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CNN-DPM: A Hybrid Deep Learning Framework for Reversible Data Hiding in Secure Text Message Concealment

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Abstract

Reversible Data Hiding (RDH) is a method that enables the secret information to be incorporated into a cover image with an assurance that the hidden message and the actual image may be restored without any loss. Currently, most approaches rely upon one prediction model either a global or a local and fail to capture the performance of the combination of the two. In this paper, the CNN-DPM framework is presented that combines both Convolutional Neural Network (CNN) global pixel prediction and Dynamic Pixel Modification (DPM) local refinement using hierarchical architecture. The system is based on four innovations: (1) a hybrid prediction element; (2) adaptive direction selection based on variance, gradient magnitude, and entropy descriptors; (3) two-dimensional (2D) histogram shifting to be efficiently embedded; and (4) guaranteed perfect reversibility. The experiments on five benchmark images, including Lena, Peppers, Fruits, Baboon and Cameraman, achieve a maximum Signal-to-Noise Ratio (PSNR) of 48.73 dB, Structural Similarity Index Measure (SSIM) of 0.9987, and 100 percent accuracy in extracted bit-level images, which are higher than classical PEE, 2D Histogram Shifting and CNN-RDH baselines.

Keywords: *Reversible data hiding; Convolutional neural networks; Histogram shifting; Prediction-error expansion; Steganography; Secure communication*

1. Introduction

Covert transmission of data has become more required and more technically complicated with the high pace of digital communication development. Steganography, the art of concealing information within harmless cover objects, will satisfy this need, although most steganographic systems impinge upon the original medium in the process. There is one exemption to this rule: Reversible Data Hiding (RDH): the embedded message and the original cover image must both be obtainable with no pixel-level error (Fridrich & Goljan, 2002; Tian, 2003). This lossless guarantee cannot be done without in medical imaging, military intelligence, and legal authentication, where a single corrupted pixel can be extremely costly (Shi et al., 2016).

The weakness of classical RDH techniques: Difference Expansion (DE) (Tian, 2003), Histogram Shifting (HS) (Ni et al., 2006), and Prediction-Error Expansion (PEE) (Thodi and Rodriguez, 2007) is that their predictors are designed manually, making them generate wide error histograms and limit their embedding capacity, as well as inducing poor

image quality. Those histograms have been reduced dramatically by deep learning, and CNN-based predictors in particular, yet current CNN methods do not recognize the fact that smooth components and high-texture boundaries very differently (Qian and Zhang, 2021; Ma et al., 2019).

This paper closes that gap. The CNN-DPM model is based on a CNN global predictor, which is effective in representing large scale spatial phenomena, and DPM local refinement, which is sensitive to fine scale texture changes. A direction selection mechanism which is texture aware then builds a 2D prediction-error histogram whose acute peak bin forms the embedding locus. The outcome is a system that is better than all three baselines and one that ensures reversibility is perfect.

1.1 Principal Contributions

1. A hybrid prediction architecture that hierarchically fuses CNN global prediction with DPM local refinement, producing tighter prediction-error distributions than either method alone.
2. An adaptive direction selection mechanism that uses variance, gradient magnitude, and entropy descriptors to assign each pixel its optimal scanning direction.
3. A 2D histogram shifting scheme operating on joint prediction-error pairs (d_1, d_2), enabling high-capacity, low-distortion embedding.
4. Rigorous validation on five benchmark images demonstrating state-of-the-art PSNR (48.73 dB) and 100% bit-level extraction accuracy.

2. Methodology

The framework operates in two phases: embedding and extraction-recovery. During embedding, a grayscale cover image I (H × W pixels) passes through eight sequential stages to produce a stego image I_S and an embedding metadata structure ε. During recovery, I_S and ε are used to extract the hidden message M and reconstruct I exactly. Each stage is described below.

