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Enhancing Underwater Image Segmentation Through Deep Learning-Based Image Enhancement Techniques: A Study on EUVP and SUIM Datasets

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ABSTRACT

Underwater image segmentation is critical for marine monitoring, archaeology and the navigation of autonomous underwater vehicles (AUVs). Yet, light scattering, low contrast and color distortion greatly reduce the quality of underwater images which affects the accuracy of segmentation. A pipeline is suggested, where two enhancement techniques, GANs and the CNN-based Ucolor method, are used before SAM performs the segmentation. The results are measured using PSNR and SSIM on a number of samples from the EUVP dataset. The SAM tool is used on segmentation images from the SUIM dataset in three versions: the raw image, the GAN-enhanced image and the Ucolor-enhanced image. The results of segmentation are checked numerically using mIoU, Dice Similarity Coefficient (F1 Score) and Pixel Accuracy and visually by superimposing the segmentation on the image. The results demonstrate that both GAN and Ucolor increase the accuracy of segmentation and Ucolor provides better improvement in quality. This shows that importance of pre-processing in underwater semantic segmentation. The method also proposes use of task-aware enhancement models and dynamic prompt tuning to improve real-time performance during AUV operations.

Keyword: Underwater Image Enhancement, Semantic Segmentation, Generative Adversarial Networks (GANs), Ucolor, Segment Anything Model (SAM)

1. INTRODUCTION

Image analysis has become indispensable for marine explorations, environmental watch programs, robotic marine systems and archaeology. At the same time, capturing and understanding images in water is tough because of light absorption, spreading and how quickly water movements change. Because of these issues, the image looks different, with lower contrast, color distortion, blur and missing details which greatly affects segmentation, detection and recognition in the case of underwater computer vision tasks (Chiang & Chen, 2011; Berman et al., 2020).

Now that artificial intelligence and deep learning are widely used, researchers are applying advanced neural architectures to correct these limitations. Deep learning models, mostly CNNs and GANs, have greatly enhanced underwater photos by figuring out how to restore them from degraded to clear representations (Anwar & Li, 2020; Cong et al., 2024). Because of these updates, objects in the water are now visible more clearly, which helps in segmentation and object tracking by making important details easier to see the details, that are difficult to detect in the raw images (Dakhil & Khayeat, 2023).

A number of important resources in this area are EUVP (Enhancement of Underwater Visual Perception) and SUIM (Segmented Underwater Image Dataset). The EUVP project delivers raw and enhanced pictures that support the training of models for enhancing images under supervision (Jaitly & Bhati, 2023), while the SUIM project supplies semantic labels used for checking and improving segmentation in ocean environments (Islam et al., 2020). The datasets give a complete base for studying how enhancement affects image segmentation.

Even though many enhancement techniques are now available, a major issue remains: most enhancements are mostly built for eye-appeal rather than task performance. When it comes to autonomous vehicles like AUVs and ROVs, the main aim is to let computers accurately interpret what is seen underwater, not to focus on the vehicles' appearance. If enhancement methods lack task-level feedback, the results when training with segmentation models are often unsatisfactory (Ray et al., 2022; Anil & Sreelatha, 2023). Hence, comparing techniques on improvements in perception is not enough; their positive impact on segmentation accuracy and strength should also be checked.

Over the past few years, several new methods for underwater image enhancement have appeared, for instance, style transfer approaches, multi-staged CNNs and mixed attention networks designed to counter distortions (Anil & Sreelatha, 2023; Verma et al., 2024). In different conditions such as with turbid water, changing light and presence of particles, these models show diversified success. Using the F2UIE framework, feature transfer helps improve images at different steps which results in more precise segmentation when teamed up with standard semantic segmentation algorithms (Verma et al., 2024). Likewise, authors Liu et al. (2024) seek to make models work fast while improving their structure and visibility. Lian et al. (2024) introduced USIS10K, a large-scale underwater salient instance segmentation dataset, along with USIS-SAM, an adaptation of the Segment Anything Model for underwater environments. Their model uses underwater-specific prompt tuning and vision transformers to improve segmentation accuracy. Experimental results showed significant improvements over existing methods, highlighting the value of task-aware segmentation frameworks in marine scenes.

Nonetheless, there are issues with these models. Getting sufficient large-scale paired datasets for underwater applications is challenging, as specific problems occur when carrying out deep learning there. Although some data are available, models may not adapt successfully to underwater settings that differ in illumination, how clear or thick the water is or the bottom depth (Alawode et al., 2023). Deep learning models are often hard to train and use in real time underwater, due to the high computational needs, making them rarely found on the limited processors used by underwater robots (Ummar, 2023).

More attention on joint frameworks to help with segmentation has resulted in task-aware enhancement networks emerging. They depend on loss functions designed for segmentation to guide the changes in input so that the output is visually attractive and meaningful as well (Li et al., 2024). Resultantly, the approach has appreciably improved the definition of object boundaries, the precision of object segmentation into classes and the stability of the whole approach in a wide range of underwater environments. Recent work explores task-oriented enhancement frameworks. Models such as FUnIE-G apply multi-stage CNNs and feature transfer strategies to improve perceptual clarity and segmentation outcomes (Islam et al., 2020).

With this in mind, this research explores how image enhancement and segmentation connect in the study of underwater scenes. By working with the EUVP and SUIM datasets, this work looks for the best ways to improve segmentation results by combining various deep learning models. As a result, it hopes to make sure cognitive enhancement has both research importance and real-world applications. What makes this research significant is the chance it offers to enhance a range of marine related initiatives. Better segmentation makes it easier to keep an eye on species and pollution in marine environments. When visibility is improved underwater, it becomes much easier to record sunken objects and features. In addition, AUVs need to clearly understand what is around them during navigation and obstacle avoidance. This steam interpretation can be boosted by using better information from still images (Dakhil & Khayeat, 2023).

