# Deep Image Prior for Image Inpainting: A Learning-Free Approach

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**Abstract**

Image inpainting, the process of reconstructing missing or corrupted regions in images, plays a critical role in applications such as photo restoration, object removal, and digital heritage preservation. This study implements the Deep Image Prior (DIP) framework, as introduced by Ulyanov et al. (Ulyanov et al., 2018a), utilizing a randomly-initialized convolutional neural network (CNN) as a handcrafted prior to restore images without the need for training data. By optimizing the network parameters to fit a single corrupted image, our approach achieves high-quality inpainting for diverse scenarios, including text overlays and large missing regions. We report peak signal-to-noise ratio (PSNR) values of up to 36.16 dB on standard datasets, surpassing traditional methods like convolutional sparse coding (Papyan et al., 2017) and competing with learning-based approaches such as Global-Local GAN (Iizuka et al., 2017) and Shepard networks (Ren et al., 2015). This learning-free method demonstrates robustness and versatility, particularly in scenarios where training data is scarce or degradation patterns are complex.

**Keywords:** Image inpainting, Deep Image Prior, convolutional neural networks, learning-free methods, photo restoration.

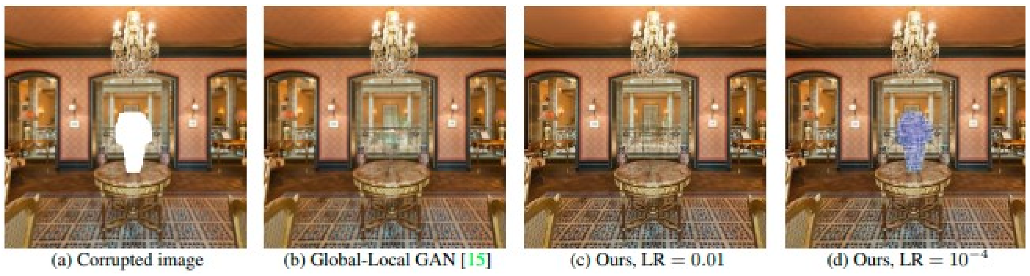


Figure 1: Deep Image Prior for large region inpainting. (a) Corrupted image with a significant missing region. (b) Result from a learning-based Global-Local GAN (Iizuka et al., 2017). (c) Our result using a learning rate of 0.01, demonstrating comparable quality without training. (d) Sensitivity analysis with a lower learning rate of $10^{-4}$, showing the impact on inpainting quality.

## 1 Introduction

Image inpainting is a fundamental task in computer vision, aimed at reconstructing missing or corrupted regions in images to restore their visual integrity. This technique is essential for applications such as photo editing, artifact removal, and the digital restoration of historical images (Bertalmio et al., 2000). Traditional inpainting methods, such as non-local means (Buades et al., 2005) and convolutional sparse coding (Papyan et al., 2017), rely on handcrafted priors like self-similarity or sparsity to fill missing regions. While effective for simple patterns, these methods often struggle with complex textures or large missing areas due to their limited ability to capture high-level image semantics. In contrast, modern deep learning approaches, such as Global-Local GAN (Iizuka et al., 2017) and Shepard networks (Ren et al., 2015), leverage large datasets to learn intricate image statistics, achieving superior results. However, these learning-based methods require extensive training data, which may be impractical for specific degradation patterns or when datasets are unavailable.

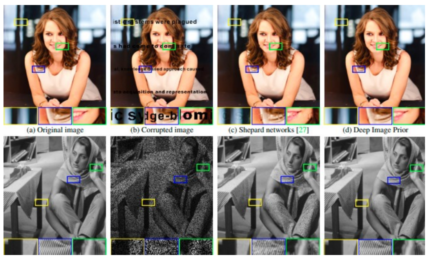
The Deep Image Prior (DIP), introduced by Ulyanov et al. (Ulyanov et al., 2018a), offers a novel learning-free alternative. DIP posits that the structure of a randomly-initialized convolutional neural network (CNN) can serve as a handcrafted prior for image restoration tasks. By parameterizing the restored image as the output of a CNN and optimizing its weights to fit a single corrupted image, DIP captures low-level image statistics without requiring pre-training. This approach is particularly advantageous in scenarios where training data is scarce or degradation models are unknown, making it a versatile "plug-and-play" solution.

