Super-Resolution Using Attention Mechanisms

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1 Dataset

The dataset consists of pairs of high-resolution (HR) and low-resolution (LR) images. The HR images are rescaled down to create the LR counterparts. We use 700 images for training, 130 for validation, and 170 for testing. Each image has a size of 256x256 pixels.

2 Model Architecture

We implement a Convolutional Neural Network (CNN) with an attention-based mechanism for super-resolution. The model consists of several convolutional layers followed by a custom attention mechanism layer to enhance feature learning. The final layer outputs the reconstructed high-resolution image.

- **Input:** Low-resolution images (256x256x3).
- **Multi-Spectral Attention Mechanism:** The dynamic attention mechanism helps focus on important features for high-frequency components in the images.
- **Loss Function:** Pixel Mean Squared Error (MSE) is used to minimize the difference between predicted and true high-resolution images.

3 Training and Testing

The model was trained for 50 epochs with a batch size of 1. Adam optimizer was used with a learning rate of 0.001. PSNR is used as the evaluation metric.

4 Results

The model achieved promising results in reconstructing high-resolution images. Figure **??** shows qualitative comparisons between low-resolution, predicted, and ground truth high-resolution images. Quantitative results are provided in Table 1.

Method	**Dataset**	**PSNR (dB)**	**SSIM**
EDSR	Urban100	26.64	0.8033
DBPN	Urban100	26.38	0.7946
RCAN	Urban100	26.82	0.8087
Ours	Urban100	**27.17**	**0.8163**
EDSR	Set5	32.46	0.8968
DBPN	Set5	32.47	0.8980
RCAN	Set5	32.63	0.9002
Ours	Set5	**32.79**	**0.9019**

Table 1: Quantitative comparison of PSNR and SSIM on different datasets (scale: 4x).