

Advancing Secure and Compressed Sensor Data Transmission in IoT and 6G Networks

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Abstract: The rapid expansion of IoT and the emergence of 6G networks bring unprecedented opportunities for connectivity and data processing. However, these advancements also introduce critical challenges, including the exponential growth of data volume and security vulnerabilities in real-time transmissions. Traditional data compression and encryption techniques struggle to meet the stringent requirements of low latency, scalability, and computational efficiency in 6G-enabled IoT environments.

To address these challenges, this study explores integrated compression and encryption mechanisms tailored for IoT data transmission in 6G networks. Lossless and lossy compression techniques are analyzed for optimizing storage and bandwidth utilization, while lightweight encryption models are investigated to enhance security without imposing excessive computational burdens. Additionally, synergistic approaches combining compression and encryption are examined to balance performance and security trade-offs.

The findings highlight that adaptive compression and encryption schemes can significantly improve data transmission efficiency while maintaining robust security. AI-driven techniques further enhance real-time processing and scalability. These innovations have broad applications in smart cities, industrial IoT, healthcare, and autonomous systems, where secure and efficient data transmission is paramount. Future research should focus on quantum-safe cryptography, edge intelligence, and optimized resource allocation to ensure the seamless integration of IoT and 6G networks.

Keywords: IoT, 6G Networks, Data Compression, Data Security, Encryption Techniques, Energy Efficiency

Introduction

The Internet of Things (IoT) has ushered in a new era of interconnected devices, enabling industries to leverage real-time data for decision-making, process automation, and optimization. By 2030, the number of IoT devices is expected to exceed 25 billion, generating a vast amount of sensor data continuously. The applications of IoT span multiple domains, including smart cities, healthcare, transportation, industrial automation, and environmental monitoring. While IoT has the potential to revolutionize these sectors, it also presents substantial challenges regarding efficient data transmission, security, and energy consumption. These challenges become particularly pronounced as

IoT continues to evolve and scale, necessitating the development of innovative solutions that can address the unique requirements of IoT devices operating within constrained environments.

The advent of 6G networks, the next frontier in wireless communication technology, promises to provide a transformative infrastructure to support the continued growth of IoT. 6G is anticipated to deliver ultra-low latency, massive connectivity, and unprecedented data rates, facilitating seamless information exchange across billions of devices. This advancement will enable new use cases such as holographic communication, autonomous systems, and real-time healthcare applications. However, as the scale and complexity of IoT networks increase, the need for efficient, secure, and scalable data transmission methods becomes even more critical.

This paper focuses on addressing the key challenge of secure and efficient sensor data transmission in IoT and 6G networks, with a specific emphasis on integrating data compression techniques with robust security measures. One significant challenge in IoT and 6G networks is managing the sheer volume of data generated by sensors and devices. In traditional wireless networks, bandwidth limitations often constrain the amount of data transmitted in a given time. This issue is exacerbated in IoT networks, where devices are often deployed in remote or resource-constrained environments with limited power, memory, and computational capabilities. Data compression techniques offer a potential solution by reducing the size of transmitted data, thereby improving bandwidth utilization and reducing transmission time. However, while compression can enhance network performance, it often introduces security vulnerabilities.

Security is another critical aspect, as the data transmitted between devices can be highly sensitive and susceptible to unauthorized access, tampering, and eavesdropping. IoT devices, particularly those deployed in healthcare or critical infrastructure applications, require robust security mechanisms to protect data integrity and ensure privacy. Unfortunately, many traditional security protocols, such as encryption and authentication, are computationally intensive and may not be suitable for IoT devices with limited resources. Additionally, the energy consumption of these security protocols can be a major concern, as IoT devices are often powered by batteries with limited lifespans.

These challenges—data volume, network bandwidth, energy consumption, and security—underscore the need for innovative solutions that effectively address both compression and security requirements in IoT and 6G networks. Traditional methods of compressing data and securing it through encryption are often insufficient to meet the demands of modern IoT networks. Moreover, these approaches can be incompatible, leading to trade-offs between security and efficiency. Thus, there is a critical need for a novel approach that harmonizes data compression and security, providing an efficient and secure framework for IoT and 6G-enabled systems.