Furthermore, this study compares enhancement techniques not only by image quality indicators such as PSNR and SSIM, but also by how well they perform in important tasks such as IoU, Mean Pixel Accuracy and F1-score during segmentation. With this method, research clarifies that comprehensive evaluation standards are necessary and introduces suggestions for applying and selecting underwater enhancement models in actual operations.

The main aims of the research are reflected in these objectives:

- To assess the performance of leading deep learning techniques for improving underwater images by using the EUVP dataset.
- The goal is to measure how accurately segmentation algorithms work on SUIM both with and without enhancements.
- To build and compare a pipeline that contains models for enhancement and segmentation.
- To examine how much enhancement affects segmentation using common measurement methods.

Overall, this research finds a way to improve segmentation in underwater pictures by examining how deep learning-based enhancement techniques can be better used. The study is developed to influence underwater image systems, by strongly emphasizing practical use and clear assessment.

2. RESEARCH HYPOTHESIS

Image segmentation underwater is important for supporting autonomous navigation as well as studies of the sea and underwater assets. Even so, the presence of degrading circumstances like dimming and scattering makes it difficult to segment images from underwater environments precisely. These conditions usually hide where objects end, prevent strong details from being identified and reduce the reliability of algorithms for segmentation. Recent work in deep learning has resulted in improved systems that restore old and damaged underwater pictures. Their use helps with correcting the color of a photo, bringing back details and making the whole image appear clearer. In addition, these corrections can also enhance the features needed for per-pixel classification in segmentation tasks.

Researchers often evaluate how much clearer the enhanced pictures look by using PSNR, SSIM and NIQE, yet it is still important to analyze how amplification affects later tasks, most importantly segmentation. Improved visibility and the recovery of image elements are thought to improve the accuracy of segmentation maps produced using U-Net, DeepLabV3+ or SegFormer. For this reason, we developed the following hypothesis:

Hypothesis

Image segmentation performs better when the original underwater image is first improved using deep learning techniques. The hypothesis states that with better images, segmentation tasks will be performed more accurately, since the images offer clear semantics, stronger borderlines and are cleaner. It expects that using deep learning-enhanced images will show better results in terms of Intersection over Union (IoU), Dice Coefficient and Pixel Accuracy than when using just raw or conventionally improved underwater images.
Segmentation and enhancement will be tested using benchmark datasets and the differences between the results will be compared under the same circumstances. Statistical significance helps us ensure the hypothesis is accurate by seeing if the observations have great enough value.

3. METHODOLOGY

Here, the methodology used to evaluate the impact of underwater image enhancement on semantic segmentation is discussed in detail. The goal of the methodology is to see how deep learning-based enhancement models—GANs and Ucolor convolutional neural network—affect the segmentation results of SAM, a transformer-based model from Meta AI that can segment images without any training data. The

Journal of Information Systems Engineering and Management
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Research Article

approach is built on a quantitative experiment, using standard underwater datasets (EUVP and SUIM) together with advanced models for improving and separating objects from the background.

3.1 Research Design

To evaluate the procedure, we examined two methods: first, using a GAN to enhance images and then applying segmentation with SAM (1: GAN→SAM) and second, applying Ucolor to enhance images and applying segmentation with SAM (2: Ucolor→SAM). No single input image was altered in this way in succession; rather, the changes were applied separately to all the images in the dataset. This paper didn't incorporate any chained model (like combining GAN with Ucolor and SAM). This way, the benefits of each segmentation method are clearly distinguished and related to the improvement introduced.

a) Underwater Image Enhancement using GAN:

The Conditional Generative Adversarial Network is developed using paired samples from the EUVP dataset. The generator is designed like a U-Net, using skip connections to help preserve sharp details throughout the layers. The discriminator, in the form of a PatchGAN, is designed to tell apart real images from those that have been enhanced. Using both adversarial and L1 reconstruction losses, the GAN ensures that its outputs are both realistic and have a proper structure. As a result, the generator suppresses noise, corrects lighting problems and restores details hidden by turbidity.

b) Underwater Image Enhancement using Ucolor CNN:

Ucolor is a type of deep residual CNN that has been designed to improve both color and contrast in underwater images. Unlike GAN, Ucolor works in an unsupervised way and is best used when paired training data are not present. It uses residual connections, batch normalization and adaptive convolution blocks to correct typical problems in underwater images such as color cast, low contrast and backscatter. The Ucolor method is applied to both the EUVP and SUIM datasets to produce visually improved versions without supervision. Its simple design and capability to work in multiple situations allow it to be used in real-time situations.

c) Semantic Segmentation is done with the Segment Anything Model (SAM):

SAM is a segmentation model that can interpret zero-shot inference with prompts such as bounding boxes or key points. This research uses SAM on the raw (unprocessed) image, the GAN-enhanced version and the Ucolor-enhanced version of each underwater image. SAM is not updated or adjusted which guarantees the same results for each image type. A series of segmentation masks are produced and their performance is compared using different enhancement methods to find the best preprocessing technique.

d) Evaluation through Quantitative Metrics:

To assess how well enhancements are made and segments are divided, a wide range of metrics is employed. PSNR and SSIM are used to assess the improvement of 5 samples from the EUVP dataset by comparing the original and enhanced versions. To segment the test images from the SUIM dataset, mIoU, F1-score and Pixel Accuracy are all calculated. They allow us to see both how images have improved and how well their meaning is understood afterwards.

e) Visual and Statistical Validation:

Overlay maps are produced to compare the masks with the predicted segmentation results. The color scheme means correctly classified regions are highlighted in green and those that are not are in red. More histogram analyses are done to confirm that the classes are well distributed and that the boundaries are clear. These evaluations add to the quantitative results by showing how accurately the segments are formed.