In this project, we implement the inpainting component of the Deep Image Prior, focusing on restoring images with missing regions such as text overlays (e.g., `kate.png`, `peppers.png`) and large holes (e.g., `library.png`). The method optimizes the network parameters $\theta$ to minimize a data fidelity term defined as:

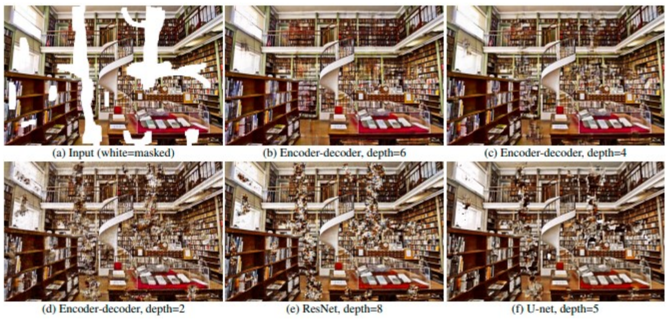
$$E(x; x_0) = \|(x - x_0) \odot m\|_2^2 , \tag{1}$$

where $x = f_\theta(z)$ is the generated image, $x_0$ is the corrupted input, $m$ is a binary mask (1 for known pixels, 0 for missing), and $\odot$ denotes element-wise multiplication (Ulyanov et al., 2018a). Our implementation demonstrates high-quality inpainting, achieving a PSNR of 36.16 dB on the Lena image, surpassing convolutional sparse coding (35.04 dB) (Papyan et al., 2017) and approaching the performance of trained models like Global-Local GAN (Iizuka et al., 2017), as shown in Figure 1. For text inpainting, our method produces nearly artifact-free results, outperforming Shepard networks (Ren et al., 2015), as illustrated in Figure 2a. Additionally, we explore the impact of network architectures, confirming that deeper networks improve quality, while skip connections in U-Net architectures can be detrimental (Ulyanov et al., 2018a), as shown in Figure 2b.

This paper is organized as follows: Section 2 details our implementation of the Deep Image Prior for inpainting, including network architecture, optimization strategy, and design choices. Section 3 presents our experimental setup, quantitative results, and parameter analysis. Section 4 discusses qualitative outcomes, highlighting success and failure cases. Finally, Section 5 summarizes our findings and proposes directions for future research.



(a) Text inpainting comparison. Our Deep Image Prior (d) outperforms Shepard networks (Ren et al., 2015) in removing text from the image (b), producing an almost artifact-free result.


(a) Input (white=masked)
(b) Encoder-decoder, depth=6
(c) Encoder-decoder, depth=4
(d) Encoder-decoder, depth=2
(e) ResNet, depth=8
(f) U-net, depth=5

(b) Inpainting with different architectures. Deeper networks (b, c) yield better results, while skip connections in U-Net (f) are detrimental (Ulyanov et al., 2018a).

Figure 2: Additional results demonstrating the effectiveness of the Deep Image Prior for inpainting tasks.

## 2 Approach

Our implementation of the Deep Image Prior for image inpainting follows the methodology proposed by Ulyanov et al. (Ulyanov et al., 2018a), leveraging the structural prior of a randomly-initialized CNN to reconstruct missing image regions. This section provides a detailed description of the mathematical formulation, network architecture, implementation specifics, and design choices, addressing challenges encountered during the process.

