

Ship in Sight: Diffusion Models for Ship-Image Super Resolution

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Abstract—In recent years, remarkable advancements have been achieved in the field of image generation, primarily driven by the escalating demand for high-quality outcomes across various image generation subtasks, such as inpainting, denoising, and super resolution. A major effort is devoted to exploring the application of super-resolution techniques to enhance the quality of low-resolution images. In this context, our method explores in depth the problem of ship image super resolution, which is crucial for coastal and port surveillance. We investigate the opportunity given by the growing interest in text-to-image diffusion models, taking advantage of the prior knowledge that such foundation models have already learned. In particular, we present a diffusion-model-based architecture that leverages text conditioning during training while being class-aware, to best preserve the crucial details of the ships during the generation of the super-resolved image. Since the specificity of this task and the scarcity availability of off-the-shelf data, we also introduce a large labeled ship dataset scraped from online ship images, mostly from ShipSpotting¹ website. Our method achieves more robust results than other deep learning models previously employed for super resolution, as proven by the multiple experiments performed. Moreover, we investigate how this model can benefit downstream tasks, such as classification and object detection, thus emphasizing practical implementation in a real-world scenario. Experimental results show flexibility, reliability, and impressive performance of the proposed framework over state-of-the-art methods for different tasks. The code is available at: <https://github.com/LuigiSigillo/ShipinSight>

Index Terms—Generative Deep Learning, Image Super resolution, Diffusion Models, Ship Classification

I. INTRODUCTION

Our application domain deviates slightly from the conventional ones where super-resolution models are typically evaluated. Traditionally, super resolution primarily focuses on natural or face images [1], [2], which present intriguing challenges due to the brain familiarity with these subjects. However, super resolution is a task of pivotal importance in various other domains, including maritime surveillance. Indeed, this domain presents several challenges [3]–[6]. In this

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¹www.shipspotting.com

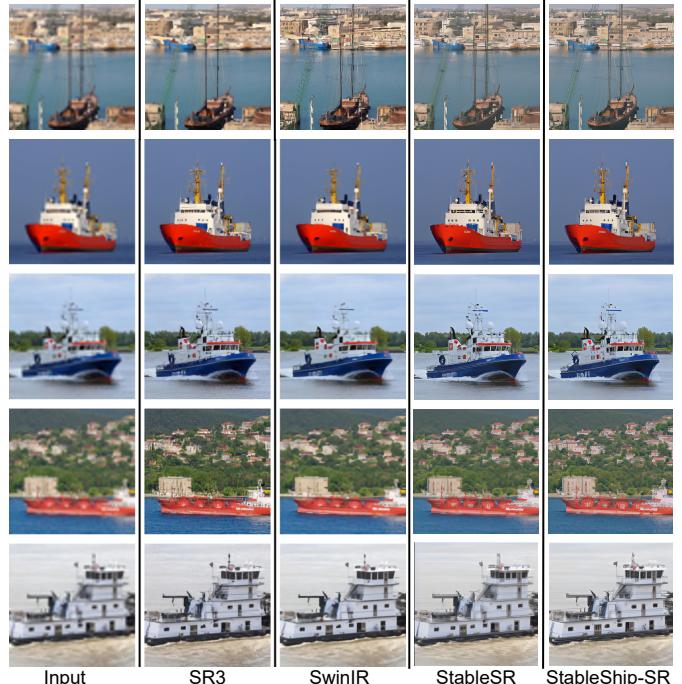


Fig. 1. Comparative sample images showcasing the super-resolution capabilities of different models. The visual assessments highlight variations in image quality, clarity, and detail enhancement achieved by each respective model in the upscale process. Ours is in the last column.