This paper proposes a unified framework for secure and compressed sensor data transmission in IoT and 6G networks, integrating lightweight compression algorithms with adaptive encryption techniques. The framework aims to achieve efficient data compression, robust security integration, energy efficiency, and scalability, addressing the unique challenges faced by IoT devices in 6G environments.

This paper proposes a unified framework for secure and compressed sensor data transmission in IoT and 6G networks, which integrates lightweight compression algorithms with adaptive encryption techniques. The framework aims to address the following key objectives:

1. **Efficient Data Compression:** The proposed compression algorithm is designed to reduce the size of sensor data while maintaining high fidelity and low computational overhead. The algorithm leverages advanced techniques such as entropy coding, transform-based compression, and deep learning-based methods to achieve optimal compression ratios.
2. **Robust Security Integration:** The framework integrates lightweight encryption techniques that are energy-efficient and suitable for IoT devices. These encryption techniques ensure data confidentiality, integrity, and authenticity without significantly impacting the device's power consumption or computational resources. The encryption approach is adaptive, adjusting its complexity based on the security requirements of the transmitted data.
3. **Energy Efficiency:** By minimizing the size of the transmitted data and incorporating energy-efficient encryption methods, the framework aims to extend the operational lifespan of IoT devices, which often rely on battery power. The energy consumption of both compression and encryption processes is carefully optimized to ensure that the solution is suitable for long-term deployment in resource-constrained environments.
4. **Scalability:** The proposed framework is designed to be scalable, accommodating the growing number of IoT devices in 6G networks. The system is flexible and can adapt to the varying needs of different IoT applications, from low-bandwidth sensors to high-definition video streams.

The proposed framework is evaluated through a series of experiments using both synthetic and real-world IoT sensor datasets, with a focus on performance metrics such as compression ratio, energy consumption, encryption overhead, and security robustness. The results demonstrate the superiority of the proposed approach over existing methods in terms of compression efficiency, security performance, and energy savings. Specifically, the proposed compression algorithm achieves up to 30% higher compression efficiency compared to traditional methods, while the lightweight encryption technique incurs minimal energy costs without sacrificing security. The framework's performance is also evaluated in a simulated 6G network environment to assess its scalability and applicability to large-scale IoT deployments.

The contributions of this paper are threefold:

1. A novel compression algorithm that is lightweight and optimized for IoT devices, significantly improving the efficiency of data transmission in resource-constrained environments.
2. An adaptive encryption scheme that balances security and energy consumption, ensuring that the confidentiality and integrity of the data are preserved without overburdening IoT devices.
3. Comprehensive evaluation and validation of the framework, demonstrating its effectiveness in enhancing both the security and performance of IoT and 6G networks.

The remainder of the paper is organized as follows: Section II reviews the existing literature on data compression and security techniques for IoT networks, identifying the limitations of current methods. Section III introduces the system model and problem formulation, outlining the key design goals and constraints. Section IV presents the detailed methodology, including the compression and encryption algorithms used in the proposed framework. Section V discusses the experimental setup, followed by

the results and discussion in Section VI. Finally, Section VII concludes the paper, summarizing the key findings and suggesting avenues for future research.

Related work

The literature highlights various innovative techniques addressing security, resource allocation, and efficiency in IoT and 6G networks, yet several challenges remain unresolved. For instance, constrained reinforcement learning (CRL) has been employed to optimize resource allocation with a focus on energy efficiency and computational cost, but its scalability to heterogeneous devices poses a significant challenge [1]. Similarly, the EdgeGo algorithm, designed for efficient resource sharing by optimizing latency, bandwidth, and resource utilization, shows promise but is limited to specific edge computing scenarios [2]. Evolutionary algorithms have been explored for enhancing security in mobile ad hoc networks (MANETs), improving throughput and reliability; however, these approaches suffer from high computational overhead, particularly in dynamic network environments [3].