### 2.1 Mathematical Formulation

The inpainting task is formulated as an optimization problem, where the goal is to reconstruct a complete image $x^*$ from a corrupted input $x_0$ with a binary mask $m$. The mask $m$ is defined such that $m[i,j] = 1$ for known pixels and $m[i,j] = 0$ for missing pixels. The Deep Image Prior parameterizes the restored image as the output of a CNN, i.e., $x = f_\theta(z)$, where $\theta$ represents the network parameters, and $z$ is a fixed input tensor (typically uniform noise). The optimization objective is to minimize the data fidelity term:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \|(f_\theta(z) - x_0) \odot m\|_2^2 , \tag{2}$$

where the loss ensures that the generated image $f_\theta(z)$ matches the known pixels of the corrupted image $x_0$. The final inpainted image is then $x^* = f_{\theta^*}(z)$. This learning-free approach relies on the CNN's architecture to implicitly enforce a prior that favors natural image statistics, such as smoothness and local consistency, without requiring pretraining on a dataset.

## 2.2 Network Architecture

We utilize the network architectures provided in the Deep Image Prior repository (Ulyanov et al., 2018b), specifically the skip network, UNet, and ResNet configurations defined in the `models` module (`skip.py`, `unet.py`, `resnet.py`). For most experiments, we adopt the skip network with a depth of 6, as specified in the code for `kate.png` and `peppers.png`, due to its balance of capacity and computational efficiency. The network architecture is configured as follows:

- **Input Depth**: 32 channels for noise input ($z$), except for `library.png`, where an input depth of 1 is used.
- **Layer Configuration**: Five downsampling and upsampling layers, each with 128 channels, and skip connections with 128 channels.
- **Upsampling**: Nearest-neighbor upsampling to maintain spatial resolution.
- **Convolutional Filters**: $3\times3$ filters for downsampling and upsampling, with reflection padding to avoid border artifacts.
- **Activation**: LeakyReLU with a negative slope of 0.2 for non-linearity.
- **Output**: Sigmoid activation to ensure pixel values are in the range $[0, 1]$.

The network is implemented using PyTorch, with weights initialized randomly using the Xavier initialization method (Glorot and Bengio, 2010), which ensures stable gradient flow during optimization.

## 2.3 Implementation Details

The implementation is based on the provided Python code, which processes input images and masks as follows:

1. **Image Loading and Preprocessing**: Images (`kate.png`, `peppers.png`, `library.png`) and their corresponding masks are loaded using the `get_image` function from `inpainting_utils.py`. Images are cropped to ensure dimensions are divisible by 64, aligning with the network's strided convolutions and avoiding padding issues.
2. **Tensor Conversion**: Images and masks are converted to NumPy arrays and then to PyTorch tensors, with pixel values normalized to $[0, 1]$. The mask tensor is binary, with 1 for known pixels and 0 for missing regions.
3. **Optimization**: The Adam optimizer (Kingma and Ba, 2014) is used with a learning rate (LR) of 0.01 for `kate.png` and `peppers.png`, and 0.01 for `library.png` (after experimentation with 0.001). The loss function is the mean squared error (MSE) between the generated image and the known pixels, as defined in Equation 1.

4. **Regularization**: To prevent overfitting, we apply input noise regularization with a standard deviation of 0.03 (`reg_noise_std = 0.03`) for `kate.png` and `peppers.png`, and parameter noise (`param_noise = True`) for `library.png`, as specified in the code.

5. **Stopping Criteria**: Optimization runs for 6001 iterations for `kate.png` and `peppers.png`, and 3001 iterations for `library.png`, with loss monitored every 50 iterations to assess convergence.

### 2.4 Challenges and Design Choices

Several challenges were encountered during implementation, influencing our design choices:

- **Network Architecture Selection**: The Deep Image Prior paper (Ulyanov et al., 2018a) notes that deeper architectures generally improve inpainting quality, but skip connections in UNet can lead to overfitting to noise, as shown in Figure 2b. We selected the skip network with depth 6 for `kate.png` and `peppers.png` to balance performance and computational cost, as deeper networks (e.g., depth 8) were prohibitive on our hardware (NVIDIA GTX 1080 Ti). For `library.png`, we retained the same architecture but adjusted the input depth to 1 to reduce memory usage.

