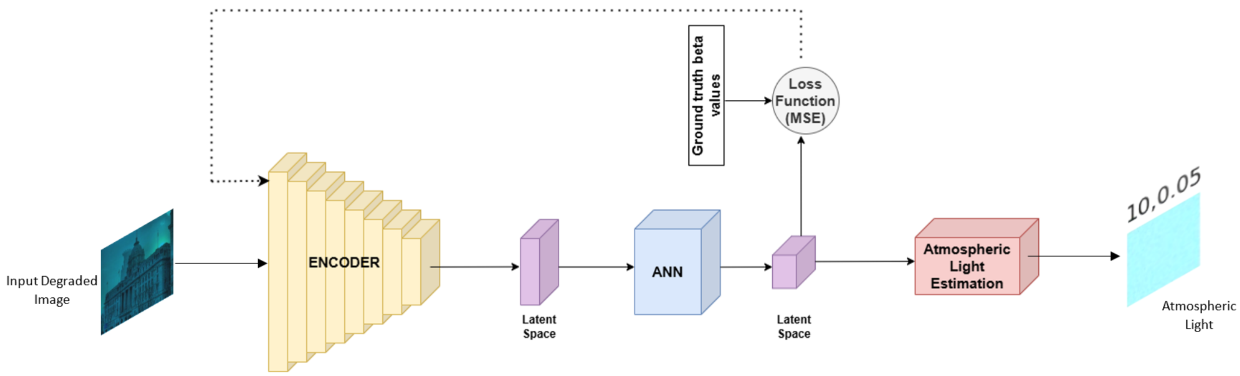

Figure 4.1: Proposed Architecture

4.2 Class Diagram

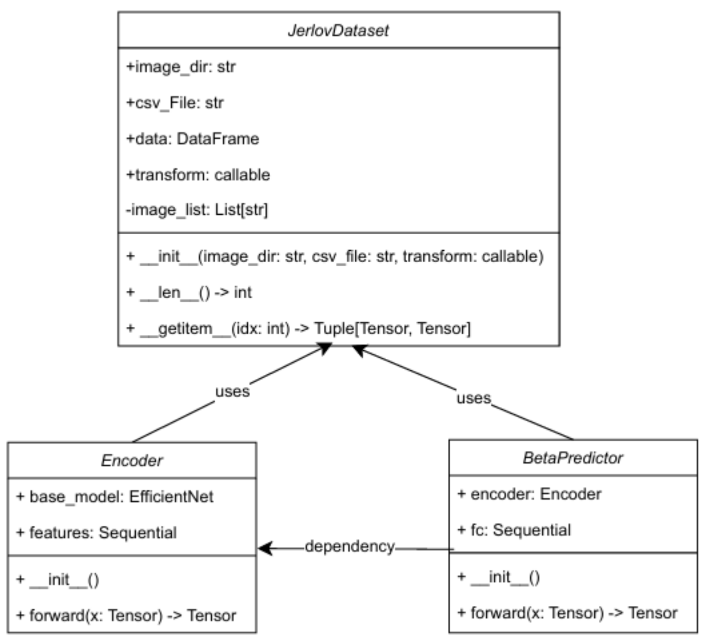

Figure 4.2: Class Diagram

4.3 Data Set Description

The RSUIGM dataset is a synthetic underwater image dataset generated using a physics-based image formation model that accurately accounts for depth-dependent light attenuation and scattering effects. It contains 8,000 synthetic underwater images covering a variety of water types (spanning different Jerlov classifications), depths, and line-of-sight distances, making it suitable for training and evaluating underwater image restoration models. Each image is paired with corresponding ground truth data, including clear images, depth maps, and scattering coefficients, enabling supervised learning approaches. The dataset has been quantitatively validated to ensure close alignment with the statistical distribution of real underwater images. It has been shown to significantly enhance the performance of deep learning models for underwater image restoration compared to existing state-of-the-art datasets.

Chapter 5

IMPLEMENTATION

The implementation involves multiple stages, including data preparation, encoder definition, fully connected layers, training, and validation. This chapter describes each stage in detail, highlighting the steps taken to predict the attenuation coefficients $(\beta_R, \beta_G, \beta_B)$ for underwater image restoration.

