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# Long-Range Ship Detection System: Enhancing Accuracy with Generative AI and Data Augmentation

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***Abstract*—Long-range ship detection is essential to maritime security; however, the performance of conventional object detection models degrades at extended distances due to the scarcity of high-quality training data for distant vessels, often resulting in missed detections and misclassifications. This study presents an AI-powered long-range ship detection system that integrates generative AI for dataset augmentation with object detection models. Specifically, three diffusion-based data generation strategies—prompt-to-image synthesis, image-to-image degradation LoRA, and style learning LoRA—are employed to construct a synthetic dataset that simulates diverse long-range maritime conditions. The synthesized and real images are then utilized to train the YOLO11n model, enhancing its robustness in detecting distant ships. Experimental evaluations on the Singapore Marine Dataset demonstrate a notable performance improvement, with Recall increasing from 0.83 to 0.88 and mAP50 from 0.88 to 0.91. These results highlight the effectiveness of generative AI in image dataset augmentation, contributing to a more reliable and adaptable long-range ship detection system for enhanced maritime surveillance and vessel identification.**

***Index Terms*—Ship detection, generative AI, and object detection**

## I. Introduction

Maritime security and vessel monitoring have become increasingly critical due to the rising threats of unauthorized ship movements and illicit activities. Long-range ship detection plays a pivotal role in enhancing maritime surveillance; however, it remains challenging due to the small apparent size of distant ships, low contrast, and the limited availability of high-quality long-range ship images. These factors contribute to increased false negatives, misclassifications, and reduced detection accuracy in conventional object detection models.

Previous studies have explored Generative Adversarial Networks (GANs) [1] for generating synthetic ship images to augment training datasets. However, GAN-based approaches exhibit inherent limitations, particularly in producing high-quality long-range ship images. These methods often generate artifacts, struggle to replicate real-world maritime conditions accurately, and require extensive labeled datasets, which are scarce in marine surveillance applications. Furthermore, controlling specific attributes such as low contrast and motion blur remains a challenge, limiting the effectiveness of GAN-generated images in improving detection performance.

In contrast, recent advances in generative AI, particularly diffusion-based models, offer a more stable and controllable approach to synthetic image generation, effectively addressing the limitations of GAN-based methods. By leveraging advanced fine-tuning techniques, diffusion-based models can produce synthetic images that closely mimic real-world long-range conditions, including degraded contrast and motion blur, enabling more effective dataset augmentation.

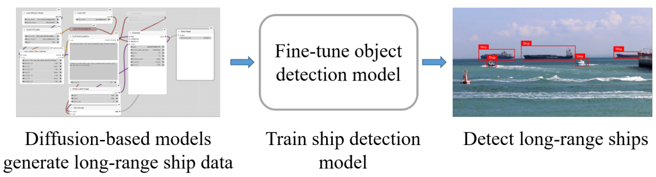


Fig. 1: The workflow of the long-range ship detection system.

This study proposes an AI-powered detection system integrating diffusion-based dataset augmentation with a YOLO-based object detection framework [2]. Through this approach, the proposed system enhances detection accuracy by leveraging synthetic data generation, improving the robustness of object detection models under long-range maritime conditions.

## II. Methods

The proposed long-range ship detection system integrates a diffusion-based model for dataset construction and an object detection module, as shown in Fig. 1.

### A. Image generation model

We construct three complementary data generation pipelines using diffusion-based models to emulate the visual characteristics of the Singapore Marine Dataset (SMD) [3].

*1) Prompt-to-Image Synthesis:* We employ Stable Diffusion 3.5 [4] and Flux.1 [5] models to generate synthetic images of small, clearly defined ships in sparse oceanic backgrounds. Prompt engineering was conducted to simulate long-range views with descriptors such as “ship, vast ocean, in the distance, clear sky, minimal waves, natural lighting”. All images are generated using each model’s default inference parameters, with the output resolution uniformly set to 1024×1024.

