

Image Super-Resolution using Enhanced Sub-Pixel Convolutional Networks (ESPCN)



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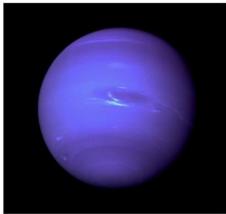
Faith in God | Moral Uprightness Love of Fellow Beings Social Responsibility | Pursuit of Excellence

Abstract

- **Problem Statement:** Super-resolution is crucial in enhancing image quality for applications like medical imaging, satellite photos, and security.
- Existing Methods:
 - Traditional Interpolation: Bicubic,
 Bilinear Fast but poor quality.
 - State-of-the-Art (e.g., Real-ESRGAN): High quality but computationally expensive.
- Our Approach:
 - We implement Efficient ESPCN, which balances performance and speed.
 - We compare results across different scaling factors (2x, 3x, 4x).
 - Also compare with and without augmentation for scale=2.

Picture of a planet 4 billion kilometres away







1. Introduction



• Existing Methods:

- Bicubic/Bilinear → Simple but low-quality
- Real-ESRGAN / EDSR → High quality, high cost

• ESPCN Motivation:

- Lightweight, real-time
- PixelShuffle-based upsampling
- Great for mobile, video,embedded or web use-cases.

2. Dataset – DIV2K (from Kaggle)

- **DIV2K Dataset**: Large, diverse collection of 2K resolution RGB images
- Train set: 800 HR images \rightarrow LR pairs for $\times 2, \times 3, \times 4$
- Validation set: 100 HR images, for feedback evaluation
- **Test set**: 100 diverse images (HR released post-challenge)
- Use case in this project:
 - Only the training HR images used to synthesize LR-HR pairs
 - Enables training of SR models on a wide variety of natural scenes

3. Proposed Methodology

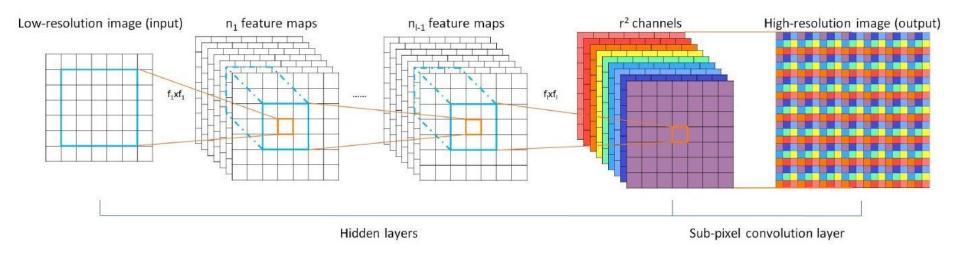
Preprocessing & Augmentation

- **Bicubic downsampling** to create LR images from HR
- Augmentation:
 - HorizontalFlip (p=0.5)
 - \rightarrow Flips the image horizontally with 50% probability.
 - RandomBrightnessContrast (p=0.3)
 - → Randomly adjusts image brightness and contrast (30% chance).
 - GaussNoise (var_limit=(5.0, 20.0), p=0.3)
 - \rightarrow Adds Gaussian noise with variance between 5–20 (30% chance).
 - ImageCompression (quality_lower=85, quality_upper=100, p=0.4)
 - → Simulates JPEG compression artifacts with 85–100% quality (40% chance).
 - RandomGamma (p=0.3)
 - → Applies gamma correction to change brightness non-linearly (30% chance).
 - HueSaturationValue (p=0.3)
 - → Randomly modifies hue, saturation, and value (HSV) channels (30% chance).

3. Proposed Methodology

ESPCN Model Architecture

- Input \rightarrow Conv (ReLU) \rightarrow Conv (ReLU) \rightarrow Conv \rightarrow Pixel Shuffle
- Uses **depth-to-space** rearrangement (efficient upscaling)
- Trained separately for scale=2, 3, 4
- Optimized using Adam, Loss: MSE



4. Evaluation Metrics

PSNR (Peak Signal-to-Noise Ratio)

PSNR measures the **pixel-level fidelity** between the original (ground truth) and a distorted (processed) image. It's based on the **Mean Squared Error (MSE)** between the two images.

A higher PSNR generally indicates that the reconstructed image is closer to the original.

Characteristics:

- Range: Typically between 20 and 50 dB for lossy image compression.
- **Higher is better**: $PSNR \ge 30$ dB is considered good.
- Limitations:
 - Doesn't consider human visual perception.
 - Sensitive to small pixel-level changes.
 - o Two images may have high PSNR but look perceptually very different.

4. Evaluation Metrics

SSIM (Structural Similarity Index Measure)

SSIM evaluates the **perceptual similarity** between two images by considering:

- Luminance (brightness)
- Contrast
- Structure

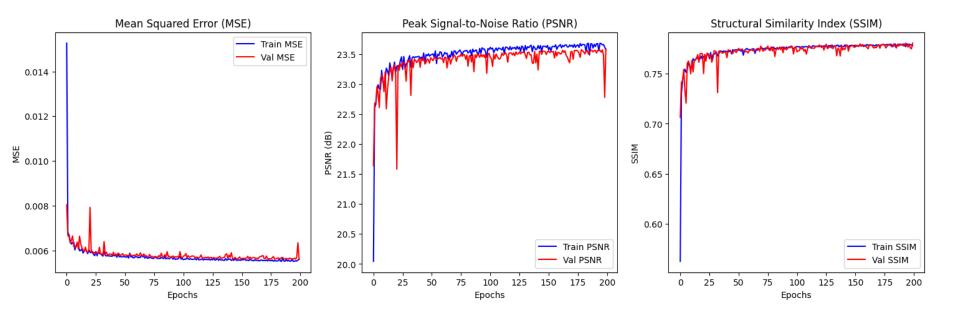
Unlike PSNR, it aligns more closely with how humans perceive image quality.

Characteristics:

- Range: [-1, 1] (Usually reported between 0 and 1)
- **Higher is better**: SSIM = 1 means perfect structural similarity.
- More perceptually aligned than PSNR.

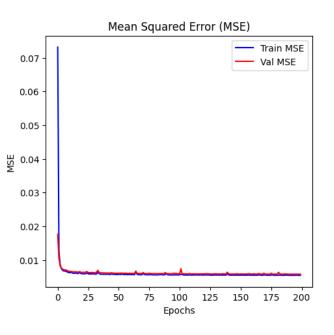
5. Results and Comparison

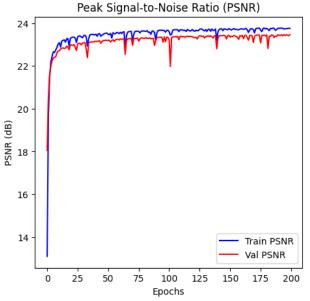
Without Augmentation:

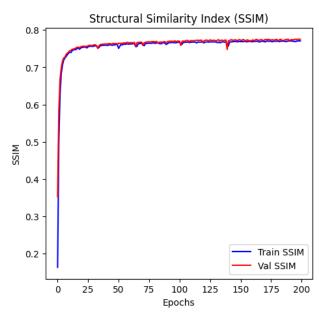


5. Results and Comparison

With Augmentation:







5. Verdict

Metric	Before Augmentation	After Augmentation	Verdict
MSE	Low, stable	Low, slightly smoother	Equal / Slightly better
PSNR	Slightly noisy, larger gap	Smoother, reduced gap	Improved generalization
SSIM	More variance, lower early on	Smoother, higher convergence	Improved structural quality



THANK YOU

Project Presentation

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