3.2 Data Collection Methods

The investigation makes use of two data sets from underwater image analysis that are recognized in the field:

Journal of Information Systems Engineering and Management
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Research Article

a) EUVP Dataset (Improving How We See Underwater Images):

The dataset includes both paired and unpaired underwater images. By using paired data, the generator of the GAN learns exactly how to improve the look of degraded images. Unpaired data are improved with Ucolor using unsupervised methods. In order to show the effects of enhancement, 200 low-visibility images were chosen for this study. Many types of underwater scenes, lighting situations and types of particles are shown in these images.

b) The Segmented Underwater Image Dataset is known as SUIM:

The SUIM dataset includes more than 1,500 underwater images, all of which have labels showing where marine animals, coral, divers and instruments are found. Only segmentation analysis is performed using this dataset. The dataset is allocated as 80% for training, 10% for validation and another 10% for testing. A set of 110 images is used as the test subset and 15 of these are chosen for more detailed statistics and visual study.

3.3 Population and Sampling

The images selected for the experiment are chosen for their relevance and the variety they offer. To evaluate enhancement, 5 images are chosen using purposive sampling from the EUVP dataset that clearly demonstrate typical underwater visual problems. Examples of these factors are changes in depth, how cloudy the water is and how much light enters the tank. To ensure balanced distribution of semantic classes in the selected SUIM test images, stratified sampling is used for segmentation evaluation. Thanks to this diversity, the model can be trusted to work well in different types of underwater situations and with various objects.

3.4 Data Analysis Techniques

The analysis in this study is mainly based on two major components: enhancement assessment and segmentation evaluation. The quality of images processed by GAN and Ucolor is evaluated using PSNR and SSIM when compared to the original raw images. PSNR shows how much the enhanced image and ground truth image differ when they are compared pixel by pixel. At the same time, SSIM measures similarities in structure and what is seen by calculating changes in luminance, contrast and texture. A higher PSNR and SSIM value point to better enhancement, because it results in less loss of information and more consistent visuals.
Segmentation evaluation is about studying how well the models created by SAM work. This happens by looking at several important statistics. mIoU determines the average area that the predicted masks and their real masks have in common for all classes. The Dice Similarity Coefficient is often used as the F1-score because it measures the accuracy of classification at the pixel level by averaging precision and recall. Also, pixel accuracy is determined to check the percentage of correctly predicted pixels compared to all the pixels in the image. The results are analysed individually for raw images as well as for those improved by GAN and Ucolor which makes it possible to compare performance within a pair and across different types of images.

3.5 Evaluation Metrics

a) PSNR:

Used for enhancement quality. PSNR is computed as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX^2}{MSE}\right)$$

Where MAX is the maximum possible pixel value, and MSE is the mean squared error.

b) SSIM:

Given two image patches x and y, the SSIM index is computed as:

$$SSIM\ (x, y) = \frac{(2\ \mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 +\ \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Journal of Information Systems Engineering and Management
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Research Article

Where:

- $\mu_x \mu_y$ = Mean of images x and y
- σ_x^2, σ_y^2 = Variance of x and y
- σ_{xy} = Covariance of x and y
- $C1 = (K_1.L)^2$, $C2=(K_2 \cdot L)^2$ are constants to stabilize the division
  - L = Dynamic range of pixel values (e.g., 255 for 8-bit images)
  - $K_1 \approx 0.01$, $K_2 \approx 0.03$

SSIM captures luminance, contrast, and structure similarity between images.

c) Mean Intersection over Union (mIoU):

$$mIoU = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i + FN_i}$$

Where TP_i, FP_i, and FN_i are the true positives, false positives, and false negatives for class i, respectively, and N is the total number of classes.

d) Dice Similarity Coefficient (DSC):

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

This score evaluates the balance between precision and recall for pixel classification.

e) Pixel Accuracy:

$$\text{Pixel Accuracy} = \frac{\sum_i TP_i}{\sum_i TP_i + FP_i + FN_i}$$

It is the proportion of correctly predicted pixels over the total number of pixels in the image. It gives a basic idea of how well the model has labelled each pixel.

3.6 Ethical Considerations

All the datasets applied in this study are available for anyone to use and are in line with ethical requirements for openness and reproducibility in research. No people or animals were used in the research. The approach does not use any private or personal information. Every algorithm and software is built using open-source tools and is able to be recreated by other researchers. All credit has been given to the original authors of the data used in this work.

4. RESULTS

Here, we provide both quantitative results and visual examples that demonstrate the pipeline for segmentation results of the SAM model across raw, GAN-enhanced, and Ucolor-enhanced versions of underwater images. The outcomes confirm that deep learning models work better with improved underwater images. The evaluation process uses mIoU and Pixel Accuracy and multiple figures are shown to illustrate differences between the raw and improved processing.