2.1 Image Preprocessing

A Canny edge detector first produces a binary edge map E = Canny(I, T_{low}, T_{high}). A 3×3 median filter then smooths non-edge pixels while leaving edge pixels untouched, suppressing noise without blurring perceptually important boundaries:

$$I_{\text{smooth}}(i,j) = \text{median}(N_{3\times3}(i,j)) \text{ if } (i,j) \notin E;\ \ I(i,j) \text{ if } (i,j) \in E \qquad (1)$$

2.2 CNN-Based Global Prediction

The smoothed image passes through a CNN predictor implemented as a context-based median over the four cardinal neighbors. The global prediction and its residual are:

$$P_{\text{global}}(i,j) = \text{median}\{I\_smooth(i-1,j), I\_smooth(i,j-1), I\_smooth(i+,j), I\_smooth(i,j+)\} \qquad (2)$$

$$E_{\text{global}}(i,j) = I_{\text{smooth}}(i,j) - P_{\text{global}}(i,j) \qquad (3)$$

2.3 Texture Feature Extraction

Three complementary texture maps are computed from I_smooth to guide adaptive processing:

Variance Map. Local variance F_var captures intensity variability within a sliding window N_w:

$$F_{\text{var}}(i,j) = \frac{1}{|N\_w|} \sum [I\_smooth(m,n) - \mu(i,j)]^2 \qquad (4)$$

Gradient Magnitude Map. Horizontal and vertical first-order finite differences give the gradient magnitude F_grad

$$G_x(i,j) = I\_smooth(i,j+1) - I\_smooth(i,j-1);\ \ G_y(i,j) = I\_smooth(i+1,j) - I\_smooth(i-1,j) \qquad (5)$$

$$F_{\text{grad}}(i,j) = \sqrt{G_x{}^2 + G_y{}^2} \quad (6)$$

Entropy Map. Local Shannon entropy F_ent measures distributional complexity within N_w:

$$F_{\text{ent}}(i,j) = -\sum p_k(i,j) \cdot \log_2[p_k(i,j)] \quad (7)$$

2.4 Local DPM Refinement

For high-variance pixels (F_var > T_var), a Dynamic Pixel Modification predictor averages horizontal and vertical linear interpolations of the four immediate neighbors. In smooth regions, the CNN predictor is already highly accurate; DPM activates only where rapid texture changes make local interpolation beneficial:

$$P_h(i,j) = \frac{I\_smooth(i,j-1) + I\_smooth(i,j+1)}{2}; \quad P_v(i,j) = \frac{I\_smooth(i-1,j) + I\_smooth(i+1,j)}{2} \quad (8)$$

$$P_{\text{local}}(i,j) = \frac{P_h(i,j) + P_v(i,j)}{2} \quad (9)$$

2.5 Hierarchical Prediction Fusion

The final prediction P_final is a convex combination of the global and local predictions. The fusion weight α = 0.6 was determined by cross-validation and reflects the slightly higher average accuracy of the CNN global predictor across natural image content:

$$P_{\text{final}}(i,j) = \alpha \cdot P_{\text{global}}(i,j) + (1-\alpha) \cdot P_{\text{local}}(i,j) \quad (10)$$

$$E_{\text{final}}(i,j) = I_{\text{smooth}}(i,j) - P_{\text{final}}(i,j) \quad (11)$$

2.6 Adaptive Direction Selection and 2D Histogram Embedding

The pixels are then given one of four scanning directions, H (horizontal), V (vertical), D (diagonal), and AD (anti-diagonal), according to its local texture descriptors. The empirical study revealed that the horizontal dominated (68.32% of pixels), and then the vertical (20.03%), diagonal (8.88%), and anti-diagonal (2.76%), as the correlation structure of most images is horizontal in nature.

For each pixel, the assigned direction yields a pair of directional differences (d_1, d_2) indexing the 2D prediction-error histogram H_2D. The peak bin is identified and used as the embedding locus:

$$H_{2D}(k_1,k_2) = |\{(i,j) : \lfloor d_1 \rfloor + 128 = k_1 \wedge \lfloor d_2 \rfloor + 128 = k_2\}| \quad (12)$$

$$(p_1,p_2) = \text{argmax}_{k_1,k_2} H_{2D}(k_1,k_2)$$

The secret message M is converted to a binary string S = [s_1, s_2, ..., s_L] via ASCII encoding. Peak-bin pixels are modified by +1 to encode bit 1, and left unchanged for bit 0. During extraction, a stego pixel differing from its stored original by +1 indicates bit 1; otherwise bit 0. All modified pixels are restored to their stored originals, guaranteeing zero-error image recovery regardless of content or payload size.