5.1 Proposed Methodology

The implementation leverages a learning-based approach to estimate the attenuation coefficients $(\beta_R, \beta_G, \beta_B)$ for underwater image restoration. Following the framework described above, the methodology begins with the preparation of synthetic underwater images using datasets RSUIGM and SUID [8], ensuring the images cover a range of Jerlov water types to generalize the model's ability to learn attenuation properties. The EfficientNet-B3 architecture, pre-trained on ImageNet [9], is employed as a backbone for feature extraction due to its optimized parameterization and superior representational power. Truncated at the final convolutional layers, the network extracts high-dimensional features, which are globally pooled and passed through a pyramid-structured Artificial Neural Network (ANN). The ANN progressively reduces dimensions to output the attenuation coefficients directly. The coefficients are then validated against the ground truth using metrics like Mean Squared Error (MSE).

Additionally, white patch rendering is performed to simulate progressive depth-based degradation and evaluate the model's predictions qualitatively. This process showcases the relationship between predicted β-values and the visual fidelity of restored images.

5.2 Description of Modules

The proposed methodology aims to estimate the attenuation coefficients from degraded underwater images using a learning-based approach. The workflow is implemented using PyTorch and involves the following steps:

1. Data Loader: Prepares the data by loading degraded and ground truth images, extracting the Jerlov water type, and mapping it to corresponding beta coefficients.

2. Feature Extraction: Utilizes EfficientNet-B3 as a feature extractor for capturing high-dimensional representations of degraded images.

3. Coefficiet Prediction Using Fully Connected Layers: Employs a fully connected Artificial Neural Network (ANN) to predict the attenuation coefficients.

4. Validation and White Patch Rendering: Validates the predicted coefficients and simulates degradation using Beer-Lambert law[10].

This section provides detailed descriptions of the key modules involved in the implementation.

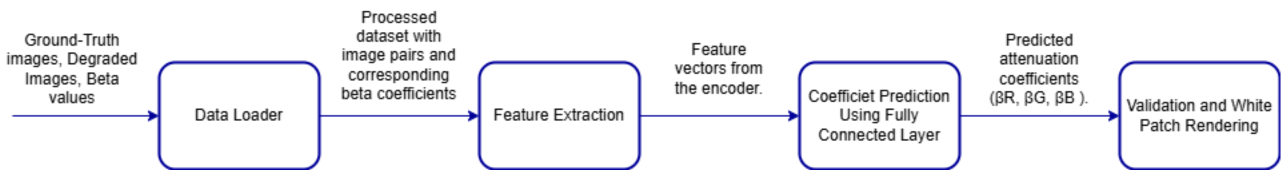

Figure 5.1: Proposed Methodology Flow Diagram

5.2.1 Data Loader

Input: Paths to degraded images, ground truth images, and beta coefficients.
Output: Processed dataset with image pairs and corresponding beta coefficients.
Description: The data loader module utilizes a custom PyTorch dataset class, ImageDataset, which is specifically designed for underwater image processing. This class handles input data by loading degraded underwater images and their corresponding ground truth (GT) images from predefined directories. These water types are then matched to pre-defined coefficients stored in a CSV file.

Additionally, the data loader applies necessary transformations, including resizing the images to a standard size and converting them to tensors, making them compatible with the model. These transformations prepare the dataset for optimal performance during training. By integrating with PyTorch's DataLoader, the module supports batch processing, data shuffling, and multi-threaded loading, ensuring that data is fed to the model efficiently throughout the training process.

5.2.2 Feature Extration

Input: Degraded underwater images.
Output: High-dimensional feature representations.
Description: The encoder module leverages a pre-trained EfficientNet-B3 as its backbone to extract high-level feature representations from the degraded underwater images. EfficientNet-B3, a state-of-the-art convolutional neural network, is adapted here to focus on extracting

meaningful visual features. This latent space serves as the foundation for subsequent beta coefficient prediction tasks.