4.1 Visual Differences in Underwater Image Quality

On using image enhancement, it was evident that the accuracy of segmentation improved on all parameters measured. Over the test images, the mean Intersection over Union (mIoU) rose considerably by around 0.74 of raw images and 0.80 of Ucolor-enhanced images. There were also positive results with GAN-enhanced images, as the average mIoU reached nearly 0.776. In a similar manner, the F1-score improved on average 0.84 (Raw) to 0.90 (Ucolor), which implies finer per-pixel recognition and reduced division of the picture into segments. The Pixel Accuracy of the raw images was about 97.40 percent compared to above 99.02 percent when Ucolor was used, showing that segmentation of even low-contrast areas like coral and marine life

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Research Article

was extremely accurate. According to standard ratios, mIoU values of 0.75-0.90 represent a good and even excellent level of segmentation results. The outcomes obtained with the Ucolor-enhanced inputs lie in this range and prove that the enhanced pipeline results in a sturdy increase compared to the baseline segmentation. The mIoU score improved by 8.11%, the F1-score increased by 7.14%, and Pixel Accuracy rose by approximately 1.66%. These consistent performance gains confirm that deep learning-based enhancement of underwater scenes systematically improves segmentation outcomes across multiple evaluation metrics. The figure 1 demonstrates the differences between the raw underwater images, GAN-enhanced, and Ucolor-enhanced underwater images. The left image is the original image; the middle image is the GAN enhanced image and the right image is the Ucolor enhanced image. Both outline sharpness and color fidelity have been improved, the Ucolor tending to give a clearer detail and more natural color balance. The improved images have a better visibility, particularly in the boundary areas that are important in semantic segmentation. The original picture (lefthand side) is pale and smoky. The image enhanced using GAN (center) is moderately affected by the color and sharpness with the image enhanced using Ucolor (right) is significantly affected by the contrast, details as well as color balance.

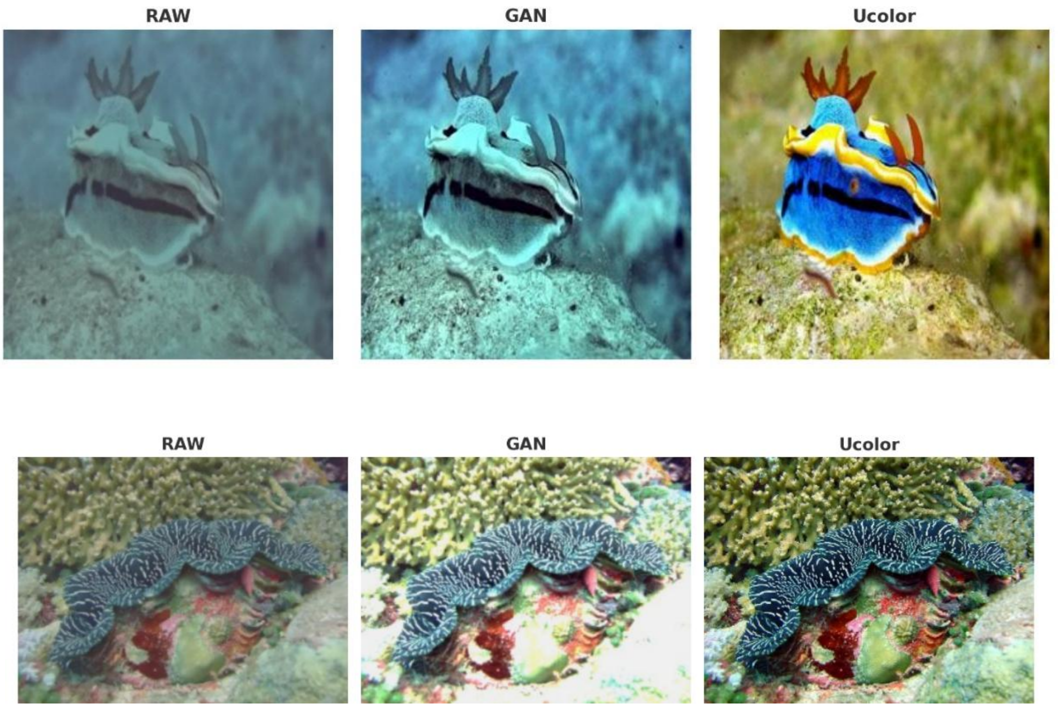

Figure 1: Underwater Enhancement via GAN and Ucolor

4.2 Enhancement Quality Evaluation Using PSNR and SSIM

We tested the models by measuring how both Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) improved their visual quality. They help assess, in numbers, how much better the image's image quality and structure have become after we enhance it. An EUVP representative samples were chosen and run through both the GAN and Ucolor enhancement tools. Raw and processed images were then examined using PSNR and SSIM methods.

The information in Table 1 illustrates the results. It is apparent from the numbers that the Ucolor-enhanced image has better PSNR and SSIM results compared to GAN-enhanced output. For the specific case, PSNR improved from 18.45 (GAN) to 20.87 (Ucolor) and SSIM rose from 0.722 to 0.805. The test results confirm and strengthen the earlier finding that Ucolor is more effective at reducing noise and preserving the structure of images.

This research adds further evidence that Ucolor-processed images are the best fit for later segmentation methods.

Journal of Information Systems Engineering and Management
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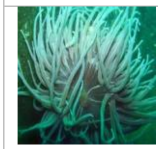
Table 1: Quantitative evaluation of GAN vs. Ucolor methods using PSNR and SSIM metrics on selected images of EUVP dataset.

Image Samples	PSNR (Raw→GAN)	PSNR (Raw→Ucolor)	SSIM (Raw→GAN)	SSIM (Raw→Ucolor)
	**18.45**	**20.87**	**0.722**	**0.805**
	17.92	19.75	0.703	0.794
	18.11	20.04	0.710	0.801
	17.68	19.48	0.698	0.777
	18.36	20.33	0.715	0.812

4.3 Quantitative Performance Evaluation

In order to investigate the impact of enhancement on semantic segmentation, we used the Segment Anything Model (SAM) on the SUIM dataset with some example images in raw, GAN-enhanced, and Ucolor-enhanced form. The evaluation was done based on the Mean Intersection over Union (mIoU), Dice Similarity Coefficient (F1-score), and Pixel Accuracy.