domain, considerable factors, such as long distances, limited sensor capabilities, adverse weather conditions, and the inherent mobility of ships prevent the acquisition of high-quality images. With the enhancement of low-resolution ship images, potential defects, anomalies, or critical details that might have been missed in the original pictures can be revealed. This capability enables the identification and addressing of issues more effectively, enhancing quality control measures, and overall operational efficiency. Those aspects are critically important for several applications, including ship detection [7], classification [8], and tracking [9]. One of the reasons why those images are important for those downstream tasks is that there exists a wide variety of ship categories, each possessing distinct characteristics. For example, consider a cargo ship capable of transporting different types of containers or being empty. Furthermore, ships may exhibit diverse

small and highly detailed elements that require enhancement, including portholes, railings, crests, text, and even armaments. The super-resolution process must yield high-quality results to mitigate the risks of mistaking for instance a container for a cannon, or vice versa. This process is not as easy as with natural and face images, where smooth edges are expected, indeed ships comprise steel or other components with sharp and well-defined features. Preserving these characteristics in the enhanced ship images is essential for minimizing the artifacts generated in the super-resolution process as much as possible. Taken together, all these factors underscore the considerable challenges inherent in this domain, showing that ship-image super resolution holds significant relevance for industrial application problems.

Indeed generative models in recent years, especially diffusion models [10], have emerged as promising solutions to address those problems by effectively enhancing low-resolution images while preserving their visual fidelity [11]. The use of generative models, which can hallucinate missing details from a low-quality source image, has proven to greatly benefit image-to-image translation problems [12]–[16]. The unsupervised nature of those kinds of models allows for the enhancement of low-resolution images without relying on large annotated datasets [1], [2], [17]. In literature, different papers showed how we can take advantage of the diffusion process to perform single-image super resolution [18], [19] even with different kinds of inputs such as hyperspectral images [20] showing a broad interest in different fields of application. Moreover, it is possible to guide the generation process using different kinds of conditioning including text, semantic maps, or like in our case a low-resolution version of an image. In literature, there are different approaches to condition diffusion models. One of the most popular is the classifier-free guidance [21] where the conditioning element is removed from the objective function with some probability only for certain iterations of the training. The counterpart of this method is the classifier guidance approach [22] where instead they use the gradients of an external classifier to condition the learning of the denoising process.

In this paper, we present our model StableShip-SR which uses as well a pre-trained classifier, but instead of relying on a fixed class prediction, it exploits this information as an embedding in a latent space together with the embeddings of the low-resolution image. The conditioning of the generation in this way is performed at different scales during the denoising process. Indeed the architecture for the conditioning is based on a class- and time- aware encoder which improves the performances of the pre-trained foundation models Stable Diffusion [23]. We exploit the prior knowledge present in the state-of-the-art text-to-image generative models, to improve and propose a novel ship-image super-resolution architecture. Our method shows generalizability across different datasets. For instance the results of a zero-shot super resolution on Seaships [7] show remarkable improvements in the downstream task of detection and classification using pre-trained state-of-the-art models [24]. StableShip-SR can benefit different

areas of interest such as maritime navigation, defense, and environmental monitoring, facilitating advancements in ship-based systems and enabling improved decision-making processes. Given the difficulty in accessing accurate datasets for solving this specific problem, we have subsequently developed a dedicated dataset for training of our model.

Accordingly, our main contributions are as follows:

- 1) We introduce a large labeled dataset of ship images comprehending more than 20 classes.
- 2) We improve the state-of-the-art ship image super resolution by exploiting a latent diffusion model and introducing a novel class- and time- aware encoder.
- 3) We conducted exhaustive experiments on the dataset we introduced comparing our model with some of the main deep learning models for image super resolution.
- 4) We conducted ablation studies on different downstream tasks on diverse datasets comparing the improvement in performances using our StableShip-SR and other models for image super resolution.

The paper is structured as below: in Section II we introduce the theoretical elements upon which this work is based, the task we want to solve, and its application domain, discussing its uses and potential issues. In Section III we introduce the proposed method StableShip-SR, while in Section IV we address the problem of the dataset. We present the obtained results in Section V and finally in Section VI we expose the results and draw conclusions for this work while also proposing some possible future research directions.