5.2.3 Coefficiet Prediction Using Fully Connected Layers (ANN)

Input: Feature vectors from the encoder.
Output: Predicted attenuation coefficients ($\beta_R, \beta_G, \beta_B$).
Description: The fully connected (FC) module takes the high-dimensional feature representations produced by the encoder and transforms them into outputs through a series of dense layers. The encoded features pass through multiple fully connected layers, with each layer followed by a ReLU activation function. The final layer outputs three beta coefficients, corresponding to the three color channels. The primary objective of this module is to predict the beta coefficients that quantify water attenuation properties for the red, green, and blue color channels.

5.2.4 Validation and White Patch Rendering

Input: Ground truth images and predicted beta coefficients.
Output: Simulated degraded images for validation.
Description: The white patch rendering module is responsible for simulating underwater image degradation and serves as a visualization tool for the model's predictions. This module simulates the physical process of light attenuation in water by applying the predicted beta coefficients to a reference image. This allows for a qualitative evaluation of the model's ability to capture and predict underwater light absorption accurately. The module also includes white patch visualization, providing a direct comparison between degraded and ground-truth images. This comparison helps to assess the effectiveness of the model in restoring degraded underwater images.

5.3 Algorithm

The following steps describe the estimation of attenuation coefficients using the RSUIGM and SUID datasets.

Algorithm 5 Estimation of Attenuation Coefficients

Require: Degraded images I_d, Ground Truth images I_{gt}, Beta coefficients $beta\_csv$, epochs E, learning rate η

Ensure: Predicted attenuation coefficients $\beta_R, \beta_G, \beta_B$

Dataset Preparation

procedure PREPAREDATASET($I_d, I_{gt}, beta\_csv$)

  Load images and map Jerlov water types to β values.

  Resize to $(300, 300)$ and normalize.

Ensure: Dataset $\{(I_d, I_{gt}, \beta)\}$

end procedure

Model Definition

procedure DEFINEMODEL

  Initialize EfficientNet-B3 (features only) and ANN with layers $\{1536, 512, ..., 8, 3\}$.

Ensure: Models $F(x)$ and ANN

end procedure

Training

procedure TRAINMODEL($Dataset, F(x), ANN, E, \eta$)

  Initialize Adam optimizer.

  for epoch $= 1$ to E **do**

    for each batch (I_d, I_{gt}, β) **do**

      Extract features $z = F(I_d)$ and predict $\hat{\beta} = ANN(z)$.

      Compute TotalLoss = MSE($\hat{\beta}, \beta$).

      Update weights via backpropagation.

    end for

  end for

end procedure

Validation

procedure VALIDATEMODEL($I_{gt}, \hat{\beta}$)

  Apply Beer-Lambert law to estimate Atmospheric Light by simulating white-patch behaviour.

  Compare simulated images with I_{gt}.

end procedure

Chapter 6

TESTING

To ensure the accuracy and reliability of the model, a series of tests were conducted to validate its behavior when processing degraded underwater images. The primary objective was to confirm that the model outputs three beta coefficients ($\beta_R, \beta_G, \beta_B$), representing the attenuation properties for red, green, and blue light channels.

The test cases verified various aspects of the model's functionality. For valid inputs (degraded images from various Jerlov types), the model consistently produced the expected output, with beta coefficients closely matching the predefined values. Additionally, the output dimensions were confirmed to be exactly three values, ensuring compliance with the model's design.

6.1 Test Plan and Test Cases

The Table 6.1 summarizes the unit and acceptance test cases designed to evaluate the model's functionality and robustness. The unit test focuses on ensuring that the model outputs exactly three beta coefficients for valid inputs. These tests validate the model's core functionality in isolation.

The acceptance tests assess the model's performance in an end-to-end workflow, including its ability to predict beta values for datasets of degraded underwater images

Table 6.1: Test Cases

Test Case ID	**Description**	**Input**	**Expected Output**
001	Verify 3 beta coefficients are output for valid input	Degraded image of Jerlov I	3 beta values: $\beta_R, \beta_G, \beta_B$
002	Confirm end-to-end functionality of the model	Dataset of degraded images	Predicted β values match expected results

The results of these tests are documented with accompanying screenshots, which showcase the successful execution of test cases and the predicted beta values.