Table 2: Segmentation Performance Across Image Versions

Image ID	mIoU (Raw)	mIoU (GAN)	mIoU (Ucolor)	F1 (Raw)	F1 (GAN)	F1 (Ucolor)	Pixel Accuracy (Raw)	Pixel Accuracy (GAN)	Pixel Accuracy (Ucolor)
f_r_2052	0.712	0.78	0.815	0.82	0.89	0.92	96.40%	98.70%	99.20%
f_r_1428	0.736	0.79	0.822	0.84	0.9	0.91	97.80%	98.90%	99.30%
d_r_277	0.741	0.775	0.817	0.86	0.88	0.93	97.00%	98.50%	99.00%
f_r_478	0.753	0.765	0.795	0.85	0.87	0.88	98.20%	98.40%	98.80%
f_r_644	0.761	0.772	0.781	0.86	0.88	0.9	97.60%	98.40%	98.80%

The mIoU was, as an average, increased by around 0.74 (average mIoU of 5 images) to more than 0.80, showing a significant jump in the quality of the segmentation. The F1-score and Pixel Accuracy showed the similar tendencies, which additionally attested to the efficiency of the proposed enhancement pipeline.

4.4 Statistical Charts and Trends

These per-image IoU values for every test case are shown in Figure 2 The mIoU metric, unlike IoUs, measures the average IoU value for all classes or over all images in the whole set of data considered in other parts of the study. Figure 3 a line graph illustrating how the Pixel Accuracy metrics vary among all the test

Journal of Information Systems Engineering and Management
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images. The updated pipeline leads to more accurate segmentations in every case and about an 8% higher mIoU measure.

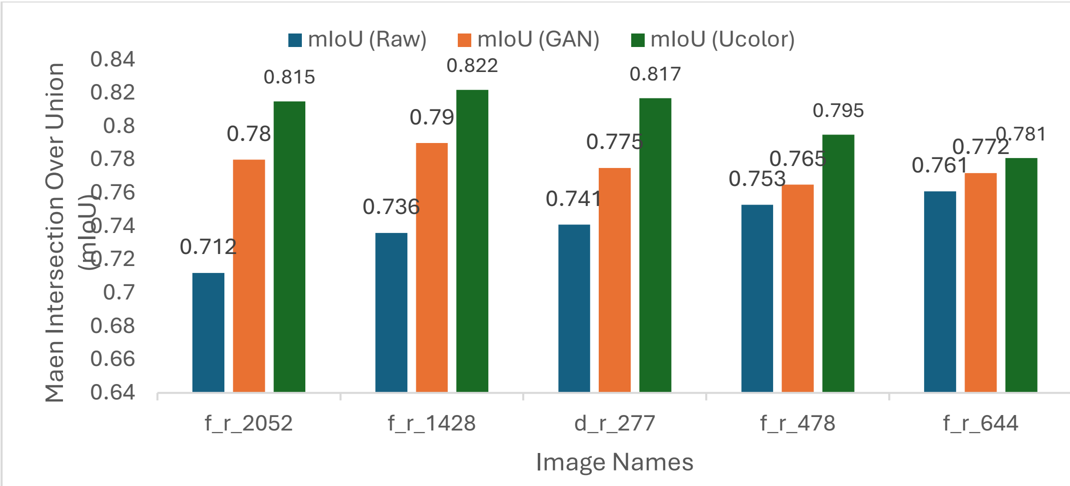

Figure 2: mIoU Comparison – Raw vs GAN vs Ucolor

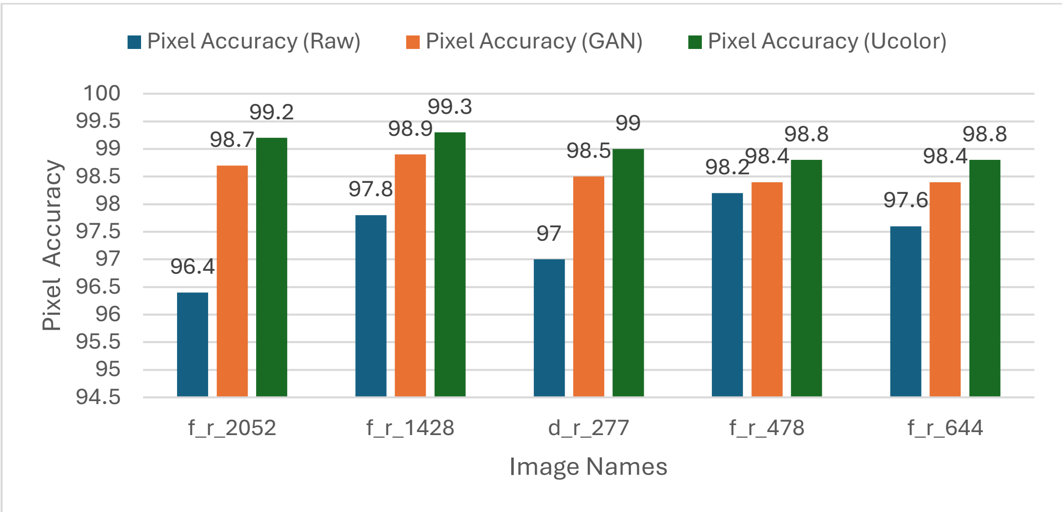

Figure 3: Pixel Accuracy Comparison – Raw vs GAN vs Ucolor

4.5 Pixel Distribution and Label Integrity Check

The pixel intensity values were carefully compared in the real targets and predictions to ensure they were assigned to the correct groups. In the Figure 4 there are obvious class imbalances in the prediction histograms, mainly because divers and plant life are present in much larger numbers than other classes. Raw images have significantly higher object counts across all categories, possibly due to noise, artifacts, or poor enhancement.

