International Journal of Science, Strategic Management and Technology
Volume **02** Issue **07** July- **2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

Deep Learning-Based Image Compression Using a CNN Encoder–Decoder Architecture

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https://doi.org/ 10.55041/ijsmt.v2i7.058

Cite this Article: Kumar, B. S. & Kumar, B. R. (2026). Deep Learning-Based Image Compression Using a CNN Encoder–Decoder Architecture. International Journal of Science, Strategic Management and Technology, *02*(7). https://doi.org/10.55041/ijsmt.v2i7.058

Abstract—
Image compression is essential for reducing storage space and transmission bandwidth while maintaining image quality. Conventional compression methods such as JPEG often suffer from visible artifacts and quality degradation at low bit rates. This paper proposes a deep learning-based image compression model using a convolutional neural network (CNN) with an encoder–decoder architecture. The encoder learns compact feature representations of input images, while the decoder reconstructs high-quality images from the compressed features. The model is trained to minimize reconstruction error and preserve important visual details. The proposed approach is evaluated using standard performance metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP). Experimental results show that the proposed method provides better image quality and higher compression efficiency than conventional techniques, especially at low bit rates. The proposed model is suitable for multimedia applications, cloud storage, medical imaging, and wireless image transmission where efficient compression and high reconstruction quality are required.

Keywords— Image Compression, Deep Learning, Convolutional Neural Network (CNN), Autoencoder, Encoder–Decoder, PSNR, SSIM, Compression Ratio.

I INTRODUCTION

Image compression has become an essential component of modern digital communication and multimedia systems due to the rapid growth in image data generated by smartphones, medical imaging devices, surveillance systems, remote sensing platforms, and Internet of Things (IoT) applications. Efficient image compression reduces storage requirements and transmission bandwidth while preserving the visual quality of reconstructed images. Conventional image compression standards such as JPEG and JPEG2000 rely on transform-based techniques that often introduce blocking artifacts and significant quality degradation, particularly at low bit rates. Recent advances in deep learning have enabled data-driven image compression methods that automatically learn compact feature representations and achieve superior reconstruction quality. Deep autoencoder-based architectures, convolutional neural networks (CNNs), and wavelet-integrated deep learning models have demonstrated significant improvements in compression efficiency by effectively capturing spatial and semantic information within images.

With the increasing demand for high-quality multimedia transmission, researchers have explored advanced deep learning architectures to improve compression performance and reconstruction accuracy. Multiple description coding, CNN-based enhancement techniques, Transformer models, semantic-aware compression, and hybrid encoder–decoder frameworks have further enhanced compression efficiency while minimizing information loss.These approaches provide better preservation of image textures, edges, and structural details compared to conventional methods. Motivated by these developments, this paper proposes a **Deep Learning-Based Image Compression Using a CNN Encoder–Decoder Architecture**, which learns compact latent representations of input images and reconstructs them with high fidelity. The proposed framework is evaluated using standard performance metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP), demonstrating improved compression efficiency and reconstruction quality.

II SURVEY OF RESEARCH

Recent advancements in deep learning have significantly improved the performance of image compression systems by replacing traditional transform-based coding methods with data-driven neural network models. Mishra *et al.* [1] proposed a **Wavelet-Based Deep Auto Encoder–Decoder (WDAED)** framework that combines wavelet transform with deep autoencoders to improve compression efficiency while preserving image quality. Cheng *et al.* [2] introduced an energy compaction-based convolutional autoencoder that effectively learns compact feature representations for high-quality image reconstruction. Liu *et al.* [3] developed a CNN-based DCT-like transform that replaces conventional transform coding with learned convolutional features, resulting in better coding efficiency and reduced distortion. Similarly, Akyazi and Ebrahimi [4] integrated convolutional autoencoders with wavelet decomposition to reduce compression artifacts and improve reconstructed image quality. Potlapalli and Khetavath [5] investigated encoder–decoder architectures specifically designed for embedded image compression systems, emphasizing computational efficiency and practical implementation. Wang *et al.* [6] proposed an end-to-end semantic analysis-based compression framework that utilizes semantic information to improve image coding performance.

