Maritime Obstacle Segmentation for Unmanned Surface Vehicles: A Semantic Approach to Navigating Dynamic Environments

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Abstract. The increasing demand for high-precision navigation in Unmanned Surface Vehicles (USVs) underscores the critical role of image segmentation in maritime environments. Accurate segmentation of maritime images into distinct categories, including sky, water, and obstacles, is essential for ensuring safe operations, mitigating collision risks, and enhancing autonomous decision-making capabilities. To address the challenges, the proposed study presents an advanced image segmentation methodology tailored for maritime applications. The proposed approach leverages a deep learning-based encoder-decoder architecture built upon the ResNet34 framework, incorporating atrous convolution techniques to facilitate multi-scale feature extraction—an essential requirement for effectively capturing the complexity of maritime environments. The architecture further integrates skip connections and upsampling layers within the decoder to enhance segmentation precision and improve predictive accuracy. The implementation framework includes preprocessing techniques such as image resizing, normalization, and standardization to optimize input quality, while post-processing aligns predictions with predefined classification categories to enhance interpretability. The model is trained on the LaRS dataset, which provides a diverse and realistic representation of maritime conditions. Experimental evaluations conducted on real-world datasets demonstrate that the proposed model achieves a Mean Intersection over Union (mIoU) of 95.4%, surpassing the performance of existing segmentation approaches. By addressing the limitations of conventional methodologies, the following research contributes to the development of more robust and reliable USV navigation systems capable of operating effectively in diverse and challenging maritime environments.

Keywords: Unmanned Surface Vehicle (USV) · Semantic Segmentation· Maritime Navigation · U-Net · ResNet-34.

1 Introduction

The segmentation of maritime images into sky, water, and obstacles is crucial for the safe navigation of Unmanned Surface Vehicles (USVs). As USVs are increasingly utilized in applications such as autonomous shipping, environmental monitoring, and defense operations, accurate scene segmentation remains a fundamental requirement for effective decision making and collision avoidance. However, the maritime environment presents significant challenges, including strong winds, rain, poor lighting conditions, and image degradation due to reflections, occlusions, and atmospheric disturbances, all of which affect the reliability of the segmentation methods [1] . The mentioned factors make it difficult to accurately detect obstacles and distinguish between navigable and nonnavigable areas. Existing segmentation techniques often struggle in maritime scenarios due to dynamic lighting conditions, wave patterns, and the presence of small, partially submerged objects. Traditional computer vision approaches relying on edge detection and handcrafted feature extraction often fail to generalize across varying conditions, leading to high false-positive and false-negative rates [2] . Recent advancements in deep learning-based segmentation have improved robustness; however, models such as U-Net [3] , PSPNet [4] , and WaSRNet [5] still find difficulties in handling extreme weather conditions and domain shifts . The reliance on large-scale labeled datasets further complicates model training, as maritime datasets are more limited than terrestrial datasets. To address these challenges, a deep encoder-decoder architecture is introduced to enhance segmentation performance in dynamic maritime conditions. The approach integrates a ResNet34-based encoder with atrous convolutions trained on the LaRS dataset dataset [6] [7] , which provides diverse and realistic maritime scenarios. The integration of ResNet34, pretrained on ImageNet, facilitates effective feature extraction through residual learning, allowing the model to capture the intricate details of the maritime environment. Atrous convolutions further contribute to segmentation by incorporating multiscale contextual information without reducing the resolution, which is particularly important in maritime image segmentation, where small and distant objects must be accurately detected despite variations in scale and distance [8] . The segmentation process is refined through a decoder incorporating upsampling layers, ensuring precise delineation between the sky, water, and obstacles. The segmentation pipeline includes a preprocessing stage that standardizes the input images through resizing and normalization, thereby enhancing the generalization ability of the model. Because maritime environments often produce ambiguous class predictions due to reflections and occlusions, refined post-processing techniques are applied to improve interpretability by mapping predictions to predefined classes. To ensures better differentiation between categories and reduces the misclassification errors. One of the key challenges in maritime segmentation is the limited availability of large-scale labeled datasets. This is addressed by leveraging the LaRS dataset, which contains extensive real-world maritime imagery, and utilizing pretrained components to maximize feature extraction, even with limited labeled data. In addition, data augmentation strategies, including synthetic perturbations simulating real-world maritime distortions, improve the robustness and adaptability of the model. The proposed segmentation approach is evaluated on real-world maritime datasets, demonstrating competitive mean Intersection over Union (mIoU) scores and exhibiting strong reliability under varying environmental conditions. Precision and recall metrics further support its effectiveness in minimizing false positives while improving true-positive detection [9]. The strategy also shows robustness in handling adverse weather conditions such as fog, rain, and changing illumination, making it a suitable solution for USV navigation. The following study contributes to the development of a reliable and computationally efficient segmentation framework for maritime applications by addressing challenges, such as dataset limitations, resolution preservation, and adaptability to environmental variations.

