# EdgeConnect+: Adversarial Inpainting with Edge and Color Guidance

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## 1. Introduction

Image inpainting is a fundamental problem in computer vision, with applications in photo restoration, object removal, and image editing. The goal of inpainting is to fill missing regions in an image with visually plausible content that is structurally and semantically consistent.

Traditional approaches to image inpainting include diffusion-based methods [1, 2], patch-based synthesis [3], and segmentation-based techniques [4]. While these methods can work well in specific scenarios, they often struggle with complex textures and large missing regions. Deep learning-based techniques [5] have shown significant improvements, with generative adversarial networks (GANs) [7] further enhancing the realism of inpainted images.

One of the most effective deep learning-based inpainting methods is EdgeConnect [8], which utilizes an edge generator to predict missing structures before performing image completion. However, EdgeConnect primarily focuses on structural accuracy and does not explicitly incorporate color information, often leading to unnatural texture transitions. To address this, we propose an enhancement to EdgeConnect by integrating color guidance in addition to edge information.

Our model consists of a three-step process: (1) an edge generator predicts missing edges based on available structures, (2) a Gaussian-blurred color map provides contextual color information, and (3) the generated edges and color hints are merged to reconstruct the missing regions. We evaluate our approach on the CelebA and Places2 datasets, which contain diverse facial and scene images.

## 2. Problem Description

Image inpainting models should generate visually coherent and semantically meaningful completions for missing regions. A key challenge in this task is to ensure structural coherence, where the generated content aligns with the global structure of the image. Additionally, color consistency is critical to avoid noticeable seams or artifacts that arise due to poor blending of inpainted areas with their surroundings. Existing approaches often struggle with generalization, performing well on specific datasets but failing when applied to diverse scenes or facial images. Our goal is to develop an inpainting model that effectively integrates both structural and color information, enabling it to restore missing regions while maintaining realism across different types of image.

### 2.1. Proposed Approach

Our method consists of three main stages:

1. Edge generation: A generative adversarial network (G1) predicts missing edges based on the visible structure of the image.
2. Color map generation: A Gaussian blur is applied to the original image to propagate color information into missing areas, forming a low-frequency color map.
3. Final inpainted image generation: A second generative adversarial network (G2) reconstructs the final inpainted image using the edge and color information from the above steps.

## 3. Datasets

We use two data sets to evaluate the proposed approach:

### 3.1. CelebA

The CelebA dataset [9] consists of 202,599 facial images with various attributes such as pose, expression, and illumination. This data set is ideal for face-in-painting tasks, where missing facial features need to be reconstructed accurately.

### 3.2. Places2

The Places2 dataset [10] contains 1.8 million scene images in 365 categories. It provides a diverse set of backgrounds, buildings, landscapes, and interiors, making it suitable for general image-inpainting tasks.

Both data sets include a train/test split, and we use randomly generated masks of varying sizes and shapes to simulate missing regions.

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