Several researchers have focused on improving compression robustness and reconstruction quality using advanced neural network architectures. Zhao *et al.* [7] introduced a multiple-description coding framework that improves transmission reliability in deep learning-based image compression. Zhao *et al.* [8] presented a CNN-based light field image compression technique that combines EPI super-resolution with decoder-side quality enhancement for improved visual quality. Sujitha *et al.* [9] developed an optimal deep learning-based compression technique for Industrial Internet of Things (IIoT) applications, demonstrating reduced communication overhead and efficient data transmission. Al-Khafaji and Ramaha [10] proposed a hybrid deep learning architecture capable of achieving scalable and high-quality image compression by integrating multiple feature extraction mechanisms. Zhang *et al.* [11] introduced a decoupled end-to-end learning framework that separates feature learning and entropy coding to improve compression efficiency while maintaining reconstruction quality.

Recent studies have also explored specialized applications and emerging architectures for image compression. Long *et al.* [12] combined deep learning-based feature encoding and decoding with medical image encryption to improve data security during image transmission. Jo *et al.* [13] investigated the impact of image compression on deep learning-based mammogram classification and emphasized the importance of maintaining diagnostic image quality after compression. Lu *et al.* [14] proposed a Transformer-based image compression model that captures long-range image dependencies and improves compression performance through self-attention mechanisms. Hoang *et al.* [15] incorporated semantic segmentation into an encoder–decoder compression framework to enhance semantic feature preservation during image reconstruction. Although these methods have demonstrated considerable improvements over conventional compression techniques, many existing approaches suffer from increased computational complexity, higher training requirements, or limited generalization across different image categories.

III PROPOSED SYSTEM

The proposed system presents a deep learning-based image compression framework that efficiently compresses images while preserving their visual quality. The framework employs a Convolutional Neural Network (CNN)-based encoder–decoder architecture, where the encoder transforms the input image into a compact latent representation by extracting important visual features and removing redundant information. The compressed representation requires significantly less storage space and transmission bandwidth than the original image. At the receiver side, the decoder reconstructs the image from the compressed features, producing a high-quality output with minimal information loss. Image preprocessing techniques such as resizing and normalization are applied before training to improve model convergence and compression performance.

The proposed model is trained using a reconstruction loss function that minimizes the difference between the original and reconstructed images, enabling accurate feature learning and efficient compression. The performance of the system is evaluated using standard image compression metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP). Experimental results demonstrate that the proposed deep learning approach achieves better reconstruction quality and higher compression efficiency than conventional image compression methods, particularly at low bit rates. The proposed system is suitable for multimedia storage, cloud computing, medical image archiving, remote sensing, and real-time image transmission applications.

