

# Deep Learning for Enhanced Clarity: Revolutionizing Underwater Image Processing

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# Introduction

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- Underwater image capturing systems often lack high-resolution capabilities at significant depths.
- Challenges such as suspended particles, light refraction, turbidity, low visibility, scattering, and contrast issues degrade image quality.
- Achieving high-quality image capture underwater requires expensive equipment.
- Deep learning-based approaches show promise in enhancing underwater image quality.



# Problem Statement

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There is a critical need to develop effective solutions for enhancing underwater image quality to advance research and applications in relevant domains. Despite various proposed algorithms aimed at addressing these challenges and improving image quality, recent advancements in deep learning have demonstrated promising results in this regard.

## GOAL:

The main objective is to leverage deep learning models for underwater image restoration, with the objective of benchmarking these results against state-of-the-art techniques and other notable models to further enhance image restoration techniques.



# Literature Review

## Conditional General Adversarial Networks (CGANs)

### FUnIE-GAN

- EUVP dataset (over 30,000 images)
- Based on the U-Net Architecture
- Employs a Markovian PatchGAN discriminator
- FUnIE-GAN outperforms UGAN-P, Pix2Pix, Uw-HL in quality
- **Results (UIQM metric)**
  - FUnIE\_GAN - 2.78
  - UGAN-P - 2.72
  - Pix2Pix - 2.65

## Neural Architecture Search (NAS)

### U-Net

- Proposes NAS-based network consists of an encoder and decoder
- 3 datasets utilised: **EUVP, UIEB, LSUI**
- Evaluation metrics: Peak Signal to Noise ratio (PSNR) and Structure SIMilarity index (SSIM)
- **Results:**

<u>UIEB</u>	<u>LSUI</u>	<u>EUVP</u>
PSNR: 25.45	PSNR: 26.13	PSNR: 29.56
SSIM: 0.9231	SSIM: 0.8608	SSIM: 0.8818

# Literature Review

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## Conditional Neural Network Regression Model

- 2 underwater image datasets - U45 (45 images) and UIEB (890 images)
- Compared against 8 state of the art techniques
- Used metrics like UIQM, UISM, PSNR, SSIM

- **Results**

U45	UIEB
- PSNR - 26.967	PSNR - 27.299
- SSIM - 0.847	SSIM - 0.793
- UIQM - 4.998	



# Methodology

## Architecture

- **Deep-WaveNet:** Deals with underwater image restoration
- **FUnIE-GANv2:** Provides a competitive performance for underwater image enhancement

## Dataset Preparation

Utilizing the EUVP dataset: The Enhancing Underwater Visual Perception Dataset containing separate sets of paired and unpaired image samples.

The test\_samples from the EUVP dataset is used for **testing** purposes.

## Model Selection

The network architecture DeepWaveNet is pipelined with FUnIE-GAN to enhance the underwater image restoration and improve the results.