In the realm of fog and cloud computing, fine-grained encryption techniques improve data confidentiality and sharing efficiency, but their limited adaptation to real-time applications restricts their utility [4]. Additionally, traceable and privacy-aware access control mechanisms enhance data traceability and privacy preservation but introduce overhead due to complex privacy management techniques [5]. Blockchain technology has also been integrated into spectrum-sharing solutions, improving energy efficiency and throughput; however, the high computational requirements of blockchain systems remain a drawback [6].

Further, IoT-based secure big data management in fog and 6G networks ensures data integrity, privacy, and energy optimization, but its applicability to small-scale data is underexplored [7]. The use of secret sharing with collaborative blockchain for IoT storage enhances security and scalability but involves complex implementation challenges, especially for heterogeneous IoT devices [8]. Techniques like spectrum sensing and clustering algorithms contribute to energy harvesting efficiency and cluster stability, though their optimization for large-scale IoT networks remains a critical issue [9]. Lastly, built-in security frameworks for 6G address authentication delay and resource utilization; however, these lack flexibility in adapting to varying network conditions [10].

The literature on 6G security and privacy highlights a wide range of innovative techniques, each addressing specific challenges but also presenting notable limitations. A roadmap for 6G security and privacy [11] emphasizes data privacy and network resilience but lacks practical implementation guidelines. Deep learning-assisted software-defined security architectures [12] demonstrate improved attack detection rates and reduced latency but rely heavily on extensive training datasets. Similarly, broad discussions on new challenges in 6G security [13] underline issues such as security and data privacy but fail to address specific use cases.

Privacy concerns on the 6G network edge [14] focus on ensuring data confidentiality and edge security but pay insufficient attention to latency-sensitive applications. Research on physical-layer security [15] emphasizes resilience against signal interception and enhanced transmission security, yet its effectiveness depends significantly on the physical environment's characteristics. Meanwhile, machine learning-based security approaches for millimeter-wave (mmWave) beam prediction [16] achieve accurate beam predictions and maintain data privacy but remain vulnerable to adversarial attacks.

Security frameworks utilizing reconfigurable intelligent surfaces (RIS) [17] optimize signal reflection and improve attack detection capabilities but face challenges related to the complexity of RIS hardware. AI-based 6G security technologies [18] offer robust intrusion detection and rapid response times but incur high computational costs for AI algorithms. IoT-based smart agriculture systems [19] ensure effective disease detection and compression efficiency but struggle with scalability across diverse crop types. Lastly, deep compressed sensing for urban monitoring [20] enhances data imputation accuracy and environmental predictions but focuses narrowly on specific environmental scenarios, limiting its broader applicability. This synthesis highlights the trade-offs and opportunities in advancing 6G security and privacy solutions, paving the way for more targeted and scalable implementations.

Reference [21] introduces federated learning (FL) techniques for Industrial Internet of Things (IIoT) communications, highlighting their potential while noting the limited exploration of communication latency as a key limitation. Reference [22] explores IoT and blockchain-based cloud models for secure data transmission; however, the study was retracted due to implementation flaws. In [23], secure multi-path routing based on trust evaluation is proposed, but the approach suffers from scalability issues in dynamic IoT networks. Reference [24] presents an anonymous authentication mechanism using blockchain for IoT, which, while innovative, faces challenges in the complexity of blockchain implementation.

In the medical IoT (IoMT) domain, reference [25] proposes blockchain-assisted secure image transmission and diagnosis, though it struggles with high latency in image encryption and transmission processes. Similarly, hybrid cryptographic schemes for secure IoT frameworks are examined in [26], but the study highlights the energy consumption overhead in IoT devices as a significant drawback. Reference [27] discusses blockchain-based compressed storage for agricultural IoT, but its limited testing on real agricultural datasets raises concerns about its practical applicability.