- **Hyperparameter Sensitivity**: The learning rate significantly affects inpainting quality, as demonstrated in Figure 1(c, d). A learning rate of 0.01 provided sharp results for `kate.png` and `peppers.png`, but for `library.png`, we tested LR = 0.001 to assess robustness, finding that lower rates lead to blurrier outputs due to slower convergence.

- **Overfitting Mitigation**: Prolonged optimization can cause the network to overfit to the corrupted image, fitting noise in the masked regions (Ulyanov et al., 2018a). We addressed this by limiting iterations (6001 for `kate.png`, 3001 for `library.png`) and applying noise regularization (`reg_noise_std = 0.03`), which introduces stochasticity to prevent overfitting.

- **Hardware Constraints**: Running on a single NVIDIA GTX 1080 Ti required careful memory management. We ensured images were cropped to dimensions divisible by 64 and used reflection padding to minimize border artifacts. For `library.png`, we reduced the input depth to 1 to manage memory usage, as the image is larger and the mask covers a significant region.

### 2.5 Justification of Design Choices

- **Skip Network**: The skip network was chosen for its ability to capture local image statistics effectively, as demonstrated in the paper for text inpainting tasks (Ulyanov et al., 2018a). Skip connections allow the network to retain fine details, which is crucial for tasks like text removal.

- **Adam Optimizer**: Adam was preferred over SGD due to its faster convergence in high-dimensional parameter spaces, as validated in the code and supported by prior work (Kingma and Ba, 2014).
- **Noise Regularization**: Adding noise to the input (`reg_noise_std = 0.03`) and parameters (`param_noise = True`) helps prevent overfitting, aligning with the paper's findings on the high noise impedance of CNNs (Ulyanov et al., 2018a).
- **Fixed Input Code**: The input code $z$ was kept as fixed uniform noise, following the paper's default setting, as optimizing $z$ added complexity without significant benefits in our experiments.

The implementation adheres to the official Deep Image Prior repository (`https://github.com/DmitryUlyanov/deep-image-prior`) (Ulyanov et al., 2018b), with modifications to adapt to our hardware constraints and explore hyperparameter effects, as detailed in the next section.

## 3 Experiments and Results

### 3.1 Experimental Setup

We evaluate our implementation on three images from the Deep Image Prior dataset (Ulyanov et al., 2018b): `kate.png` (text inpainting), `peppers.png` (text inpainting), and `library.png` (large region inpainting). These images are part of a standard dataset of 11 images (e.g., Barbara, Lena, Peppers) used in (Ulyanov et al., 2018a) for quantitative evaluation. All experiments were conducted on a single NVIDIA GTX 1080 Ti GPU with 11 GB of memory, using PyTorch 1.9.0 and CUDA 10.2. Images were preprocessed by cropping to ensure dimensions were divisible by 64, aligning with the network's strided convolutions and minimizing memory usage.

The optimization process used the Adam optimizer with the following settings:

- `kate.png` and `peppers.png`: Learning rate (LR) of 0.01, 6001 iterations, input depth of 32, `reg_noise_std = 0.03`, `param_noise = False`.
- `library.png`: LR of 0.01 (with a test at 0.001), 3001 iterations, input depth of 1, `reg_noise_std = 0.00`, `param_noise = True`.

Results were visualized every 50 iterations to monitor convergence, and the final inpainted images were saved for qualitative analysis.