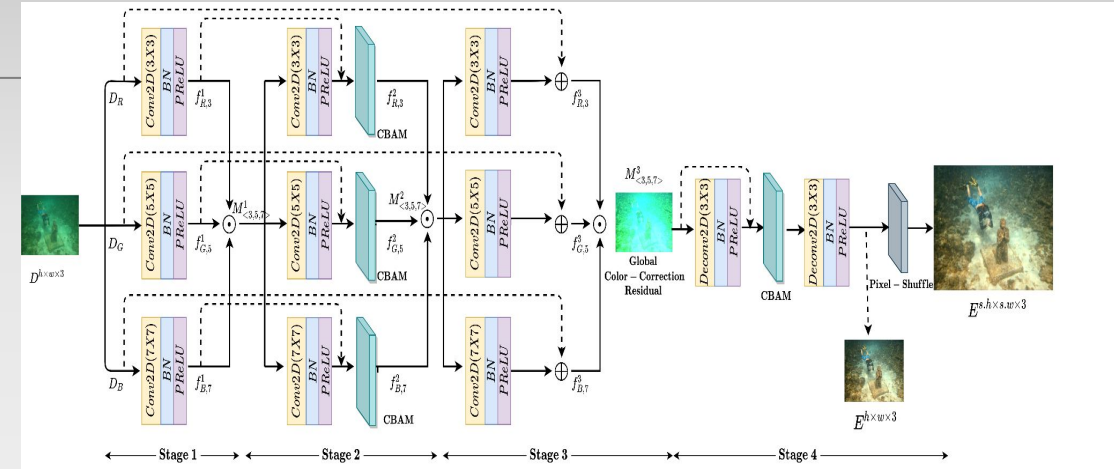


Figure 1: Deep-WaveNet Architecture

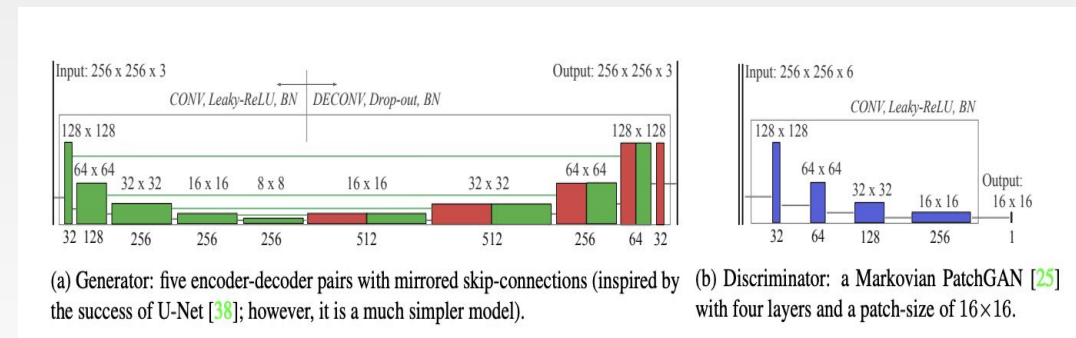


Figure 2: FUnIE-GAN Model

# Implementation

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Here are some points with a bit more detail:

- 3 underwater image sets used: underwater\_imagenet, underwater\_dark, underwater\_scenes
- These sets segregated into trainA (hazy images) and trainB (enhanced/ground truth images)
- Training pipeline:
  - First, DeepWaveNet architecture trained on trainA (hazy) images
  - Output images from DeepWaveNet stored in MiddleDataset directory
  - MiddleDataset then used to train FuNIE-GAN (train.py) for further image enhancement
- Two-stage training process:
  - Stage 1: Train DeepWaveNet on hazy images
  - Stage 2: Use DeepWaveNet output to train FuNIE-GAN for enhancement