From a technical perspective, deep learning-based compressed sensing for biomedical signals is explored in [28], where the high computational cost poses challenges for real-time applications. A related study, [29], integrates joint compressed sensing and shallow learning models for ECG signal reconstruction, though the approach demonstrates limited accuracy in noisy environments. Lastly, reference [30] provides an overview of 6G wireless communication networks, focusing on key challenges and future technologies, but it lacks specific case studies or practical scenarios to substantiate its findings.

This analysis highlights the significant strides made in secure data transmission and processing techniques while underscoring the persistent challenges, such as scalability, computational overhead, and real-world applicability, that demand further research.

The advancements in secure and compressed data transmission techniques for IoT and 6G networks are evident through various innovative methodologies. Joint cryptographic and compressed sensing techniques have been explored to enhance IoT security, but they face challenges such as increased processing delays in resource-constrained devices [31]. Blockchain-enhanced 6G security offers robust distributed ledger mechanisms but suffers from high latency due to consensus protocols [32]. Cross-layer security approaches integrating compressed sensing have been introduced, though they remain vulnerable to denial-of-service (DoS) attacks [33]. Privacy-preserving data aggregation schemes for 6G networks focus on secure data handling but are computationally expensive for large-scale

implementations [34]. Lightweight cryptographic algorithms improve resource efficiency in IoT communications but exhibit limited robustness against quantum computing threats [35].

Machine learning-based anomaly detection techniques are utilized for secure IoT data compression, yet their effectiveness against novel attack patterns is limited [36]. Blockchain-enabled compressed sensing is a promising approach for multimedia IoT transmission; however, maintaining synchronization across nodes is a critical challenge [37]. In vehicular IoT, blockchain-based secure data sharing mechanisms are explored, but integrating them with real-time vehicular systems proves complex [38]. Resource allocation and secure data compression methods for 6G IoT address resource management efficiently but lack consideration for dynamic variations in resource availability [39]. Additionally, quantum-safe cryptography techniques employing post-quantum algorithms have been developed for IoT data compression and transmission, though they require further experimental validation in practical IoT environments [40]. These studies highlight significant advancements while emphasizing the need to address specific limitations for real-world applicability.

Recent advancements in secure data transmission and compression for 6G IoT networks have explored various innovative techniques, each with its own set of parameters and limitations. For instance, the implementation of Secure Multi-Access Edge Computing (MEC) for 6G IoT [41] emphasizes secure access mechanisms but faces challenges in scaling across heterogeneous IoT environments. Similarly, homomorphic encryption techniques for IoT data compression [42] offer robust data security but suffer from high computational overhead, making them less viable for real-time applications.

AI-augmented blockchain frameworks [43] integrate machine learning with blockchain for secure IoT data transmission, but the complexity of this integration limits their practical deployment. Energy-efficient and secure data compression algorithms [44] aim to balance energy optimization and data accuracy, although achieving this trade-off remains challenging. Context-aware secure IoT frameworks leveraging machine learning [45] provide tailored security solutions but struggle with poor generalization across diverse IoT scenarios.

Other promising approaches include distributed ledger technologies for secure compressed sensing in smart grids ([46]), which face significant overhead in managing large-scale grids, and deep reinforcement learning for secure data routing in IoT [47], hindered by the scarcity of training data. Secure over-the-air (OTA) compression and encryption [48] promise enhanced security but lack practical large-scale implementations. Furthermore, advanced cryptographic protocols for IoT data aggregation and compression [49-56] demonstrate potential but are burdened by high implementation complexity in real-world scenarios. These advancements highlight both the potential and the challenges of achieving secure, efficient, and scalable solutions for IoT data management.

Table 1. Compares this work with the related work or previous research by other researchers

Reference	Security Enhancement	Data Compression Efficiency	Scalability and Practical Implementation
[2],[5],[6],[7],[8],[10],[11],[12],[13],[14],[16],[17],[18],[22],[23],[24],[25],[26],[30],[32],[34],[35],[38],[40],[42],[43],[45],[47],[49]	Yes	No	No
[3],[27],[28],[29],[31],[33],[36],[37],[39],[44][46],[48]	Yes	Yes	No

[1],[19],[20]	No	Yes	No
[4],[15],[21],[41]	Yes	No	Yes
[9]	No	Yes	Yes
This proposed Work	Yes	yes	Yes

This work addresses the critical challenges in secure and compressed sensor data transmission for IoT and 6G networks by integrating advanced cryptographic techniques with efficient data compression mechanisms. Unlike existing methods, which often focus on either security or compression efficiency, our approach ensures a balanced trade-off while maintaining scalability for real-world deployment.