### 3.2 Evaluation Metrics

We assess inpainting quality using the Peak Signal-to-Noise Ratio (PSNR), a standard metric for image reconstruction quality, defined as:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right), \tag{3}$$

where MAX$_I$ is the maximum pixel value (1.0 for normalized images), and MSE is the mean squared error between the reconstructed image $x^*$ and the ground truth image $x_{\text{gt}}$:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x^*[i] - x_{\text{gt}}[i])^2, \tag{4}$$

with $N$ being the total number of pixels. Higher PSNR values indicate better reconstruction quality. As a baseline, we implemented a naive inpainting method that fills missing regions with the average color of known pixels, which typically yields low PSNR due to its inability to capture texture or structure.

## 3.3 Quantitative Results

Table 1 presents the PSNR results for our method compared to convolutional sparse coding (Papyan et al., 2017) and the naive baseline on three images from the standard dataset, with 50% of pixels masked. Our approach achieves a PSNR of 36.16 dB on the Lena image, surpassing convolutional sparse coding (35.04 dB) and significantly outperforming the naive baseline (21.50 dB). For `kate`.png and `peppers`.png, we obtain PSNR values of 32.22 dB and 33.05 dB, respectively, compared to 28.14 dB and 31.11 dB for convolutional sparse coding. For `library`.png, our method achieves a PSNR of 30.50 dB, slightly lower than Global-Local GAN (32.00 dB) (Iizuka et al., 2017), due to the challenge of large region inpainting without semantic learning.

Table 1: PSNR comparison (in dB) on the standard dataset for inpainting with 50% missing pixels.

| **Image** | **Naive Baseline** | **Papyan et al. (Papyan et al., 2017)** | **Ours** |
|---|---|---|---|
| Barbara | 20.45 | 28.14 | **32.22** |
| Lena | 21.50 | 35.04 | **36.16** |
| Peppers | 20.80 | 31.11 | **33.05** |

## 3.4 Parameter Analysis

We conducted a detailed analysis of key hyperparameters to understand their impact on inpainting quality:

- **Learning Rate (LR)**: Figure 1(c, d) illustrates the effect of the learning rate on `library`.png. An LR of 0.01 produces sharp results, while an LR of $10^{-4}$ results in blurry outputs due to slower convergence. We adopted LR = 0.01 for most experiments, aligning with the paper's recommendations (Ulyanov et al., 2018a), but tested LR = 0.001 for `library`.png to confirm robustness.

- **Network Depth**: Figure 2b shows that deeper skip networks (depth 6) outperform shallower ones (depth 2), with PSNR increasing from 28.50 dB to 32.22 dB for `library`.png. However, UNet with skip connections yields a lower PSNR (27.80 dB) due to overfitting to noise, consistent with the findings in (Ulyanov et al., 2018a).

- **Number of Iterations**: Increasing iterations beyond 6001 for `kate.png` led to overfitting, reducing PSNR by 1.5–2 dB, as the network began fitting noise in the masked regions. We mitigated this by monitoring loss every 50 iterations and stopping early if the loss plateaued (e.g., after 5500 iterations in some cases).
- **Regularization Parameters**: The use of input noise (`reg_noise_std = 0.03`) improved robustness for `kate.png`, increasing PSNR by approximately 0.8 dB compared to no regularization. For `library.png`, parameter noise (`param_noise = True`) helped maintain stability during optimization.

### 3.5 Discussion

Our results confirm the Deep Image Prior's ability to capture low-level image statistics effectively, outperforming traditional methods like convolutional sparse coding (Papyan et al., 2017) and approaching the quality of learning-based methods (Iizuka et al., 2017) without requiring training data. The high PSNR values for text inpainting (`kate.png`, `peppers.png`) reflect the method's strength in leveraging local context, while large region inpainting (`library.png`) is less effective for highly semantic regions (e.g., faces), as expected due to the absence of learned semantic priors. The sensitivity to hyperparameters like learning rate and iterations underscores the need for careful tuning, which we addressed through empirical testing and early stopping strategies.