The remainder of the paper is organized as follows. Section 2 reviews the related work, and Section 3 covers data preparation and processing. Section 4 describes the model architecture, followed by the training and validation in Section 5. Finally, Section 6 presents the evaluation and post-processing.

2 Related Work

Obstacle segmentation in maritime environments has evolved from traditional computer vision techniques to deep-learning-based methods. Early approaches, such as edge detection and thresholding, relied on handcrafted features to differentiate between water, sky, and obstacles, but struggled with varying illumination, dynamic wave patterns, and occlusions, leading to high false-positive and false-negative rates [10]. The advent of deep learning introduced CNN-based architectures like U-Net [3] and DeepLabv3+ [11] , which improved segmentation accuracy through skip connections and atrous convolutions, preserving spatial details while enabling multi-scale feature extraction. WaSRNet [5] , designed for maritime obstacle detection, incorporates a water-edge classification module for enhanced boundary delineation, whereas PSPNet [4], uses pyramid pooling to capture contextual information at multiple scales. More recently, transformer-based models, such as K-Net [12] have demonstrated superior performance by leveraging self-attention mechanisms to model long-range dependencies, which is particularly beneficial for detecting small and distant objects in complex maritime environments. Beyond architectural advancements, domain adaptation techniques have been explored to mitigate the scarcity of labeled maritime datasets, with adversarial training [13] and self-supervised learning [14] proving effective in bridging the domain gap between synthetic and real-world images. However, challenges persist in segmenting maritime environments under extreme weather conditions and varying illumination, where existing methods often struggle with dataset limitations and generalizations.

Building on prior work, the proposed approach integrates a ResNet34-based encoder with atrous convolutions to enhance feature extraction while maintaining spatial resolution. Additionally, leveraging the LaRS dataset and incorporating data augmentation strategies further improves robustness and ensures adaptability across diverse maritime scenarios.

3 Data preparation and processing

For model training and validation, we used the LaRS dataset, designed for maritime scene segmentation, which consists of 4008 images categorized into general images and a minimal-content subset (containing less than 5% content). The general images were split into 2605 training, 200 validation, and 1203 testing images, whereas the minimal-content subset included nine training images, ensuring diverse scene representations. Each image is paired with a grayscale segmentation mask as shown in Figure 1 , where pixel intensities indicate specific classes, such as sky, water, obstacles, or undefined regions, enabling precise feature localization. To optimize the training efficiency for high-resolution 1280×720 pixel RGB images, preprocessing involved patching, where images were divided into 256×256 sections using a sliding window approach to reduce the computational load while preserving spatial integrity. The images were resized to dimensions which are divisible by the patch size, and pixel values were normalized to [0,1], preventing the dominance of high-intensity values. Segmentation masks were one-hot encoded to effectively distinguish different classes, and data were processed in mini-batches of 16 images to balance the memory efficiency and stable convergence. To enhance model generalization, data augmentation was applied dynamically to simulate real-world variations, such as random rotations (0°, 90°, 180°, 270°), horizontal and vertical flips, elastic deformations, and brightness and hue adjustments. The following techniques help address lighting variations, adverse weather conditions, and viewpoint changes, thereby ensuring robustness across diverse maritime environments. By combining structured dataset organization, effective preprocessing, and targeted augmentation, the model achieves improved segmentation accuracy and reliability, even under challenging conditions, advancing maritime scene analysis.
Table 1 provides an overview of the LaRS dataset and its pre-processing pipeline, outlining the dataset structure and key transformations applied before training.