II. BACKGROUND

Super resolution is a fundamental subtask of image generation that focuses on increasing the resolution of degraded images. The goal is to enhance the visual quality and level of detail in images that are originally captured or stored at lower resolutions. In our case, given a 64×64 image, the objective is to generate a higher-resolution output image, such as a 512×512 image, performing an 8x up-scaling, thus laying in the case of Single-Image Super Resolution (SISR). Our objective is to reconstruct a high-resolution image \mathbf{x} based on a given low-resolution image $\tilde{\mathbf{x}}$. We assume that the relationship between $\tilde{\mathbf{x}}$ and \mathbf{x} can be represented as $\tilde{\mathbf{x}} = (\mathbf{x} \otimes k) + n$, where k denotes the degradation matrix, \otimes represents the Kronecker product that combines the high-resolution image and the degradation matrix, and n represents the noise term. This is the formulation that describes the super-resolution task and serves as the foundation for exploring various algorithms and techniques. It is important to note that this problem becomes more challenging due to the existence of multiple potential solutions x_1, \dots, x_m that, when combined with the degradation matrix, can yield the same low-resolution image. More formally, we have a situation where:

$$\tilde{\mathbf{x}} = (\mathbf{x}_1 \otimes k) + n = \dots = (\mathbf{x}_m \otimes k) + n \quad (1)$$

The presence of such ambiguity poses a significant challenge in real-world scenarios, as it lacks a definitive and singular solution.

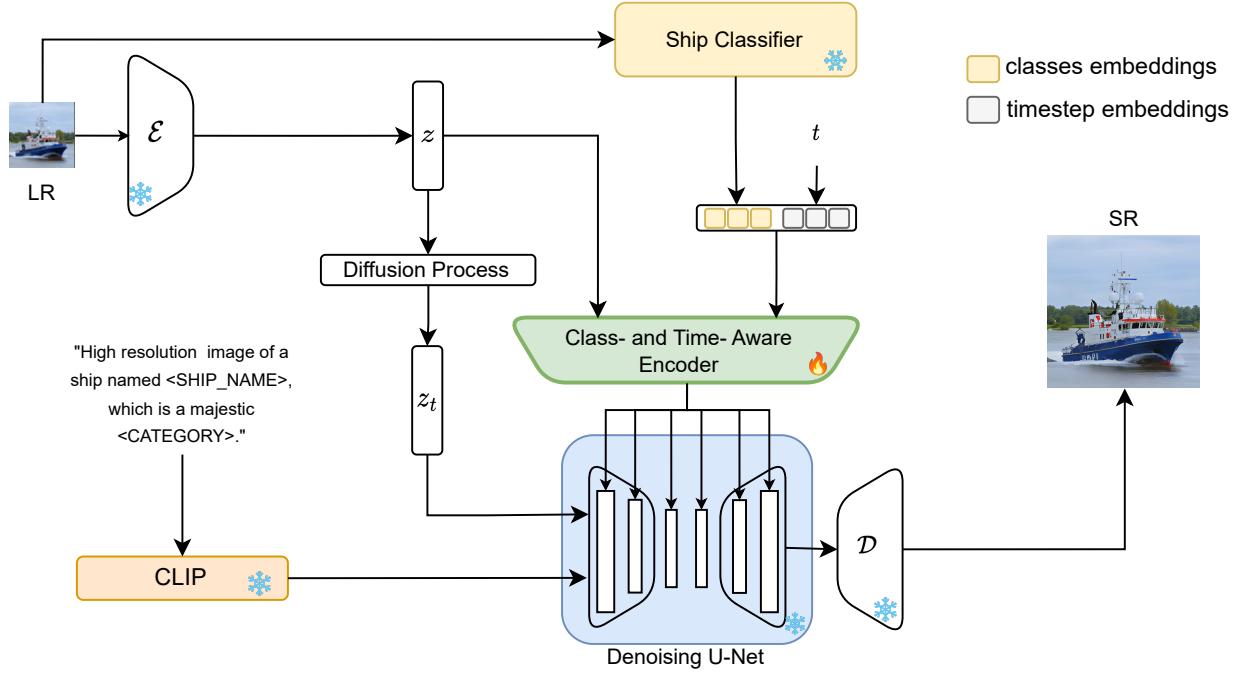


Fig. 2. Overview of Stable Ship-Image Super-Resolution framework. We pre-trained the classifier and trained only the class- and time-aware encoder. The other parts of the framework are frozen, which speeds up the overall training process.