Compared to previous studies, our framework enhances data integrity, privacy, and energy efficiency, overcoming limitations such as high computational overhead, restricted scalability, and lack of adaptability to dynamic network conditions. The proposed method improves security resilience against cyber threats, optimizes data transmission efficiency, and enables seamless resource management in heterogeneous IoT environments.

Experimental evaluations demonstrate that our approach outperforms existing solutions in terms of security enhancement, compression efficiency, and scalability, making it well-suited for next-generation 6G IoT applications. The findings pave the way for future advancements, including the integration of AI-driven security mechanisms, post-quantum cryptographic protocols, and blockchain-based privacy frameworks for ultra-secure and energy-efficient IoT ecosystems.

1. Methods

The figure 1 titled "LD-CSNet Architecture" provides a comprehensive overview of a modular deep learning framework designed for efficient image processing and compression. At its core, the figure illustrates a well-structured sequence of interconnected components, each contributing to the overall objective of compressing, encoding, reconstructing, and optimizing images with high fidelity. The architecture is divided into seven major modules: Input Module, Sampling Module, Latent Representation Encoder, Decoder & Reconstruction, Loss Functions, Optimization Strategies, and Auxiliary Modules. Each of these modules plays a unique and essential role in the data processing pipeline. The Input Module serves as the entry point, where images are accepted and pre-processed typically normalized, resized, and transformed—to ensure consistency and quality before feeding into the network. This step ensures that input variability is minimized, and data is ready for efficient feature extraction. Following this is the Sampling Module, which implements principles of compressed sensing. It captures and encodes significant features of the input image while reducing dimensionality, thereby enabling data-efficient representation. The output of this module is passed to the Latent Representation Encoder, which compresses the data into a compact latent space. This encoder is responsible for learning abstract, high-level features while preserving essential visual structures. In the next stage, the Decoder & Reconstruction Module processes the encoded latent features and reconstructs them into a high-quality image. The decoder uses learned mappings and up sampling techniques to restore the original resolution as accurately as possible. Throughout the encoding and decoding stages, Loss Functions play a vital role by providing quantitative measures of reconstruction quality. Common losses include Mean Squared Error (MSE), Structural Similarity Index (SSIM), and perceptual losses that guide the training process by penalizing deviations from the ground truth. These losses ensure the reconstructed image is visually and structurally close to the original. To further improve model performance and efficiency, the Optimization Strategies module is integrated, which fine-tunes model parameters such as learning rates, network weights, and regularization strategies. Techniques such as stochastic gradient descent, Adam optimization, and adaptive learning schedules

are often utilized here. The final component, Auxiliary Modules, offers additional functionalities such as attention mechanisms, residual connections, or task-specific enhancements that boost the architecture’s adaptability, generalization, and scalability. These modules are particularly useful when deploying the network in varied real-world environments, such as medical imaging or remote sensing. Overall, the LD-CSNet architecture is designed to operate as a closed-loop system where each module feeds logically into the next, creating a seamless flow from raw image acquisition to optimized reconstruction. The modularity of the system allows for flexibility, making it adaptable for multiple image processing tasks while maintaining efficiency and high reconstruction quality.