4 Model architecture

The UNet architecture is used as a base model to make the segmentation model, the model adopts an encoder-decoder architecture with ResNet-34 as the encoder backbone, incorporating skip connections to retain spatial information and enhance the gradient flow. The encoder leverages residual blocks consisting of 3 × 3 convolutions, batch normalization, and ReLU activation, with a skip connection ensuring efficient gradient propagation and mitigating vanishing

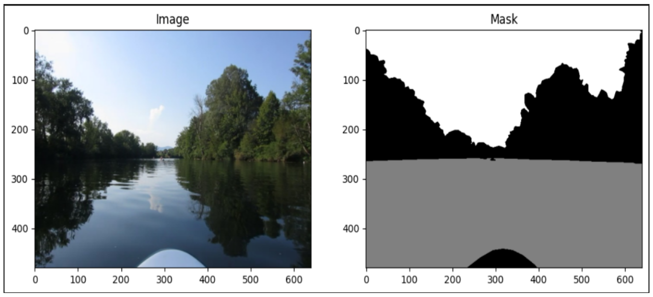


Fig. 1: Input image Vs corresponding grayscale mask

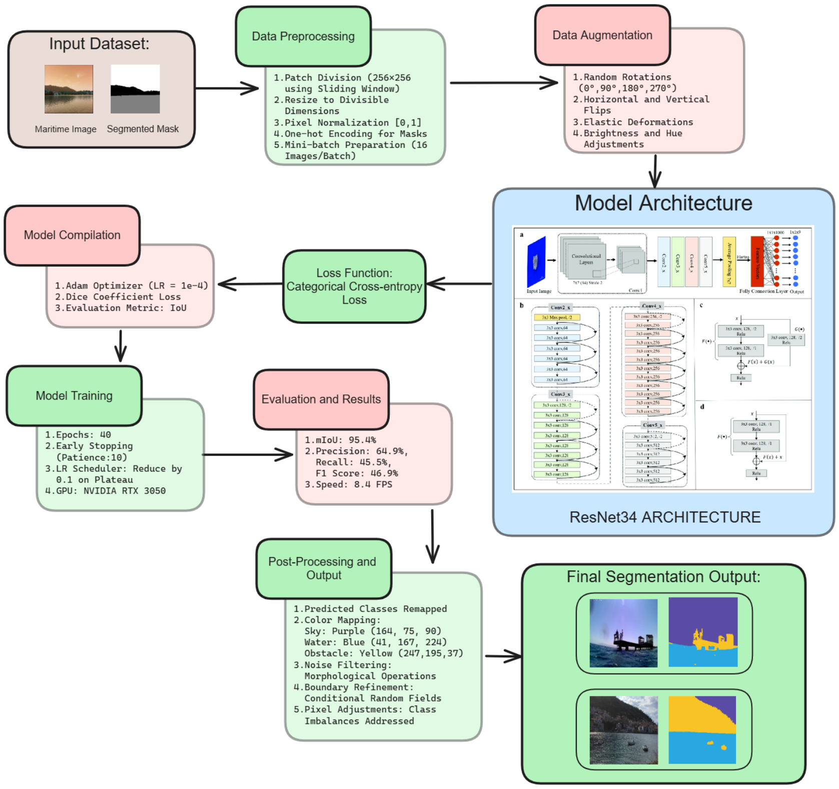
Table 1: Overview of the LaRS dataset and its preprocessing pipeline