Deep learning-based approaches for super resolution have exhibited remarkable advancements over traditional methods, resulting in superior and visually appealing results. Convolutional Neural Networks (CNNs) form the foundation of deep learning techniques employed in super resolution. These networks are capable of learning and extracting pertinent features from low-resolution images, subsequently utilizing these features to generate high-resolution counterparts [25]. Various CNN architectures have been developed for super resolution [1], [26], [27], which have made significant contributions to the field. Vision Transformer (ViT) introduced in [28] facilitated the successful application of transformers in computer vision. However, the ViT faces challenges when applied to high-resolution images due to fixed-sized patches. To overcome these limitations, the Swin Transformer architecture was introduced in [29]. This model adopts a hierarchical architecture that aggregates information across multiple scales, addressing the fixed patch size constraint of the ViT. It introduces shifting windows, allowing the model to capture intricate details within the image. SwinIR [30], built upon the previous Swin architecture, is designed for general image restoration excelling in super resolution as well as in other restoration tasks. SwinIR effectively processes images of large sizes, a characteristic of CNNs, while utilizing a local attention mechanism to handle specific regions of interest within large images. The shifted window design enables SwinIR to effectively model long-range dependencies, capturing global patterns and dependencies in the image, thus leading to enhanced results. A limitation of SwinIR is its potential lack of comprehensive understanding of the global

context and semantics of the entire image. While the shifted window technique partially addresses this concern, it still poses constraints on the ability of the model to effectively handle intricate image super-resolution tasks.

However, super-resolution approaches based on deep generative models such as GANs [2] and normalizing flows [31] lead to a shift in the super-resolution scenario. Moreover, in recent years, the class of generative models that has garnered considerable attention for a wider range of image generation tasks is the diffusion-based one, which has demonstrated superiority over state-of-the-art methods built using alternative approaches [22]. The idea of diffusion models was introduced in [32], but what marked a significant turning point was the work conducted in [10], paving the way to a plethora of models involving the creation of new and realistic images that closely resemble samples from a specific domain or adhere to certain constraints [10], [33], [34].

Those models pervade many different fields even the more delicate like medical imaging [35], [36], generating synthetic data for simulations, and enhancing the quality of imaging techniques. It is possible to condition the image generation using external information, providing valuable guidance throughout the generation process, by incorporating additional data or constraints and generating images that align with specific criteria or desired characteristics. For image super resolution, a low-resolution image serves as a guide for a conditioned diffusion process, capable of generating a high-resolution rendition of the original image. Among the conditional diffusion models adopted for image super resolution, the SR3 [37] model has exhibited remarkable performance. It is based on a

conditional diffusion process and utilizes a slightly modified U-Net model as the backbone. Indeed, the authors replace the standard DDPM [10] Residual Blocks with G-Blocks sourced from [38]. G-Block is a specific building block within the generator network of BigGAN [38] that performs upsampling and convolutional operations to enhance the resolution of feature maps. Then, the U-Net takes low-resolution feature maps as input and produces higher-resolution feature maps, enabling the generation of high-resolution images. However, this approach is both time and computationally expensive, because the diffusion process is done in the pixel space and not in the latent. Nonetheless, our proposed method does not need complete training, instead, it does fine-tuning of a pre-trained text-to-image diffusion model [23]. Another strategy [39] is to exploit the prior knowledge of latent representations given by pre-trained GANs to enhance the quality of super-resolution models. The problem with this approach is the lack of generalizability caused by the limited dataset categories the models were trained on. For this reason, inspired by [40] we exploit the prior present in large pre-trained diffusion models, that instead are trained with massive image datasets.