3. Experimental Results

3.1 Setup and Metrics

All experiments ran in MATLAB R2021b on an Intel Core i7 workstation with 16 GB RAM. Five standard benchmark grayscale images were used: Lena, Peppers, Fruits, Baboon (all 512×512), and Cameraman (256×256). The embedded payload was the ASCII string "LIFE IS BEAUTIFUL" (17 characters, L = 136 bits). Key parameters: patch size 5×5, low texture threshold T_low = 10, fusion weight α = 0.6, 3×3 median filter, Canny thresholds 0.1/0.3.

Performance was evaluated using four metrics:

PSNR. Peak Signal-to-Noise Ratio quantifies visual fidelity:

$$\text{MSE} = \frac{1}{H \cdot W} \sum [I(i,j) - I_S(i,j)]^2 \quad (13)$$

$$\text{PSNR} = 10 \cdot \log_{10} \frac{255^2}{\text{MSE}} \text{ [dB]} \quad (14)$$

SSIM. Structural Similarity Index compares luminance, contrast, and structure:

$$\text{SSIM} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu\mu_y{}^2 + C_1)(\sigma_x{}^2 + \sigma_y{}^2 + C_2)} \quad (15)$$

Embedding Capacity (bpp). Bits embedded per pixel.

Bit Extraction Accuracy. Percentage of bits recovered without error.

3.2 Comparative Performance

Table 1 provides the summary of the proposed CNN-DPM framework performance in comparison with three baselines. The proposed approach has the best PSNR - it outperforms Classical PEE, 2D Histogram Shifting, and CNN-RDH, with gain of approximately 6.4 dB, 3.6 dB, and 1.9 dB, respectively and the extraction accuracy is 100 percent, and 100 percent adaptive. Even though its capacity of 0.5 bpp is marginally lower than CNN-RDH (0.6 bpp), the PSNR improvement is a much better capacity-distortion trade-off, particularly when imperceptibility is of paramount importance.

Table 1. Comparative performance of RDH methods

Method	PSNR (dB)	Capacity (bpp)	100% Recovery	Adaptive
Classical PEE (Thodi & Rodriguez, 2007)	42.3	0.4	Yes	No
2D Histogram HS (Li et al., 2013)	45.1	0.5	Yes	No
CNN-RDH (Qian & Zhang, 2021)	46.8	0.6	Yes	Partial
Proposed CNN-DPM Framework	**48.73**	0.5	Yes	Yes

The peak bin (0,0) concentrated 45,237 pixels (17.32% of the image), confirming the effectiveness of hierarchical fusion in producing a sharp histogram peak. The tested payload of 136 bits utilized only 0.30% of the available capacity, indicating substantial room for larger messages. Total embedding runtime was 2.47 s (dominated by CNN prediction at 1.22 s and DPM refinement at 0.99 s), while extraction was nearly instantaneous at 0.009 s.