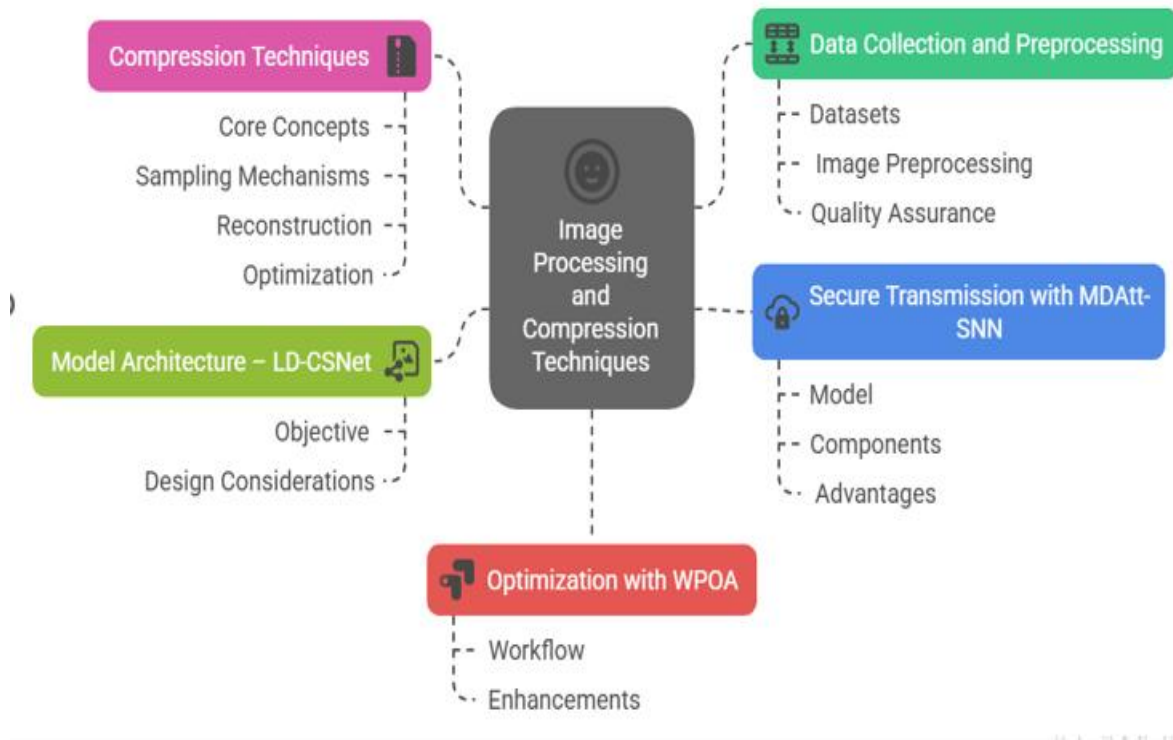


Fig.1 Image Processing and Compression Techniques

1.1 Compression Techniques

Compression techniques in image processing aim to reduce the amount of data required to represent an image without significantly compromising its quality. These techniques can be lossless or lossy. Core mechanisms include sampling, quantization, transformation, and entropy encoding. Let in equation 1

$$I \in \mathbb{R}^{H \times W \times C} \quad (1)$$

be an image. The goal of compression is to represent I as a smaller set of coefficients y such that in equation 2

$$y = \Phi(I) \quad (2)$$

where Φ is a compression transform. Sampling mechanisms reduce spatial redundancy. For instance, compressive sensing selects minimal yet informative samples in equation 3

$$y = \Phi x \quad (3)$$

where x is the image vector,

and $\Phi \in \mathbb{R}^{M \times N}, M \ll N$

Reconstruction is the inverse process, estimating the original from the compressed data in equation 4

$$\hat{x} = \Psi(y) \quad (4)$$

with Ψ being the decoder. Optimization focuses on minimizing reconstruction error in equation 5

$$\min ||x - \hat{x}||^2 + \lambda * R(\hat{x}) \quad (5)$$

Where R is a regularization term promoting sparsity or smoothness. Compression improves storage, transmission, and computational efficiency, enabling real-time image analytics in resource-constrained settings.