Attribute	Description
Total Images	4008 (General: 4008, Minimal-content: 23)
Dataset Split	Training: 2582 (General: 2605, Minimal-content: 9)
	Validation: 191 (General: 200, Minimal-content: 0)
	Testing: 1203 (General: 1203, Minimal-content: 0)
Image Details	Resolution: 1280 × 720 pixels (original)
	Patch Size: 256 × 256 pixels
	Channels: 3 (RGB) for images, 1 for masks
Segmentation Info	4 Classes (Sky, Water, Obstacles, Undefined)
	Mask Encoding: One-hot (h, w, c)
Preprocessing	ResNet34-based, normalization [0,1]
Augmentation	Rotations, flips, elastic deformations, brightness & hue adj.
Batch Size	16 images per batch

gradients. Mathematically, it is expressed as $Y = F(X, W) + X$, where X is the input, W is the convolutional weights, and $F(X, W)$ is the transformation. The following design allows learning modifications rather than starting from scratch, thus addressing vanishing gradients. The encoder extracts multiscale features at 64, 128, 256, and 512 channels, reducing the resolution via stride-2 convolutions. Skip connections bridge the encoder-decoder layers, preserving fine details crucial for segmentation. Figure 2 shows the pipeline and architecture of the model.The decoder reconstructs the segmentation map by upsampling with transposed convolutions and refining the features through convolutional layers. The skip connections seamlessly integrate encoder details, ensuring fine-grained reconstruction, expressed as $S_i = Concat(F_i, U_{i+1})$, where F_i is the encoder's feature map, and U_{i+1} is the upsampled decoder output. The final map is generated via a 1×1 convolution, followed by softmax or sigmoid activation for classification. The strategic use of skip connections balances the local feature retention and global context understanding, thereby enhancing high-resolution segmentation. Table 2 provides an overview of the encoder-decoder architecture and summarizes the key components and their interactions.

Table 2: Overview of the encoder-decoder architecture.

Block	Layers	Kernel	In Ch.	Out Ch.	Activation
Encoder					
Conv1	1	7×7	3	64	ReLU
Max Pool	1	3×3	64	64	N/A
Res1	6	3×3	64	64	ReLU
Res2	1	3×3	64	128	ReLU
Res2	7	3×3	128	128	ReLU
Res3	1	3×3	128	256	ReLU
Res3	11	3×3	256	256	ReLU
Res4	1	3×3	256	512	ReLU
Res4	5	3×3	512	512	ReLU
Avg Pool	1	7×7	512	512	N/A
FC	1	N/A	512	4	SoftMax
Decoder					
Block1	1	2×2	512	256	ReLU
Block2	1	2×2	256	128	ReLU
Block3	1	2×2	128	64	ReLU
Block4	1	2×2	64	64	ReLU
Block5	1	2×2	64	3	Sigmoid



Data Preprocessing

1. Patch Division (256×256 using Sliding Window)
2. Resize to Divisible Dimensions
3. Pixel Normalization [0,1]
4. One-hot Encoding for Masks
5. Mini-batch Preparation (16 Images/Batch)

Data Augmentation

1. Random Rotations (0°,90°,180°,270°)
2. Horizontal and Vertical Flips
3. Elastic Deformations
4. Brightness and Hue Adjustments

Model Compilation

1. Adam Optimizer (LR = 1e-4)
2. Dice Coefficient Loss
3. Evaluation Metric: IoU

Model Training

1. Epochs: 40
2. Early Stopping (Patience:10)
3. LR Scheduler: Reduce by 0.1 on Plateau
4. GPU: NVIDIA RTX 3050

Evaluation and Results

1. mIoU: 95.4%
2. Precision: 64.9%, Recall: 45.5%, F1 Score: 46.9%
3. Speed: 8.4 FPS

Post-Processing and Output

1. Predicted Classes Remapped
2. Color Mapping:
   Sky: Purple (164, 75, 90)
   Water: Blue (41, 167, 224)
   Obstacle: Yellow (247,195,37)
3. Noise Filtering: Morphological Operations
4. Boundary Refinement: Conditional Random Fields
5. Pixel Adjustments: Class Imbalances Addressed

Fig. 2: Model Pipeline and Architecture Overview.