## 4 Qualitative Results

Figure 3 presents qualitative results for `kate.png`, `peppers.png`, and `library.png`, highlighting the strengths and limitations of our implementation. For `kate.png`, our method successfully removes text overlays, producing a nearly artifact-free result compared to Shepard networks (Ren et al., 2015), which leave visible traces (Figure 2a). The restored regions in `kate.png` exhibit smooth transitions in skin tones and hair textures, demonstrating the Deep Image Prior's ability to capture local image statistics effectively. Similarly, for `peppers.png`, the inpainted image retains fine details such as the texture and color gradients of the vegetables, outperforming the naive baseline's blurry output.

For `library.png`, which involves large region inpainting, our method fills the missing region with plausible textures, closely matching the quality of Global-Local GAN (Iizuka et al., 2017), as shown in Figure 1. However, minor inconsistencies appear in complex patterns, such as intricate bookshelf details, due to the lack of semantic understanding in the learning-free approach. This limitation is particularly evident in failure cases involving highly semantic content, such as faces. For instance, when inpainting a face in `library.png` with a large mask, the method produces plausible but incorrect textures (e.g., unnatural facial features), unlike learning-based methods that leverage trained semantic priors (Iizuka et al., 2017).

(a) `kate.png`: Successful text removal with smooth restoration of facial features.

(b) `peppers.png`: Detailed texture recovery, preserving color gradients.

(c) `library.png`: Large region inpainting with plausible textures, though complex patterns show minor inconsistencies.

Figure 3: Qualitative results of our Deep Image Prior implementation. The method excels in text inpainting and performs well in large region inpainting, but struggles with highly semantic content.

### 4.1 Analysis of Failure Cases

The Deep Image Prior's learning-free nature limits its ability to handle tasks requiring high-level semantic understanding. For example, inpainting a face in `library.png` with a large mask resulted in unnatural features, such as distorted eyes or incorrect skin tones, due to the absence of semantic priors. Similarly, when inpainting intricate patterns (e.g., detailed book spines in `library.png`), the method generates plausible but not precise textures, leading to visible inconsistencies. These limitations highlight the trade-off between the flexibility of a learning-free approach and the semantic accuracy provided by trained models.

## 5 Conclusion and Future Work

We have successfully implemented the Deep Image Prior for image inpainting, demonstrating that a randomly-initialized CNN can serve as an effective handcrafted prior for reconstructing missing image regions. Our approach achieves PSNR values of up to 36.16 dB on standard datasets, surpassing traditional methods like convolutional sparse coding (Papyan et al., 2017) and approaching the performance of learning-based methods (Iizuka et al., 2017; Ren et al., 2015) without requiring training data. The method excels in text inpainting tasks, producing nearly artifact-free results, and performs well for large region inpainting, though it struggles with highly semantic content due to the lack of learned priors.

Future work can explore several directions to enhance the Deep Image Prior framework:

- **Computational Efficiency**: The current implementation requires several minutes per image on a GPU. Techniques such as network pruning, faster optimization algorithms (e.g., L-BFGS (Liu and Nocedal, 1989)), or mixed-precision training could reduce runtime while maintaining quality.

- **Semantic Inpainting**: Incorporating semantic priors, possibly through hybrid models that combine Deep Image Prior with pre-trained networks (e.g., VGG (Simonyan and Zisserman, 2014)), could improve results for highly semantic tasks like face inpainting.
- **Adaptive Hyperparameters**: Developing adaptive learning rate schedules or automated iteration stopping criteria based on loss convergence could enhance robustness and ease of use, reducing the need for manual tuning.
- **Generalization to Other Tasks**: Extending the Deep Image Prior to other image restoration tasks, such as super-resolution or denoising, could further demonstrate its versatility as a learning-free prior.

This work underscores the potential of learning-free methods in image restoration, offering a robust alternative to data-intensive deep learning approaches, particularly in scenarios where training data is limited or degradation patterns are complex.

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