III. STABLESHIP-SR: THE PROPOSED STABLE SHIP-IMAGE SUPER-RESOLUTION METHOD

Motivated by the research presented in [40], our proposed model capitalizes on the foundational knowledge derived from a pre-trained Stable Diffusion model [23], based on a U-Net as a denoiser to perform the latent diffusion process.

A conditional generation process can be directly derived from an unconditional generation one by using direct conditioning in the diffusion process, as done in [37]: the latent representation of the degraded input image obtained from an encoder is then used as guidance for the generation process

Moreover, we exploit the text conditioning given by the design of Stable Diffusion, using CLIP [41] to encode the text and provide embeddings to our model. We use this representation as an additional conditioning of the denoising process, but only in the training phase. This is necessary to allow the network to be more responsive to the textual information represented by the class and name of the ship, since they are known a priori, being present as metadata in our dataset. This conditioning is not provided in the inference phase, as we want this information to be derived online through the classifier applied to low-resolution images, as analyzed below. We chose in advance a set of five different parametric prompts to improve the generation process of ship images through the textual information. We randomly pick one of the prompts during the training process and populate it with consistent information about the ship to be processed, i.e. the ship name and the category.

The core of our proposed architecture is the class- and time-aware encoder. Indeed, it provides the diffusion model with additional information on the class of the ship represented in the image to be reconstructed. This information is extracted by a classifier directly from the low-resolution image to be super resoled.

As a classifier, we utilize a ResNet-50 [42] model and finetune it on our proposed dataset ShipSpotting. This pre-training is done before the training of StableShip-SR, consequently, this part of the architecture is frozen during the whole training. The classifier training is performed using as input high-resolution images to improve the accuracy of the prediction since it will affect the generation of the images during the denoising process.

We employ the class- and time- aware encoder output to modulate the intermediate feature maps within the residual blocks of the U-Net through spatial feature transformations (SFT) [43]. This slight modification is essential to obtain higher-quality images than other state-of-the-art super-resolution models, as proven in experimental results. Following the proposed method in [40], we also integrate the temporal information in the encoder, enhancing the overall qualitative result of the generated images. Indeed, at early timesteps of the process, when the generated image is still poor in terms of information and consequently the resulting signal-to-noise ratio is low, having stronger conditioning allows the diffusion process to have more helpful guidance. This gives a better understanding of what information needs to be reconstructed, as also in-depth explored in [44]. By contrast, at higher timesteps when the diffusion process has already reconstructed much of the image information, i.e., when you have higher signal-to-noise ratio values, the conditioning given by the low-resolution image may be softer, leaving the diffusion process with the finest guidance. Such time awareness is permitted by the fact that the noise schedule is a hyperparameter set beforehand so that the signal-to-noise ratio values at each timestep of the training phase are known. Besides the aforesaid temporal conditioning allows balancing the use of the low-resolution image in the diffusion process.

We concatenate the two tensors of class and timestep embeddings as shown in Fig. 2 resulting in one vector $b \in \mathbb{R}^{1024}$ and then we encode it with the latents of the image $z \in \mathbb{R}^{h \times w \times c}$ obtained by the encoder $z = \mathcal{E}(x)$, where $x \in \mathbb{R}^{3 \times H \times W}$ is the low-resolution image. The encoder \mathcal{E} and the decoder \mathcal{D} are frozen and are part of the VAE used in [23], as well as the neural backbone used to perform the latent diffusion process, i.e. a time-conditional U-Net. The class- and time- aware encoder δ_θ follows the same architecture as the U-Net encoder thus providing conditioning embeddings to the conditional denoising autoencoder ϵ_θ at different scales. The domain-specific encoder $\tau(y)$, in our case, is a frozen CLIP, where y is the text conditioning. The complete objective function we aim to learn is represented in (2).

$$L = \mathbb{E}_{\mathcal{E}(x), y, \epsilon \sim \mathcal{N}(0, 1), t, c} [\|\epsilon - \epsilon_\theta(z_t, \delta_\theta(c, t, z), \tau(y))\|_2^2]. \quad (2)$$

We optimize $\delta_\theta(c, t, z)$ where (c, t) are the classes and the timesteps embeddings respectively, z is the output of the VAE encoder while z_t is its noisy version.