5 Training and Validation

To develop a deep learning model for image segmentation, the training process was meticulously configured to maximize performance. The input images were resized to 256×256 pixels with three channels to accommodate RGB formats. A Unet-based architecture with a ResNet34 backbone was chosen due to its effectiveness in feature extraction, particularly for segmentation tasks. The backbone was initialized with pre-trained ImageNet weights, leveraging existing learned representations to enhance the model's ability to distinguish between different regions in an image. After configuring the initial training setup, attention was turned toward optimizing the performance of the model. The Adam optimizer was selected with a learning rate of 1e-4 to ensure stable convergence. To measure the segmentation accuracy, the Dice coefficient loss was employed, which quantifies the overlap between the predicted and actual segments, thereby reducing the impact of class imbalance. Additionally, the Intersection over Union (IoU) metric was used to evaluate the precision of the model predictions. Training was conducted for 40 epochs with a batch size of 16, balancing computational efficiency with effective learning. A learning rate scheduler was implemented to reduce the rate by a factor of 0.1 upon plateauing validation loss, preventing stagnation. Early stopping with a patience value of 10 was applied to halt training if no further improvements were observed, thereby conserving computational resources. The model was trained on an NVIDIA RTX 3050 GPU utilizing its parallel processing capabilities to accelerate the computations. Optimizations culminated in a model that demonstrated promising segmentation capabilities, as evidenced by the training dynamics shown in Figure 3, which illustrates the loss reduction, accuracy progression, and IoU score evolution across epochs.

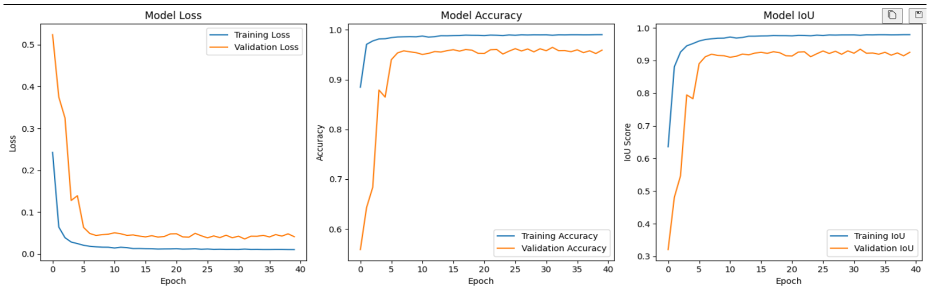


Fig. 3: Graphs representing performance metrics epochs Vs loss, accuracy,IoU score(left to right)