*2) Image-to-Image Degradation LoRA:* A Flux.1-based LoRA is fine-tuned using real low-visibility ship images from the SMD dataset. This LoRA is integrated into a ComfyUI [6] image-to-image workflow, transforming high-resolution, close-range ship images into blurry, low-contrast outputs. The gen-

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(a) (b) (c) (d)

Fig. 2: Comparison between AI-generated and real ship images under oceanic conditions. (a) prompt-to-image synthesis, (b) image-to-image degradation LoRA, (c) style learning LoRA, (d) real-world ship captured frame from SMD

TABLE I: Dataset composition used in different training groups. The test set remains fixed across all experiments.

| | train | validate | test |
|---|---|---|---|
| **Real Dataset** | 808 | 202 | 219 |
| **Synthetic Dataset** | 632 | 157 | 0 |

eration parameters include 25 steps, a denoise strength of 1, and an output resolution matched to the input.

*3) Style Learning LoRA:* We apply the same LoRA fine-tuning pipeline to simulate realistic long-range ship imagery. This LoRA is fine-tuned using the first frames from 40 videos in SMD. This enables the fine-tuned LoRA model to learn object scale and overall scene composition, generating synthetic images resembling real surveillance footage with visual styles.

All generated images are filtered based on visual realism and specific criteria. Fig. 2 compares results from three methods.

### *B. Ship Detection Model*

Using real and generated datasets, we train the YOLO11n model [2] for ship detection. Performance is evaluated using Precision, Recall, mAP50, and mAP50-95 metrics.

## III. Experiment

### *A. Dataset Preparation and Experimental Methodology*

Two datasets are constructed to evaluate the impact of synthetic image augmentation. The real dataset contains only real-world ship images, while the synthetic dataset consists of images generated using three different methods as described in Section II-A. Table I summarizes the composition of each dataset. A YOLO11n model [2] is trained separately on each dataset with both models initialized using pretrained weights.

### *B. Results and Analysis*

Fig. 3 presents a comparative model performance analysis across three distinct datasets. “Real dataset” is composed entirely of real images. “Synthetic dataset” is composed entirely of synthetic images, and “Synthetic + 5 dataset” is composed of all synthetic images in the Synthetic Dataset with five real images in the Real Dataset. The model trained on “Synthetic + 5 dataset” outperforms the others, achieving the highest scores in Precision (0.88), Recall (0.88), mAP50 (0.91), and mAP50–95 (0.52). These results demonstrate the effectiveness of synthetic data augmentation, especially when supplemented with minimal real-world data. The performance highlights its potential to enhance detection robustness under constrained training conditions.

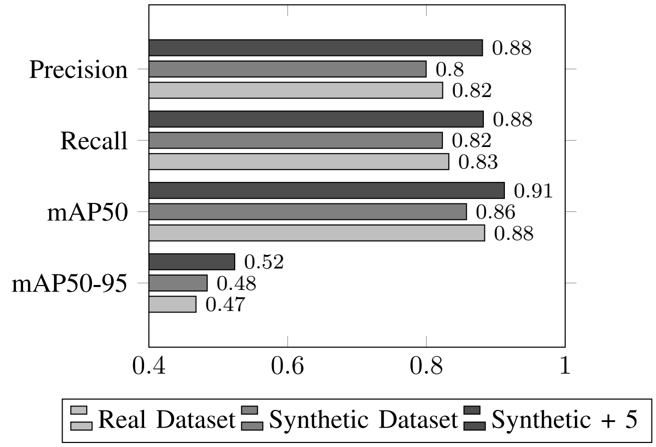


Fig. 3: Performance comparison across different training configurations: Real-only, Synthetic-only, and Synthetic + 5 real images.

## IV. Conclusion

This study presented an AI-powered long-range ship detection system combining the YOLO11n model with three diffusion-based image generation strategies: prompt-to-image synthesis, image-to-image degradation LoRA, and style learning LoRA. These methods generate synthetic training data that simulate diverse long-range maritime conditions regarding object scale, contrast, and scene composition. Experimental results showed that this approach enhances detection performance, increasing Recall from 0.83 to 0.88 and mAP50 from 0.88 to 0.91 on the Singapore Marine Dataset. These findings underscore the practical value of diffusion-based generative models for maritime object detection in data-scarce environments.

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