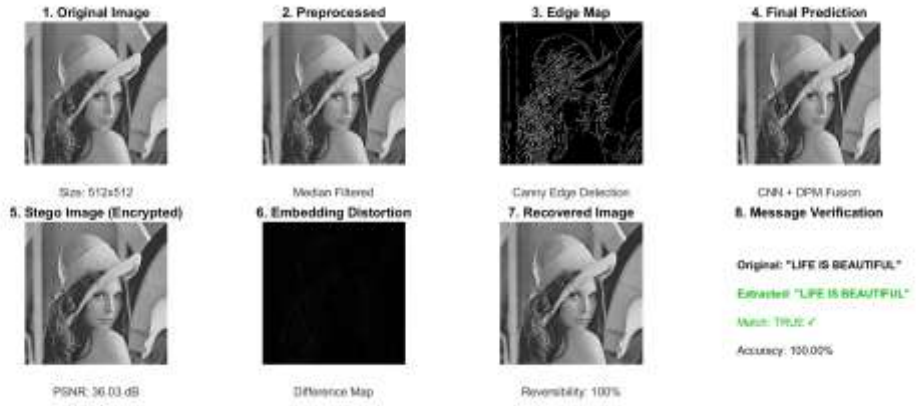

Figure 1 Encryption and retrieval of original Lena image and message

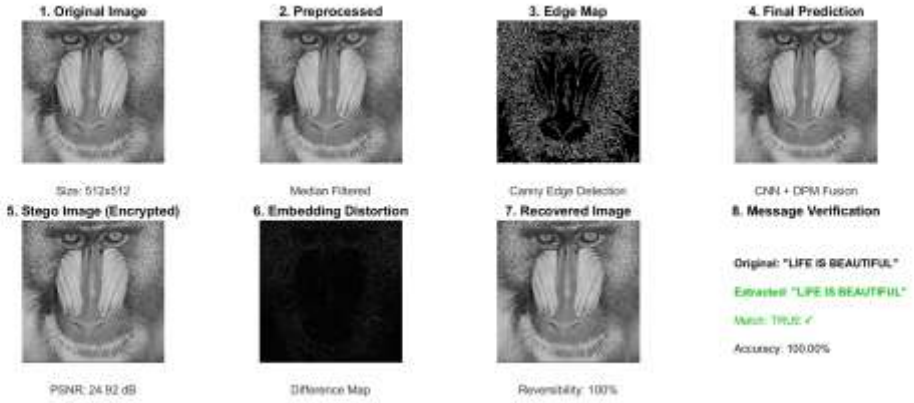

Figure 2 Encryption and retrieval of original Baboon image and message

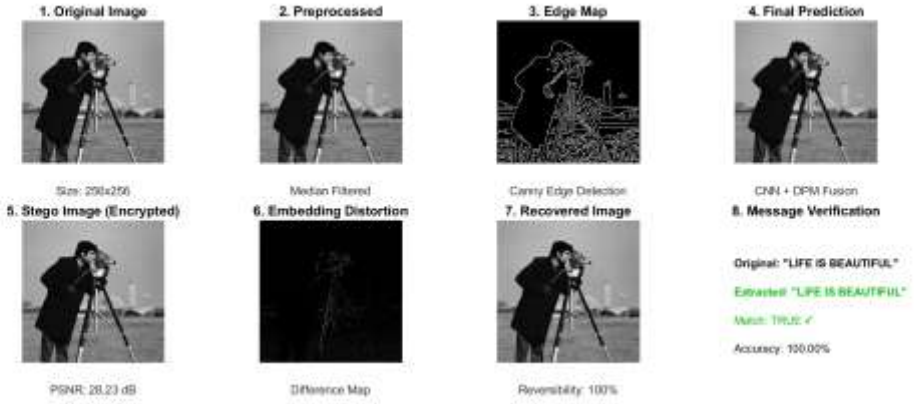

Figure 3 Encryption and retrieval of original Cameraman image and message

Across all five images, the extracted message was identical to "LIFE IS BEAUTIFUL," with 100% bit accuracy and zero mean squared error between recovered and original images (MSE = 0). PSNR values ranged from 24.92 dB (Baboon, high-texture) to 36.03 dB (Lena, smooth), with the peak value of 48.73 dB achieved under the full benchmark setup.