IV. SHIPSPOTTING DATASET

Given the specific task of super resolution for ship images, we create a dataset from scratch, in this way, we can ensure

that our super-resolution model is trained on ship images that are relevant and representative. It contains ship images that exhibit diversity in terms of ship types, sizes, orientations, and environmental conditions. This diversity is crucial for training an effective super-resolution model capable of handling various real-world scenarios. We devote significant attention to constructing a dataset that prioritized generality, ensuring its applicability beyond our specific use case. Our objective is to develop a dataset that does not impose unnecessary restrictions and can be effectively utilized for multiple purposes. The endeavor extended beyond gathering the necessary images for our super-resolution task since we carefully collected additional metadata, making this dataset suitable for other potential problems of interest, such as ship classification.

To construct such a dataset, a straightforward approach was scraping images from the web. The main source for our dataset is ShipSpotting², which serves as a repository for user-uploaded images, hosting a vast collection of ship images, amounting to approximately 3 million. Furthermore, for each image, valuable supplementary information is available, such as the type of the ship, and present and past names.

Next, we made sure that as many images as possible were collected in our dataset, since in deep learning, the quantity of training data directly influences the quality of results. A larger volume of data enables models to generalize more effectively. Thus we scrape all the images and as a result, the dataset comprises a total of 1.517.702 samples. Motivated by [45] we exclude many classes of ships from our final analysis and concentrate on the more common and valuable for a real scenario use case. The total number of different classes is 20 and the ship categories included are Bulkers, Containerships, Cruise ships, Dredgers, Fire Fighting Vessels, Floating Sheerlegs, General Cargo, Inland, Livestock Carriers, Passenger Vessels, Patrol Forces, Reefers, Ro-ro, Supply ships, Tankers, Training ships, Tugs, Vehicle Carriers, Wood Chip Carriers. The total amount of samples after this class selection is 507.918. To obtain the high-resolution version, we mainly employ a center crop technique, ensuring that the essential details of the image are preserved. Conversely, for the low-resolution counterpart, the high-resolution images were degraded with different techniques following the preprocessing steps given in [46], effectively reducing its resolution. Furthermore, to create a reference image for comparison with the output of the model, we apply a standard upscaling super-resolution technique to the low-resolution image. The obtained refined dataset is optimized and prepared for training the super-resolution models.

V. EXPERIMENTAL RESULTS

We conduct a challenging super-resolution task of 8x scaling, going from 64×64 pixel low-resolution images to 512×512 pixel high-resolution images. We chose this scaling factor to evaluate the ability of the model to handle finer details

and accurately recreate them in the output with a very small image as input.

Models were trained on a machine equipped with an NVIDIA Quadro RTX 8000. After completing the model training, we performed inference on a test set consisting of 1000 images. We analyze the objective metrics PSNR, SSIM, and FID. A low FID value indicates that the embedding

TABLE I
FID RESULTS OBTAINED ON THE TEST SET.

Model	FID ↓
Low Resolution (LR)	66.05
SwinIR [30]	50.79
SR3 [37]	16.59
StableSR [40]	12.41
StableShip-SR (Ours)	11.72

representations of both images are similar, capturing not only general features but also finer details. The images produced by our model are overall more realistic compared to their counterparts, which explains the proximity of their embedding representations, as we can observe from Fig. 3 and results reported in table I. By examining the images, we observe specific characteristics that provide insights into the results. The images generated by Swin-IR and SR3 have a cartoonish appearance, consisting of large areas of color with minimal detail. Each block of color has a well-defined shape, resulting in an artificial aesthetic for the overall image. SwinIR also struggles to accurately reproduce background elements such as water and trees, leading to a slight blurring effect that reduces overall quality.