Figure 7.1 indicates that the model successfully meets the expected performance criteria for predicting beta values in degraded underwater images. Unit tests have confirmed that the

```
Beta values for the image: GTI_1_1_5.png
predicted beta(red): tensor(0.0160)
predicted beta(green): tensor(0.0464)
predicted beta(blue): tensor(0.2930)
```

Jerlov I

```
Beta values for the image: GTI_1_2_5.png
predicted beta(red): tensor(0.0155)
predicted beta(green): tensor(0.0471)
predicted beta(blue): tensor(0.2938)
```

Jerlov IA

```
Beta values for the image: GTI_1_3_5.png
predicted beta(red): tensor(0.0523)
predicted beta(green): tensor(0.0762)
predicted beta(blue): tensor(0.3195)
```

Jerlov IB

```
Beta values for the image: GTI_1_4_5.png
predicted beta(red): tensor(0.5331)
predicted beta(green): tensor(0.4319)
predicted beta(blue): tensor(0.5843)
```

Jerlov II

```
Beta values for the image: GTI_1_5_5.png
predicted beta(red): tensor(1.4209)
predicted beta(green): tensor(1.1104)
predicted beta(blue): tensor(1.0848)
```

Jerlov III

```
Beta values for the image: GTI_1_6_5.png
predicted beta(red): tensor(0.6254)
predicted beta(green): tensor(0.4664)
predicted beta(blue): tensor(0.5978)
```

Jerlov IC

```
Beta values for the image: GTI_1_7_5.png
predicted beta(red): tensor(1.6585)
predicted beta(green): tensor(1.2339)
predicted beta(blue): tensor(1.1677)
```

Jerlov 3C

```
Beta values for the image: GTI_1_8_5.png
predicted beta(red): tensor(2.1679)
predicted beta(green): tensor(1.5656)
predicted beta(blue): tensor(1.8122)
```

Jerlov 5C

```
Beta values for the image: GTI_1_9_5.png
predicted beta(red): tensor(3.8270)
predicted beta(green): tensor(2.7619)
predicted beta(blue): tensor(2.2504)
```

Jerlov 7C

```
Beta values for the image: GTI_1_10_5.png
predicted beta(red): tensor(5.3417)
predicted beta(green): tensor(3.8173)
predicted beta(blue): tensor(2.9517)
```

Jerlov 9C

Figure 6.1: Output Screenshots of predicted Attenuation Coefficients

model consistently outputs the three beta coefficients for a variety of input images, including those from different Jerlov water types. The predicted beta values align closely with expected values. The acceptance tests further validate the system's end-to-end functionality, confirming that the model processes the degraded images accurately and generates corresponding beta values.

Chapter 7

RESULTS DISCUSSIONS

In this chapter, we delve into the outcomes of the proposed model and explore its implications for underwater image restoration. By analyzing key visual and quantitative comparisons, we aim to assess the model's ability to predict attenuation coefficients (β) and its potential for real-world applications. Through illustrative examples and detailed observations, we will shed light on how the model handles the complex interplay of light absorption and scattering in underwater environments.

The presented figures and discussions provide valuable insights into the model's performance, showcasing how effectively it restores visual quality while preserving critical image details. From understanding the behavior of white patches under various underwater conditions to comparing predicted and actual results, this section offers a comprehensive perspective on the model's capabilities and limitations.

