Exploring Novel Self-Supervised Learning Techniques for Image Reconstruction Tasks

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Abstract: *Image reconstruction tasks, such as super-resolution, inpainting, and denoising, play a crucial role in various computer vision applications. Traditional methods often rely heavily on large labeled datasets for training, which can be costly and time-consuming to acquire. Self-supervised learning has emerged as a promising alternative, aiming to reduce this dependency by leveraging the inherent structures within the data itself. In this paper, we explore novel self-supervised learning techniques tailored specifically for image reconstruction tasks. We propose approaches that exploit the inherent relationships between low and high-resolution images, utilize context-aware information for inpainting, and incorporate generative adversarial networks for denoising. Through extensive experimentation, we demonstrate the efficacy of our methods in achieving competitive performance compared to supervised approaches while significantly reducing the need for labeled data. Our findings pave the way for more efficient and scalable solutions in image reconstruction, offering practical benefits across a wide range of applications.*

Keywords: Self-supervised learning, image reconstruction, super-resolution, inpainting, denoising, computer vision, deep learning

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