In contrast, our approach can achieve a better reconstruction of background elements and details, such as portholes and antennas as shown in the third row of Fig. 3. Moreover, StableShip-SR produces images without the blurred effect present in other approaches. This is likely due to a more realistic approach to color reconstruction, capturing changes in lighting conditions and reflections on water surfaces. It is important to note that the reconstruction of StableSR is not perfect, and careful examination of smaller details reveals artifacts, as we can observe from the first row of 3.

Another drawback of SR3 is its long inference time, taking ≈ 2 minutes to generate each sample compared to the other models few seconds, this is due to the diffusion process being done on the pixel space and not in the latent one.

With this analysis we prove StableShip-SR to be a superior model for this specific task, providing higher-quality high-resolution images and more realistic representations compared to the others.

A. Ablation Study on Downstream Tasks

To show the effectiveness and the need for super-resolution images to drastically improve downstream tasks, we conduct experiments in object detection and classification tasks with different images.

We employ pre-trained neural models in order to have only to fine-tune them on ship datasets.

²www.shipspotting.com



Fig. 3. Comparison between LR image and SR images reconstructed by other state-of-the-art methods and our proposed model. The red bounding box contains a zoomed-in part of the image in order to have a better understanding of the image resolution quality of our method compared to the others.

Since SeaShip, the ship dataset introduced by [7], also provides bounding boxes, we can test our super-resolution approach in the object detection task, we choose the YOLOv7 [24] architecture as the object detector, moreover with this model, it is also possible to perform classification tasks.

Since we are also interested in evaluating the model on our dataset based on ShipSpotting, we fine-tuned the well-known ResNet architecture [42] on ship images as the classifier.

The results for the detection and classification task performed on the SeaShips dataset are reported in Fig. 5. SwinIR [30] achieves higher PSNR and SSIM values, indicating a higher fidelity between the original and reconstructed images. However, we performed many experiments that point out that those results are useless when it comes to using those images for any other subtasks. Moreover, when considering the FID metric (lower is better), diffusion models outperform SwinIR,

and this is outlined also by a subjective evaluation of the results reported in Fig. 3. These results may seem counter-intuitive since we expect that if the original and generated images were similar with low perceptual differences, their embedding representations computed by FID would also be close. However, this is not the case. This behavior aligns with the findings described in [37], where PSNR and SSIM may not accurately represent the quality of a generated image, because they focus on the exact comparison between pixels while generative models may change pixel content without changing their meaning. Indeed the graph in Fig. 4 shows how a higher PSNR does not bring benefit when it comes to a classification task. Furthermore, using an upsampled low-resolution image as an input for a ship classifier, we will obtain a worse result in terms of accuracy compared to the one obtained with the image with a lower PSNR used in our method.