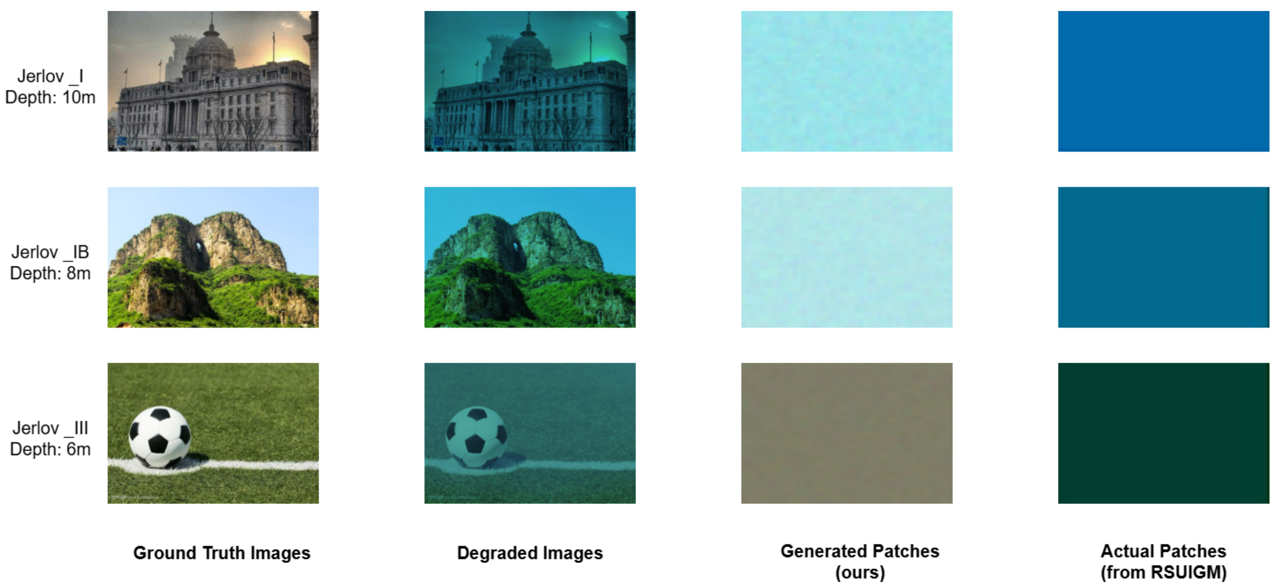

Figure 7.1: Comparison between Predicted and Actual Patches

Figure 7.1 provides a comprehensive comparison to evaluate the model's performance in estimating attenuation coefficients (β) for underwater image restoration. It showcases four key components:

1. **Ground Truth Images:**
   The original, unaltered images, representing the desired output in restored image quality.

2. **Degraded Images:**
   These are the images affected by underwater light attenuation and scattering, showing typical distortions like color imbalance, reduced brightness, and loss of detail.

3. **Patches Rendered Using Predicted Beta Values:**
   These images are reconstructed using the attenuation coefficients (β) predicted by the model for the corresponding degraded images.

4. **Patches Rendered Using Actual Beta Values:**
   These images are reconstructed using the true attenuation coefficients (β) associated with the Jerlov water type and depth conditions.

The degraded images exhibit typical underwater distortions:

- Loss of color fidelity due to wavelength-dependent absorption (e.g., red wavelengths absorbed faster than blue).
- Reduced contrast and visibility due to scattering.