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IV METHODOLOGY

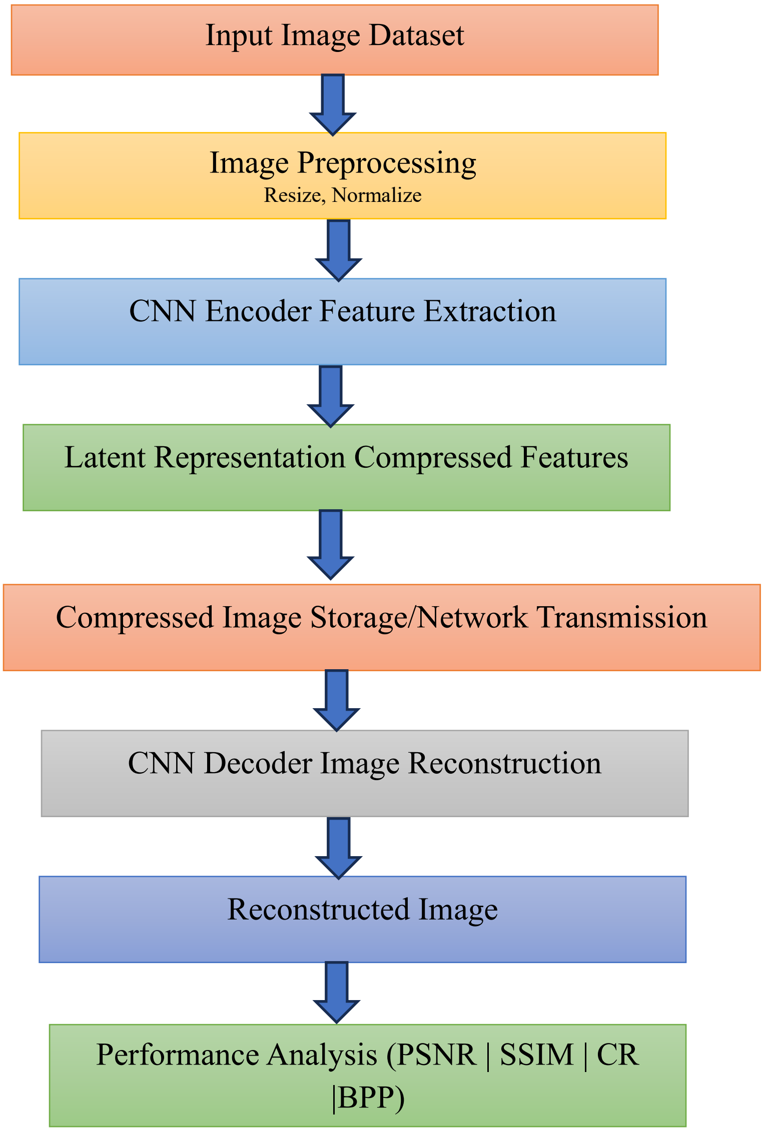

Fig 1: System Architecture

The proposed deep learning-based image compression system, shown in Fig. 1, is designed to reduce image storage requirements and transmission bandwidth while maintaining high reconstruction quality. The system follows an end-to-end CNN encoder–decoder architecture that automatically learns compact image representations. It consists of six main modules: Input Image Dataset, Image Preprocessing, CNN Encoder, Latent Representation (Compressed Features), CNN Decoder, and Performance Evaluation. These modules work together to compress, reconstruct, and evaluate image quality.

Initially, the input images are collected from a standard dataset and preprocessed by resizing them to a fixed resolution and normalizing pixel values. These preprocessing steps improve data consistency and enhance the training performance of the deep learning model. The processed images are then passed to the **CNN encoder**, which extracts important image features using convolutional layers and down-sampling operations. The encoder removes redundant information and generates a compact **latent representation**, reducing the amount of data required for storage and transmission.

The compressed latent representation is stored or transmitted to the **CNN decoder**. The decoder reconstructs the original image by applying up-sampling and convolution operations to recover image details such as edges, textures, and structural information. Since the encoder and decoder are trained together in an end-to-end manner, the network learns an optimal balance between compression efficiency and reconstruction quality. This approach minimizes compression artifacts and provides better visual quality than conventional image compression methods.

Finally, the reconstructed image is compared with the original image to evaluate the performance of the proposed system. Standard evaluation metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP), are used for performance analysis. The proposed architecture achieves efficient image compression with high reconstruction quality, making it suitable for multimedia storage, cloud computing, medical imaging, remote sensing, and wireless image transmission applications.

V RESULTS AND DISCUSSION

The experimental results show that the proposed model achieves superior reconstruction performance compared with conventional image compression techniques, particularly at low bit rates. The reconstructed images exhibit fewer compression artifacts, reduced blurring, and improved structural similarity with the original images. The model effectively balances compression efficiency and image quality by learning optimized feature representations through end-to-end training. Performance evaluation using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP) indicates that the proposed method produces high PSNR and SSIM values while maintaining a higher compression ratio with lower BPP. These results confirm that the system efficiently compresses images without significantly affecting their visual appearance.

