Image Super-Resolution using Convolutional Neural Networks

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Abstract: *Image super-resolution is the process of enhancing the resolution of an image, typically from a lower resolution input to a higher resolution output. This research aims to explore the application of convolutional neural networks (CNNs) for image super-resolution. Specifically, the study will focus on developing a deep learning model capable of generating high-resolution images from low-resolution inputs. Various CNN architectures, such as SRCNN (Super-Resolution Convolutional Neural Network) or SRGAN (Super-Resolution Generative Adversarial Network), will be investigated and compared for their effectiveness in producing visually pleasing and perceptually accurate high-resolution images. Additionally, techniques such as residual learning, attention mechanisms, and adversarial training may be incorporated to further improve the quality of super-resolved images. The performance of the proposed models will be evaluated using standard image quality metrics and subjective assessments. This research has practical applications in enhancing the visual quality of low-resolution images in fields such as medical imaging, surveillance, and entertainment.*

Keywords: Image super-resolution, Single-image super-resolution, Perceptual loss, Mode collapse

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