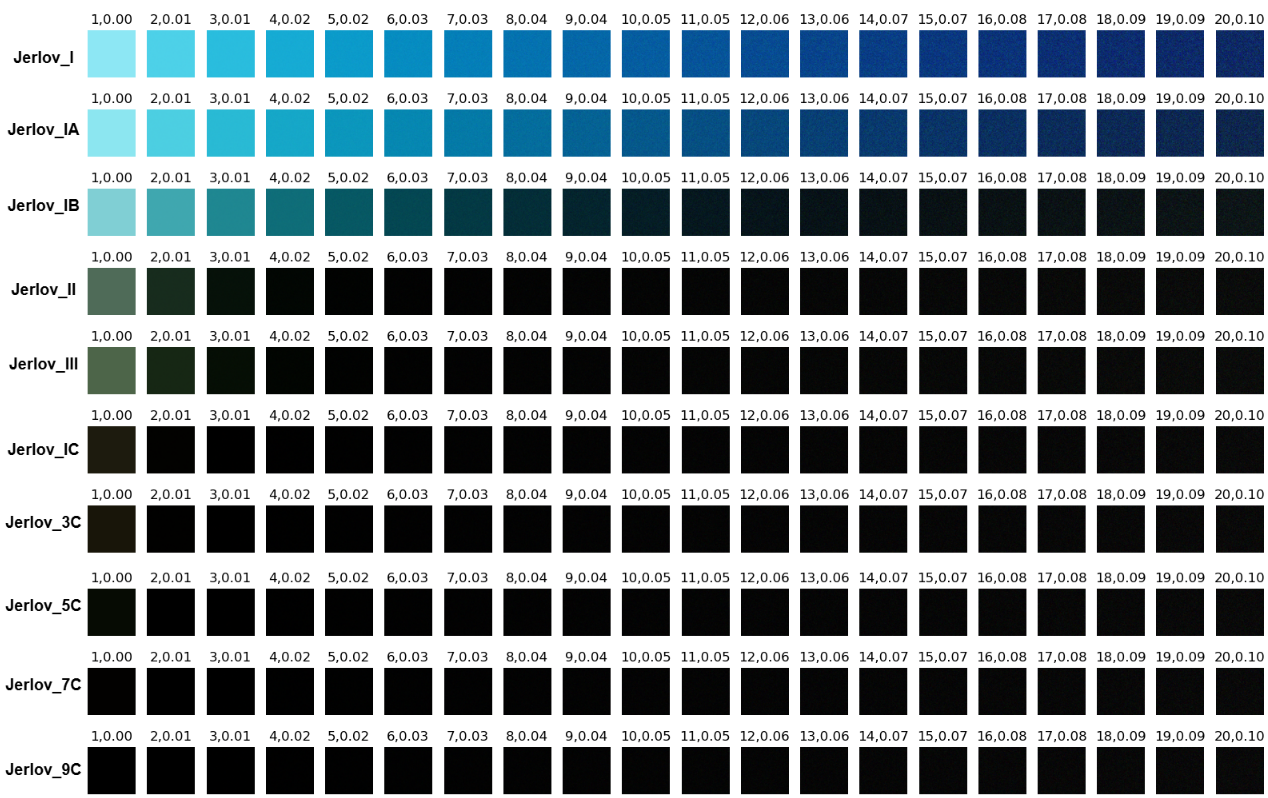

Figure 7.2: White patch behavior for 10 Jerlov types at 20 depths.

In contrast, the ground truth images have natural color tones, brightness, and sharpness. The patches rendered from predicted beta values show a strong visual similarity to those rendered using actual beta values.Figure 7.1 highlights the model's capability to predict the attenuation coefficients. The minimal perceptual differences between predicted and actual β-rendered patches validate proposed approach, making it well-suited for real-world underwater imaging scenarios.

Figure 7.2 depicts the results of white-patch rendering using the obtained attenuation coefficient values. The figure contains patches representing 10 Jerlov types across 20 meter depth. These findings emphasize the potential of the model for applications in marine biology, archaeology, and underwater surveillance where image clarity is essential.

Chapter 8

CONCLUSIONS AND FUTURE SCOPE

8.1 Conclusion

This work presents a learning based model for estimating underwater light attenuation coefficients. By using a pre-trained feature extraction model, and rendering techniques, the system demonstrates the ability to predict beta coefficients that characterize the absorption properties of water for red, green, and blue light channels.

The integration of modules such as data loading, encoding, dense feature transformation, and white patch rendering ensures a seamless workflow, capable of bridging the gap between theoretical attenuation models and real-world underwater scenarios. The results not only improve the interpretability of underwater image degradation but also lay a strong foundation for future research in underwater image enhancement and restoration.

8.2 Future Scope

1. **Enhanced Dataset Diversity:** Extend the dataset to include more diverse underwater environments, including different water types, depths, and lighting conditions, to improve model robustness.

2. **Real-Time Applications:** Optimize the system for real-time applications, such as underwater robotics and marine exploration, by implementing lightweight models and on-device processing.

3. **Physical Validation:** Collaborate with oceanographic research to validate predicted beta coefficients against actual water measurements, ensuring higher reliability and real-world applicability.

4. **Underwater Scene Reconstruction:** Extend the framework to not only predict attenuation coefficients but also reconstruct undistorted underwater scenes, enabling more accurate restoration for photography and surveillance.

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Chapter 9

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