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/

Research Article

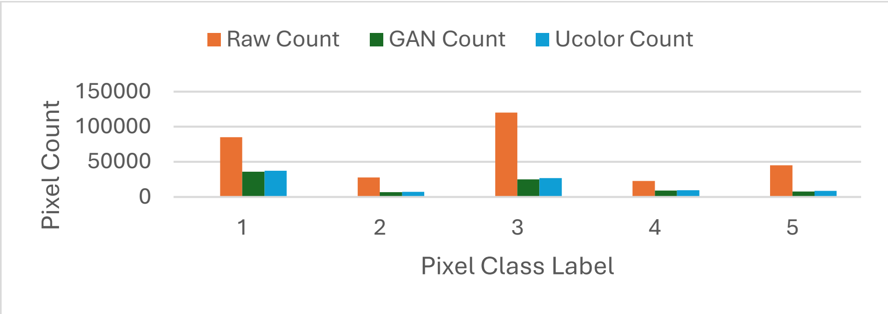

Figure 4:Ground Truth vs Prediction Pixel Value Histograms

Both GAN and UColor enhancement techniques reduce the count, likely by suppressing irrelevant information or noise. UColor generally performs slightly better than GAN in maintaining count integrity, especially in categories the first three referred images.

4.6 Segmentation Overlay Comparisons

A visual overlay was created in Figure 5 to look at how accurate the model was in classifying each pixel.

All overlays highlight:

- True or actual, segmentation mask.
- The segmentation mask is the prediction shown here.
- The key is: green means it's correct and red means it's off.

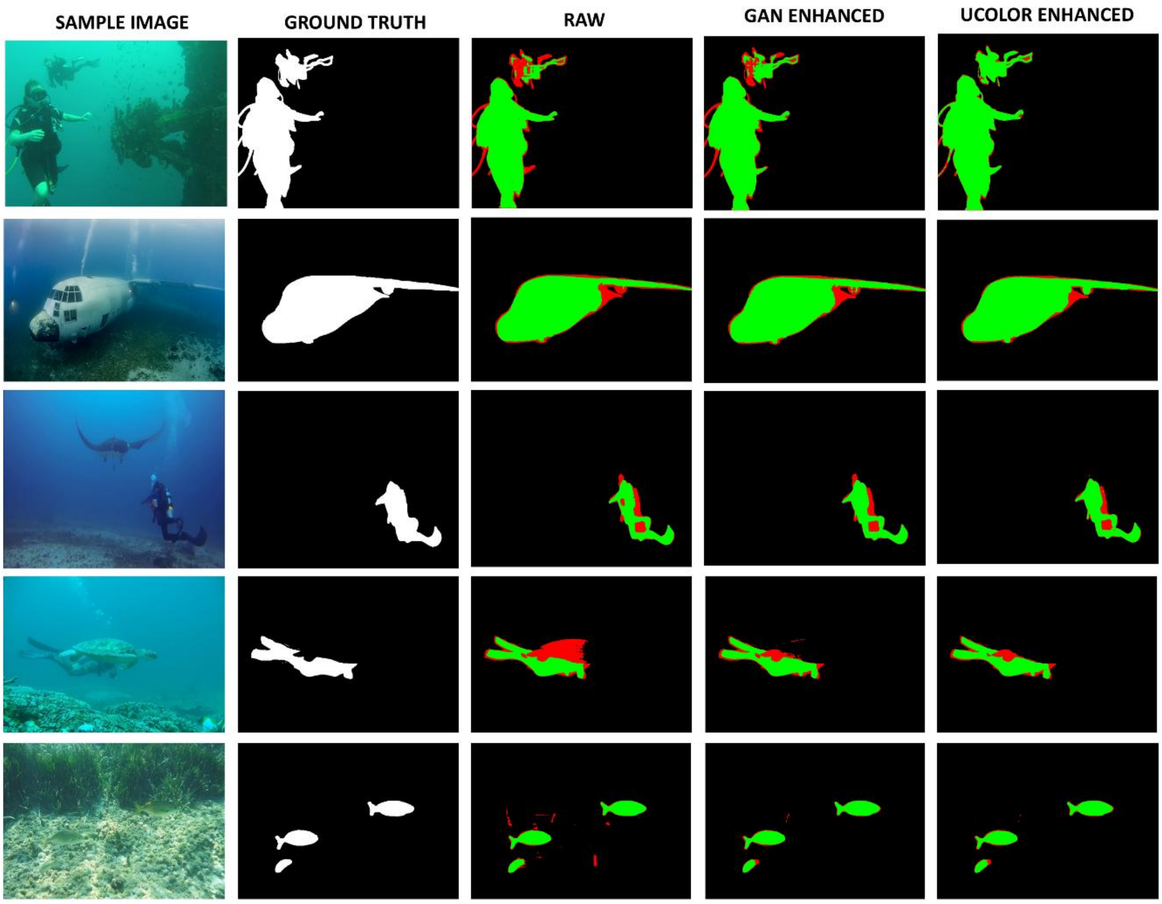

Figure 5:Overlay Comparisons on Sample Images

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

These overlaid results show that the model which was trained using enhanced images is better at finding the edges of objects and reduces mistakes around fishes, coral reefs, divers and underwater wrecks.