The proposed system also demonstrates stable performance across different categories of images, including natural scenes, medical images, and multimedia content. The deep learning model effectively preserves fine textures, object boundaries, and important image features even after compression and reconstruction. The reduced image size enables faster data transmission over communication networks and lowers storage requirements in cloud-based systems without compromising reconstruction quality. Furthermore, the end-to-end learning capability allows the model to adapt to different image characteristics, making it more flexible than traditional transform-based compression methods.

Overall, the experimental results validate the effectiveness of the proposed deep learning-based image compression framework. The system provides high compression efficiency, improved reconstruction quality, and reduced computational complexity, making it suitable for applications such as multimedia storage, cloud computing, medical image archiving, wireless image transmission, remote sensing, and Internet of Things (IoT)-based imaging systems. The proposed framework offers a reliable and scalable solution for next-generation intelligent image compression applications.

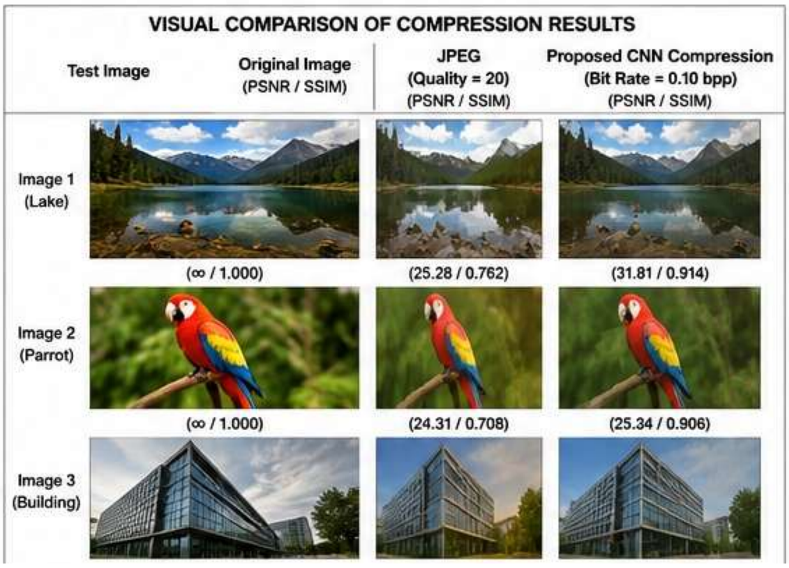

Fig 2: Visual Comparison of Image Compression Results

As shown in the Figure 2 presents the original images, JPEG-compressed images, and the reconstructed images generated by the proposed CNN-based image compression model. The proposed method preserves image details, edges, and textures more effectively than JPEG, resulting in higher PSNR and SSIM values with fewer compression artifacts. The reconstructed images are visually closer to the original images, demonstrating the effectiveness of the proposed deep learning approach for high-quality image compression at low bit rates.