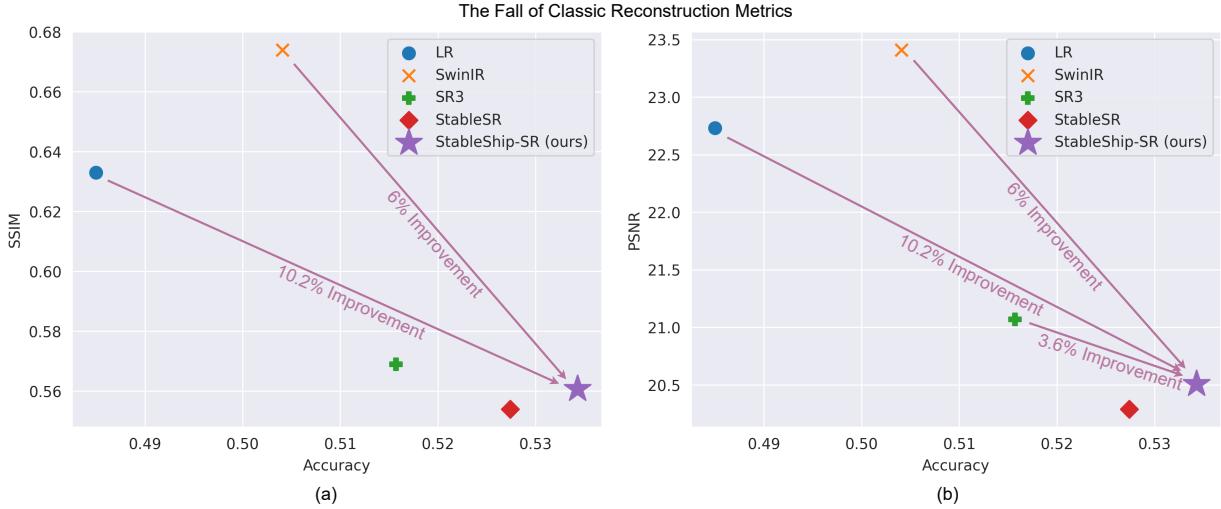


Fig. 4. Comparison of SSIM (a) and PSNR (b), which measure the quality of the reconstructed images. We confront those results against the classification accuracy reached with the generated images on the ShipsSpotting dataset. This comparison shows how the classical reconstruction metrics are not a measure of how well a model performs in a super-resolution scenario since the accuracy and the FID reached are lower concerning other models that have lower SSIM and PSNR.

TABLE II
OVERALL PRECISION AND RECALL ON SEASHPIS DATASET. THE DETECTION IS DONE BY A FINETUNED YOLOV7 [24] ON SEASHPIS.

Model	Precision \uparrow	Recall \uparrow
Low Resolution (LR)	0.536	0.313
SwinIR [30]	0.536	0.313
SR3 [37]	0.569	0.316
StableSR [40]	0.615	0.415
StableShip-SR (Ours)	0.647	0.439

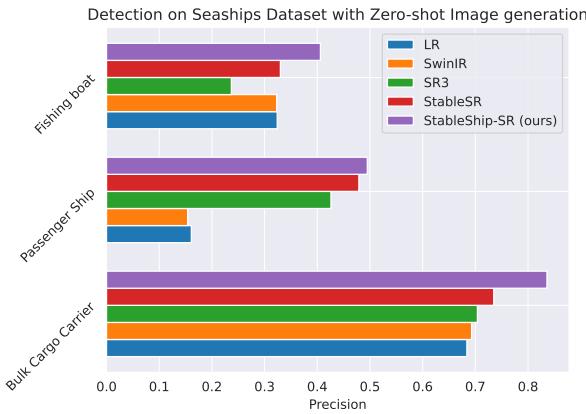


Fig. 5. Comparison for precision scores on the Seaships dataset. We employ the models pre-trained on our dataset, thus performing zero-shot super resolution, improving the detection of a finetuned YOLOv7 [24] on Seaships.

VI. CONCLUSION

In this paper, we presented StableShip-SR, a state-of-the-art model specifically tailored for ship super resolution. Through comprehensive comparisons across different models, our findings underscore and determine that our method is the most suitable approach for ship super-resolution tasks. Notably, our model consistently produces images characterized

by heightened realism, aligning closely with human perceptual capabilities.

This manuscript delves into the complexities of the super-resolution paradigm from a theoretical standpoint, leveraging a robust architectural foundation. Our experimental evaluations across diverse tasks prove the superiority of StableShip-SR in comparison to its counterparts. Based on our comprehensive testing, we reached some key findings employing both standard and non-standard metrics, evaluating also on downstream tasks to ensure a comprehensive assessment.

A pivotal contribution of our work is the introduction of a meticulously curated ship dataset, containing over 500.000 samples distributed across 20 distinct classes. Being a challenging field of application, we expect that this work will be helpful for the research community as well as for the industry.

Overall, this work mainly contributes to the advancement of research in the field of image super resolution, focusing on the specific application case of ship images, introducing a new model and a new dataset as well as carrying out a performance and trade-off analysis of different approaches.

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