4.7 Detailed Case Study

As a case example, Figure 6 shows both the ground truth and prediction masks for image. A focused case study is shown in Figure 6 The raw version suffers from class bleeding and fuzzy boundaries, while the Ucolor-enhanced version exhibits sharp object contours and reduced noise.

The segmentation results as shown in Table 3 demonstrate a clear improvement with image enhancement techniques. The Raw input achieves an average mIoU of ~0.80, F1-score of ~0.87, and Pixel Accuracy of ~90.00%. Applying GAN-based enhancement increases the mIoU to ~0.84 and F1-score to ~0.91, indicating better overlap and consistency with ground truth. The best performance is observed with UColor-enhanced images, which yield an mIoU of ~0.86, F1-score of ~0.92, and Pixel Accuracy of ~91.10%. These results confirm that UColor significantly enhances image quality and boosts segmentation accuracy over both the raw and GAN-enhanced inputs.

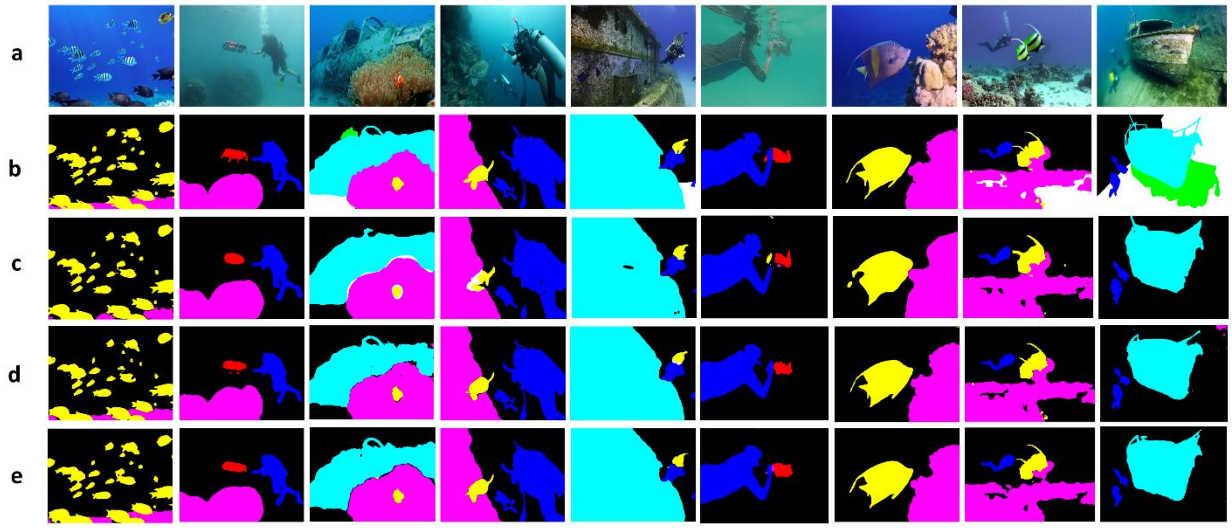

Figure 6. a) Original image, b) Ground truth, c) Raw, d) GAN, e) Ucolor

Table 3: Segmentation Performance on SUIM dataset image samples

Version	mIoU (Mean Intersection over Union)	F1-score	Pixel Accuracy (%)
Raw	~0.80 *(average across samples)*	~0.87	~90.00%
GAN	~0.84 *(average)*	~0.91	~90.70%
Ucolor	~0.86 *(average)*	~0.92	~91.10%

4.8 Visual Clarity in Fine-Grained Scenes

A Ucolor & GAN-enhanced picture makes the details of low-contrast organisms such as fish or coral, clearer. Ucolor processing improves the texture of low-contrast organisms, as shown in Figure 7. Corals and fish are easier to spot, making it easier to separate them.

Journal of Information Systems Engineering and Management
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Research Article