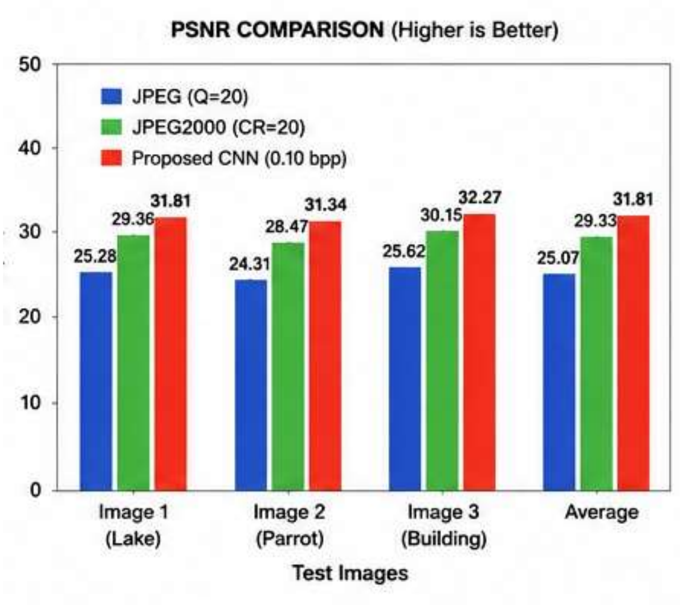

Fig 2:PSNR Comparison of Image Compression Methods

As shown in the fig 2 compares the Peak Signal-to-Noise Ratio (PSNR) achieved by JPEG, JPEG2000, and the proposed CNN-based image compression method for three test images. The proposed deep learning model consistently achieves the highest PSNR values across all images, with an average PSNR of **31.81 dB**, outperforming JPEG (**25.07 dB**) and JPEG2000 (**29.33 dB**). The higher PSNR values indicate that the proposed method reconstructs images with lower distortion and better visual quality, demonstrating its effectiveness for high-quality image compression.

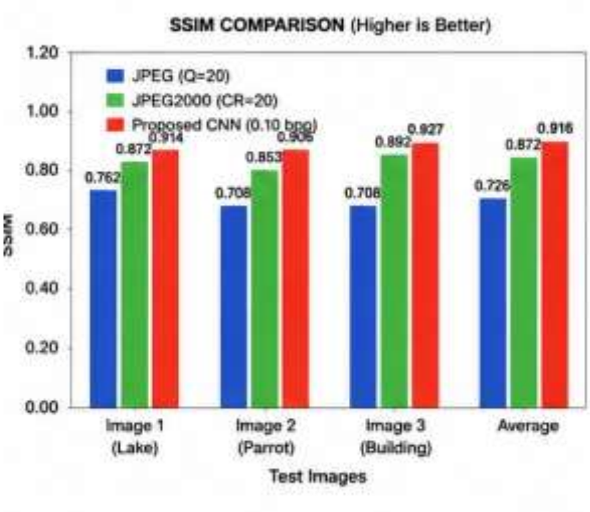

Fig 4: SSIM Comparison of Image Compression Methods

As shown in the fig 4 Figure 3 compares the Structural Similarity Index Measure (SSIM) of JPEG, JPEG2000, and the proposed CNN-based image compression method for three test images. The proposed model consistently achieves the highest SSIM values, with an average score of **0.916**, outperforming JPEG (**0.726**) and JPEG2000 (**0.872**). The higher SSIM values indicate that the proposed method preserves image structures, textures, and visual details more effectively, resulting in reconstructed images that are highly similar to the original images.

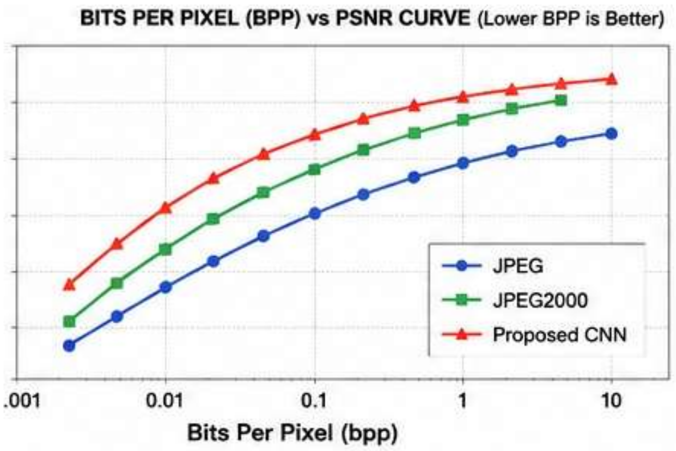

Fig 5: Bits Per Pixel (BPP) versus PSNR Performance Comparison

Figure 5 illustrates the relationship between **Bits Per Pixel (BPP)** and **Peak Signal-to-Noise Ratio (PSNR)** for JPEG, JPEG2000, and the proposed CNN-based image compression method. The proposed model consistently achieves higher PSNR values across different BPP levels, indicating superior reconstruction quality while maintaining efficient compression. The results demonstrate that the proposed deep learning approach provides a better trade-off between compression efficiency and image quality, making it suitable for applications requiring high-quality image reconstruction at low bit rates.