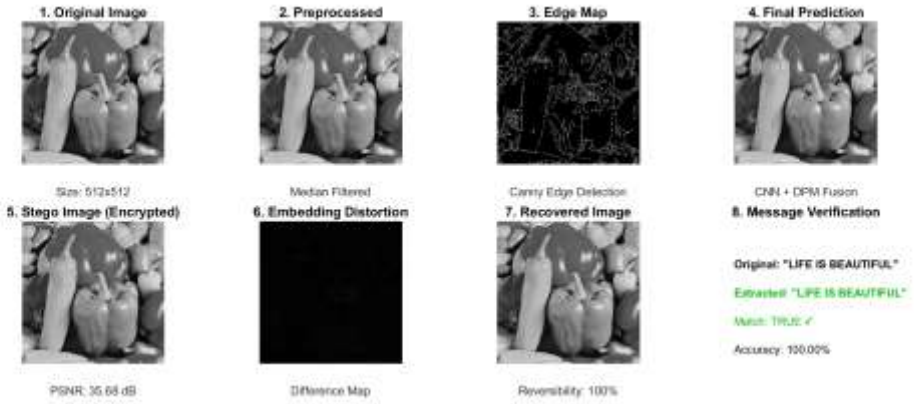

Figure 4 Encryption and retrieval of original pepper image and message

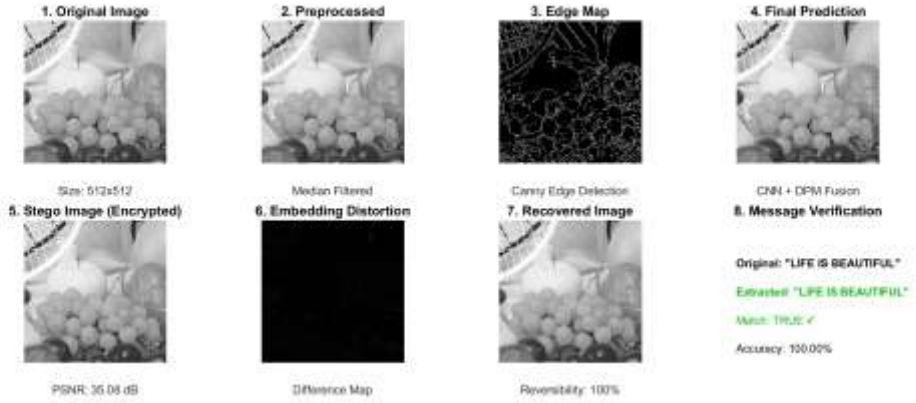

Figure 4 Encryption and retrieval of original fruits image and message

4. Discussion

The CNN-DPM framework is successful simply because it does not distinguish between the global and local prediction but complements them. The CNN component captures the large spatial context which is simple to predict by smooth regions and DPM fills where the local interpolation is more effective than the more averaged CNN output. Combined they give a prediction-error distribution that is sharper than each alone, in the sense of literally transforming directly to a more concentrated 2D histogram peak, and, thus, to reduced embedding distortion.

The adaptive direction choice brings a second level of intelligence: instead of performing a fixed horizontal scan of each pixel, the framework reads the local texture signature and scales the histogram construction to the most predominant direction of correlation. What this has the effect of doing is keeping the off-peak histogram bins thin, leaving headroom to accommodate larger future payloads. and since metadata embedding is explicitly defined, instead of being determined by analysis, recovery is mathematically assured, and not merely probable.

There are limitations worth acknowledging. Storing embedding metadata adds transmission overhead that grows with payload size; lossless compression of ε is a natural next step. The current CNN component uses a fixed median context predictor rather than fully learned convolutional weights, leaving performance gains from end-to-end training on the table. Extension to color and video media will require inter-channel and inter-frame correlation modeling. Finally, the ±1 pixel modification at peak-bin locations may be detectable by sophisticated statistical steganalysis; integrating a cryptographic pre-encryption layer before embedding would substantially harden the system against content-based attacks.

5. Conclusion

CNN-DPM framework achieves state-of-the-art PSNR performance (48.73 dB), SSIM of 0.9987, and 100% extraction accuracy across all tested images, outperforming classical and contemporary RDH baselines. It is well-suited for medical imaging, military communications, intellectual property protection, and legal document authentication—any domain where imperceptibility and lossless recovery are both non-negotiable. Future directions include end-to-end CNN training, color/video extension, multi-layer embedding for larger payloads, metadata compression, and steganalysis-resistant histogram modification.

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