6 Results and Post-Processing

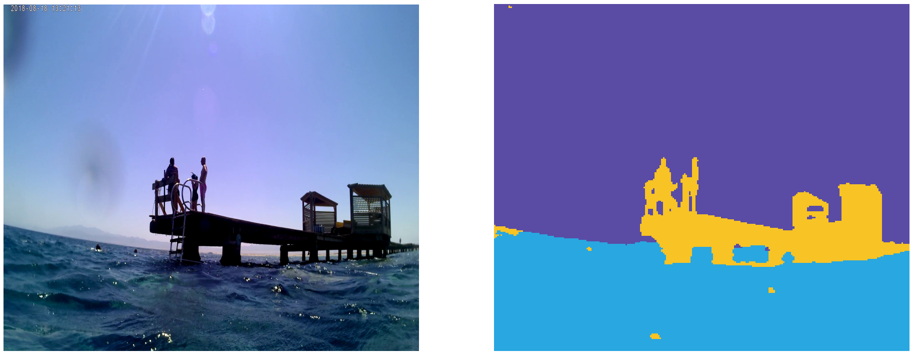
The proposed semantic segmentation model demonstrates remarkable accuracy, achieving an mIoU of 95.4%, as shown in Table 3, reflecting a robust overlap between the predicted and ground truth regions even under challenging conditions. For context, KNet [12] reports 54.3%, PV-S3 [15] 63.67%, and DeepLabv3+ [3] 63.67%. The model's precision of 64.9% and recall of 45.5% represent a carefully chosen balance aimed at minimizing over-segmentation while ensuring high-confidence predictions, as further indicated by an F1 Score of 46.9%. Beyond the following evaluations, several post-processing steps have been implemented to refine the segmentation quality: predicted classes are remapped to application-specific labels for consistency, and a tailored color mapping is applied, assigning sky to purple ([164, 75, 90]), water to blue ([41, 167, 224]), and obstacle to yellow ([247, 195, 37]). Noise filtering through morphological operations, boundary refinement via Conditional Random Fields, and pixel-level adjustments to address class imbalances collectively enhance the robustness and visual appeal of the final segmentation output. Figure 4 depicts the input image, and its corresponding output mask, highlighting the model's ability to accurately delineate distinct regions within complex scenes.

Table 3: Comparative Analysis with State-of-the-Art Methods

Architecture	**Backbone**	**Precision**	**Recall**	**F1 Score**	**mIoU**	**FPS**
UNet [3]	-	88.83%	91.44%	90.10%	84.07%	-
PSPNet [3]	-	63.90%	67.81%	65.74%	55.24%	-
DeepLabv3+ [15]	-	80.12%	86.29%	82.03%	70.74%	-
DeepLabv3+ [3]	-	79.67%	75.33%	76.67%	63.67%	-
BiSeNetv1 [16]	Res 18	-	-	-	74.4%	65.5
STDC1-Seg [17]	SRDC1	-	-	-	73.0%	197.6
STDC2-Seg [17]	STDC2	-	-	-	73.9%	152.2
PV-S3 [15]	-	79.67%	75.33%	76.67%	63.67%	-
KNet [12]	Swin-T	-	-	-	54.3%	6
Proposed Method	**ResNet34**	**64.9%**	**45.5%**	**46.9%**	**95.4%**	**8.4**

7 Conclusion

Segmentation of maritime images into sky, water, and obstacles is crucial for the safe navigation of Unmanned Surface Vehicles (USVs). Recognizing the critical need for precise obstacle detection, the following study focuses on a specialized



(a) Sample test image input to the proposed model.

(b) Semantically segmented image output from the proposed model.

Fig. 4: Comparison of input image and segmented output.

approach that leverages advanced machine-learning techniques. A U-Net architecture with a ResNet34 encoder pretrained on ImageNet was employed, achieving an impressive mean Intersection over Union (mIoU) of 95.4%. Advanced preprocessing techniques, such as histogram equalization and noise reduction, enhanced image clarity; dynamic data augmentation strategies, including random cropping, rotation, and scaling, allowed the model to adapt to various lighting and weather conditions; and meticulous post-processing procedures, such as threshold-based filtering, further refined the segmentation outputs. Experimental evaluations on real-world datasets revealed a significant reduction in false positives, which is a critical factor in enhancing navigation safety by ensuring that USVs make accurate decisions without unnecessary maneuvers, thereby directly reducing the collision risk. Future research should explore lightweight architectures to enable real-time processing on resource-constrained platforms, and consider integrating multimodal data such as LiDAR or sonar to further improve obstacle detection in complex maritime environments, ultimately laying a solid foundation for the development of more efficient and safe autonomous USV navigation systems.

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