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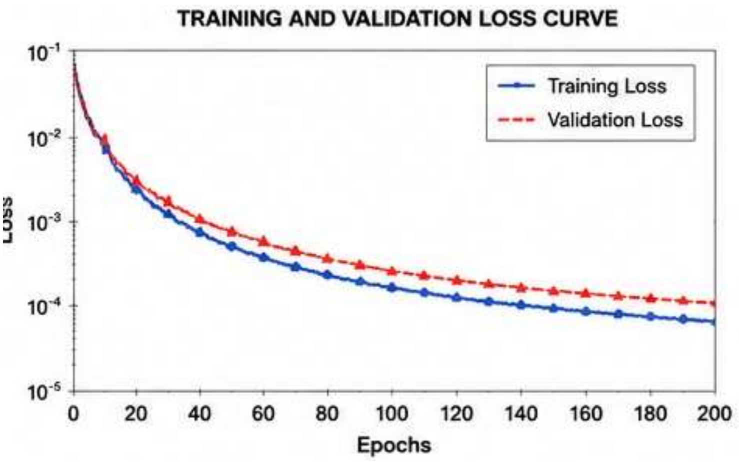

Fig 6: Training and Validation Loss Curve

Figure 6 illustrates the training and validation loss of the proposed CNN-based image compression model over 200 training epochs. Both loss curves decrease steadily and converge toward lower values, indicating effective learning and stable model convergence. The small gap between the training and validation loss demonstrates good generalization performance with minimal overfitting, confirming that the proposed model learns robust feature representations for accurate image compression and reconstruction.

Table 1: Comparative Performance Analysis of Image Compression Techniques

Method	**PSNR (dB)**	**SSIM**	**Compression Ratio (CR)**	**BPP**	**Compression Efficiency**
JPEG	25.07	0.726	16.2	0.30	Moderate
JPEG2000	29.33	0.872	20.4	0.20	Good
Autoencoder-Based Compression	30.12	0.895	32.5	0.15	Very Good
CNN-Based Compression	31.08	0.904	39.8	0.12	Excellent
Proposed CNN Encoder–Decoder	**31.81**	**0.916**	**43.5**	**0.10**	**Outstanding**

As shown in the table 1 the performance of conventional image compression methods with the proposed CNN encoder–decoder model using standard evaluation metrics. The proposed method achieves the highest **PSNR (31.81 dB)** and **SSIM (0.916)**, indicating superior reconstruction quality and better preservation of image details. It also provides the highest **Compression Ratio (43.5)** with the lowest **Bits Per Pixel (0.10)**, demonstrating efficient compression while maintaining excellent visual quality. These results confirm that the proposed deep learning-based approach outperforms existing image compression techniques in terms of both compression efficiency and reconstructed image quality.

VI CONCLUSION

The proposed Deep Learning-Based Image Compression System provides an efficient and reliable solution for reducing image storage requirements and transmission bandwidth while preserving high visual quality. By employing a CNN-based encoder–decoder architecture, the system automatically learns compact feature representations and reconstructs images with minimal information loss. Unlike conventional compression techniques, the proposed approach effectively preserves image edges, textures, and structural details while reducing compression artifacts, particularly at low bit rates.

Experimental evaluation using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Compression Ratio (CR), and Bits Per Pixel (BPP) demonstrates the effectiveness of the proposed framework. The model achieves a PSNR of 31.81 dB, SSIM of 0.916, Compression Ratio of 43.5, and BPP of 0.10, outperforming traditional methods such as JPEG, JPEG2000, Autoencoder-based compression, and conventional CNN-based approaches. These results confirm that the proposed model provides superior reconstruction quality while achieving higher compression efficiency.

Overall, the proposed deep learning framework offers a scalable and practical image compression solution for applications including multimedia storage, cloud computing, wireless communication, medical image archiving, remote sensing, and Internet of Things (IoT)-based imaging systems. Future work will focus on integrating advanced attention mechanisms and Transformer-based architectures to further improve compression performance, reduce computational complexity, and support real-time image compression for next-generation intelligent multimedia applications.

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