# Results

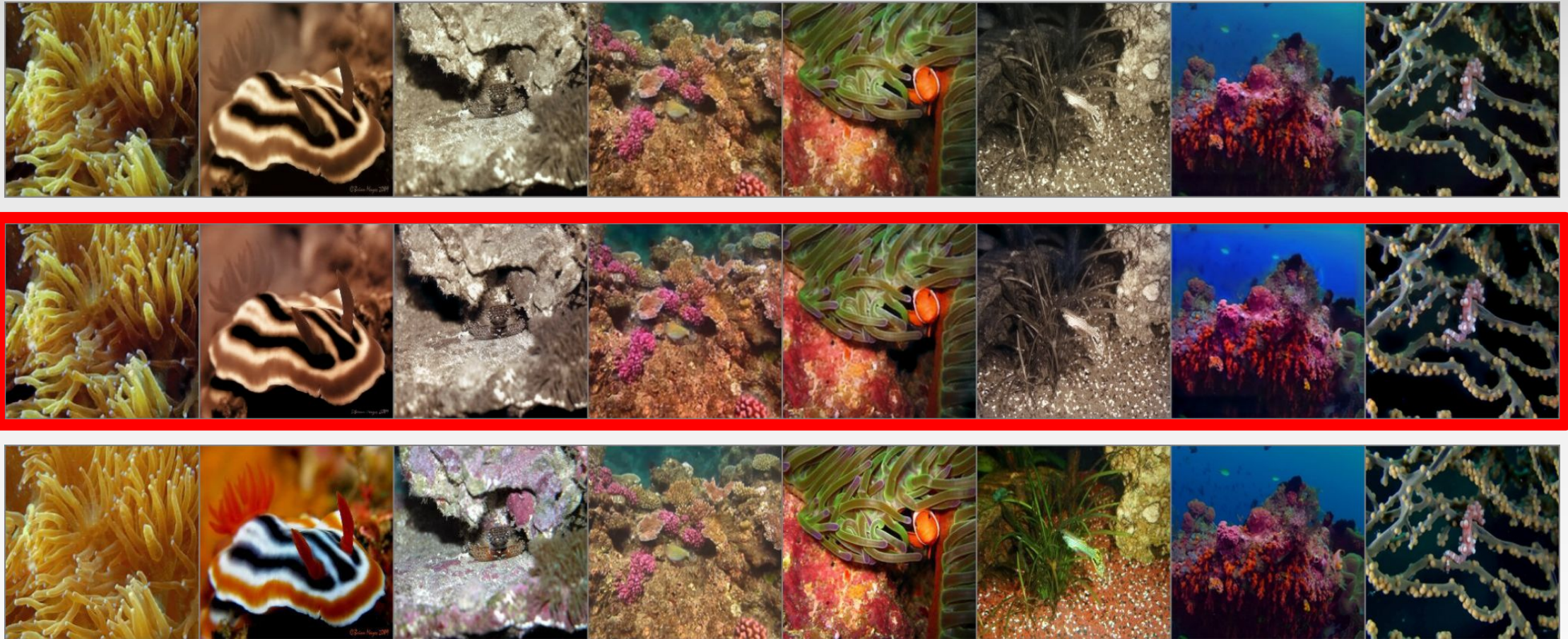


Figure 3: Distorted, Fake (Generated Output), Ground Truth Images Respectively



# Performance evaluation

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The following evaluation metrics are used to evaluate the results obtained from the combined model:

## **SSIM:**

- Measures structural similarity between images
- Higher values (closer to 1) = higher similarity

## **PSNR:**

- Measures signal-to-noise ratio
- Higher values (>30dB) = better quality

## **UIQM:**

- Evaluates underwater image quality
- Accounts for color cast, blur, low contrast

# Discussion

The results upon training and testing are as follows:

→ **TRAINING**

The best generator weights/parameter are obtained once the combined model was trained on 11435 samples, giving the results listed below:

**SSIM:** mean = **0.840**, std = 0.086

**PSNR:** mean = **28.051**, std = 3.822

When trained on the 25th epoch generator weights, the model performed really well:

**SSIM:** mean = **0.838**, std = 0.089

**PSNR:** mean = **28.503**, std = 4.021

→ **TESTING** (performed on 515 samples)

**SSIM**

Mean: **0.8394**  
std: 0.0596

**PSNR**

Mean: **28.2197**  
std: 2.9108

**UICM**

Mean: 5.2112  
std: 3.2094

**UISM**

Mean: 6.6808  
std: 1.3495

**UICONM**

Mean: 0.2462  
std: 0.0696

**UIQM**

Mean: 3.00  
std: 0.4781

# Work Division

NAME	CONTRIBUTION
AADHITH SHANKARNARAYANAN	<ul style="list-style-type: none"><li>Combined the architecture of DeepWave-Net and FUnIE-GAN</li><li>Performed the training and testing after combining the model and creating the pipeline of data between the two models</li><li>Filmed the demonstration video</li></ul>
ANANYA SUDHEER	<ul style="list-style-type: none"><li>Worked on the data ingestion (data collection, loading as dataloader for train and test, preprocessing)</li><li>Presentation</li></ul>
VIBHA BHAVIKATTI	<ul style="list-style-type: none"><li>Loading the models and the necessary files for DeepWave-Net and FUnIE-GAN</li><li>Creating the files for train, test and inference with the pipeline of the two models being combined</li><li>Presentation</li></ul>

# Demonstration

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