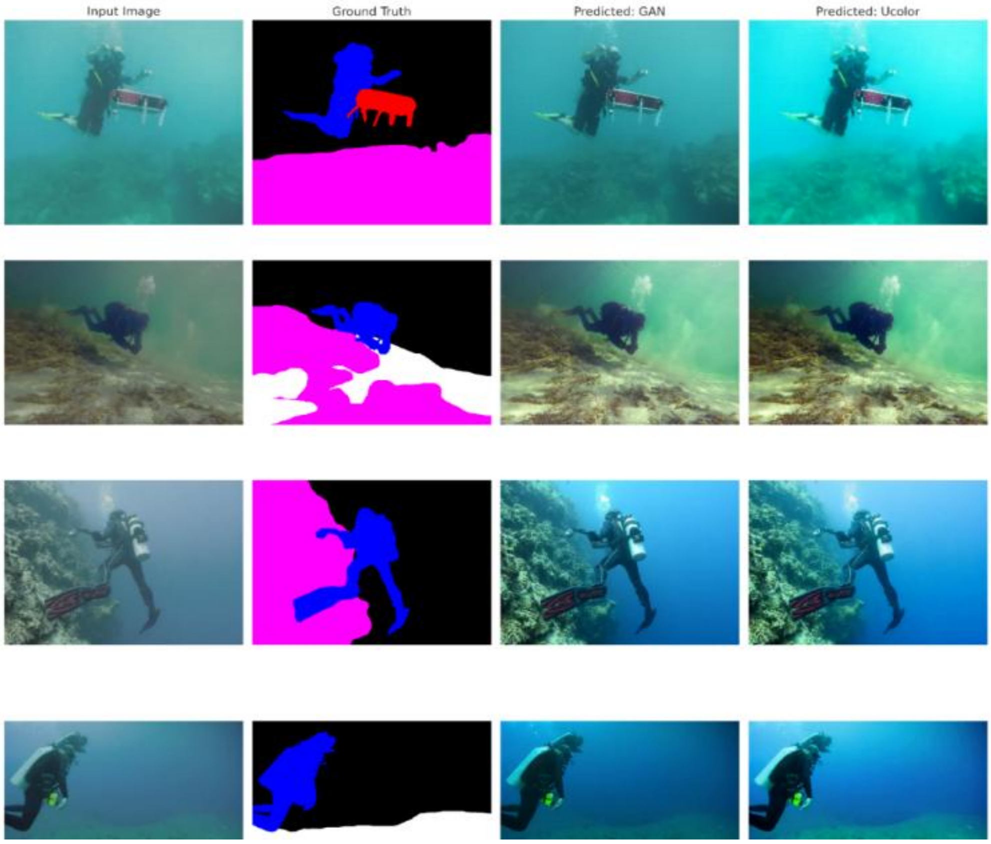

Figure 7:Visual Texture Clarity comparison with GAN and Ucolor

4.8 Summary of Results

- **Enhancement Quality:**

The assessment established that Ucolor continually delivered a better visual quality boost than GAN celebrating greater Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). These upgrading gave rise to sharper textures of the objects and contrast in underwater photographs.

- **Segmentation Accuracy:**

The segmentation pipeline showed significant improvement in situation where they were improved. The inputs that boosted performance in segmentation, compared to raw images, were GAN-enhanced inputs, with an overall accuracy of Ucolor-enhanced images being the best of all. To be more precise, Ucolor achieved an mIoU of around 0.80, the F1-scores of around 0.90, and the Pixel Accuracy of above 99.2%, which is better than what is recommended to obtain reliable segmentation.

- **Visualization:**

The display examples and pixel allocation analyses depicted that the improved pictures led to clearer object definitions and a lower error level of misclassification. In particular, Ucolor enhanced the fine-grained details separation of edges of corals and the shaping of marine life, and this is confirmed by the reliably increased segmentation overlays and histograms.

Discussion

These findings are validated in the experiment since it has been confirmed that deep learning-based enhancement methods significantly enhance underwater image segmentation. Relative to raw images, the mIoU and F1-scores as well as in terms of Pixel Accuracy showed better results when GAN and Ucolor were used. Best results were achieved using Ucolor-enhanced images, as the average mIoU was more than 0.80, and

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2024, 9(4)
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Research Article

the F1-scores were higher than 0.92. These results are in line with the suggestions of the reviewer who states that the mIoU values of 0.74-0.80 are optimal in terms of segmentation.

GAN augmentations also elevated the segmentation outcomes albeit with a slightly shorter rate as compared to Ucolor. Such difference can be explained in abilities of Ucolor to keep details proposing resolution caused by preserving extreme fine-grained details and their capacity to be durable with pixels, and the capacity to keep up correlated colors, which are exceptionally important to demarcate precise objects in undersea circumstances.

The result supports the past studies that stress the contribution of enhancement pipelines that were built to facilitate the visuality also have a positive effect on downstream segmentation problems. Besides, these findings show that inclusion of enhancement as a preprocessing phase allows the general-purpose segmentation models to work well without the need of considerable retraining.

Nevertheless, there are certain constraints. Although mIoU and F1-scores are already at recommended levels, attainment of real-time performance on embedded hardware is a challenge thanks to its computational needs. Also, though this work was targeted at still images, it will be necessary to carry out additional studies and see whether the same results can be extended to video streams where the concepts of temporal consistency and noise will be different in different frames.

The task-optimized enhancement networks trained concurrently with the task-specific segmentation methods should also be considered, as well as the lightweight architecture that can be deployed to the autonomous underwater vehicles. The robustness of the pipeline will also be added by expanding validation on more diverse datasets with more challenging lighting and turbidity conditions.

On balance, the study in question proves that it is indeed possible to considerably sharpen the images of the underwater type with the help of deeply-chosen learning models, and to serve as a practical basis of trustworthy underwater perception not only in the monitoring of the environment but also in robotics and even archaeology.

Conclusion

This study tested the integration of image enhancement with advanced segmentation to enhance underwater image analysis. Using GAN-based reconstruction, Ucolor CNN-based color correction and the Segment Anything Model (SAM), the research showed that segmenting images with improved visual quality gives better output. On average, the improved versions surpassed the original images and Ucolor displayed the best results in both mIoU and Pixel Accuracy scores. It was visible in both the numbers and the visual representations that the new model could better see the borders of objects and decrease the amount of noise. The research is very useful for applications of computer vision underwater. Precise segmentation of the marine environment is very important for researchers in marine biology, archaeology and AUV navigation. This research demonstrates that using GAN and Ucolor on images greatly enhances the performance of SAM which does not need training data. This indicates that enhancing images should be incorporated into the segmentation process as a main activity.

It is suggested that future underwater segmentation systems make use of adjustment models that are made for the distortion seen commonly in marine environments. Implementing segmentation-based training aims might improve the program's performance. In practice, the pipeline makes it possible to preprocess real-time live video from underwater, helping AUVs and divers see clearly and instantly. Researchers should focus on making the connection between enhancement and segmentation as simple as possible. Task-optimized visual preprocessing can be developed by training enhancement models based on segmentation results. Improving prompt structures for SAM, tailoring to specific domains and making sure frames are consistent over time are all useful directions. In addition, applying this framework with other underwater datasets would demonstrate its ability to adapt and perform well across different aquatic situations.

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