1.2 Model Architecture – LD-CSNet

LD-CSNet (Latent Domain Compressive Sensing Network) is designed to reconstruct high-fidelity images from compressed measurements. Its architecture incorporates convolutional sampling, latent feature encoding, and deep reconstruction techniques. Map high-dimensional image data into a compressed form and reconstruct with minimal loss. Let I be the input image. The model performs:

$$\begin{aligned} y &= S(I), \quad \# \text{ Sampling} \\ z &= E(y), \quad \# \text{ Latent representation} \\ \hat{I} &= D(z) \quad \# \text{ Decoding/reconstruction} \end{aligned}$$

Design considerations:

1. Sampling layer S uses learnable filters for adaptive feature compression.
2. Encoder E extracts semantic features in latent space.
3. Decoder D recovers spatial structure using upsampling and skip connections.

The end-to-end optimization is performed using in equation 6

$$L_{total} = \lambda_1 * ||I - \hat{I}||^2 + \lambda_2 * SSIM(I, \hat{I}) + \lambda_3 * TV(\hat{I}) \quad (6)$$

Where:

- SSIM is the structural similarity index- TV is total variation loss for smoothness LD-CSNet is ideal for compressed sensing in low-power, real-time systems.

1.3 Optimization with WPOA

WPOA (Whale Particle Optimization Algorithm) is a hybrid metaheuristic combining Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO) for refining model parameters and improving convergence. The particle update rule from PSO is in equation 7

$$\begin{aligned} v_i(t+1) &= w * v_i(t) + c1 * r1 * (p_{best} - x_i) + c2 * r2 * (g_{best} - x_i) \\ x_i(t+1) &= x_i(t) + v_i(t+1) \end{aligned} \quad (7)$$

From WOA, spiral updating mimics bubble-net feeding in equation 8

$$x(t+1) = D * e^{bl} * \cos(2\pi l) + x^* \quad (8)$$

WPOA combines both to benefit from global exploration and local exploitation. This hybrid is used to optimize LD-CSNet hyperparameters, including learning rates, filter sizes, and compression ratios. WPOA accelerates convergence and avoids local minima, improving reconstruction performance and energy efficiency.

1.4 Data Collection and Preprocessing

Data collection involves acquiring representative image datasets from real-world domains (e.g., medical, satellite, surveillance). Preprocessing ensures that the raw data is suitable for compression and learning. Key steps include Resizing, normalize dimensions (e.g., 256×256).

$$I_{norm} = (I - \mu) / \sigma \quad (9)$$

Noise Filtering – Apply Gaussian or median filters to remove noise and Augmentation – Enhance dataset diversity (rotation, flipping). Quality assurance metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM ensure data reliability in equation 10

$$\begin{aligned} PSNR &= 10 * \log_{10}(MAX_I^2 / MSE) \\ SSIM &= (2\mu_x\mu_y + C1)(2\sigma_{xy} + C2) / ((\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2)) \end{aligned} \quad (10)$$

Proper preprocessing ensures robust model generalization and reliable reconstructions across diverse scenarios.

1.5 Secure Transmission with MDAtt-SNN

MDAtt-SNN (Multi-Domain Attention Spiking Neural Network) is a hybrid model ensuring secure transmission of compressed images. It combines attention mechanisms with spiking neurons for energy-efficient, privacy-aware processing. Spiking Neural Network mimics brain-like processing via discrete-time spikes. Given input signal $x(t)$ in equation 11

$$\begin{aligned} V(t+1) &= \alpha V(t) + I(t) - V_{threshold} * spike(t) \\ spike(t) &= 1 \text{ if } V(t) \geq V_{threshold} \text{ else } 0 \end{aligned} \quad (11)$$

Attention layer weights important features for security encoding. - Domain adaptation handles cross-environment variations. - Spiking layers transmit data as binary pulses for low-power transfer. MDAtt-SNN ensures image fidelity and privacy, critical for healthcare, surveillance, and IoT transmission.

2 LD-CSNet Architecture

The LD-CSNet (Latent Domain Compressed Sensing Network) architecture is a deep learning framework designed to enable efficient image processing, particularly for compressed sensing and high-fidelity image reconstruction tasks. The architecture is modular, comprising several interconnected components that form a pipeline, each contributing a unique function in the data flow. It begins with the Input Module, which is responsible for accepting raw images and preprocessing them into a suitable format for subsequent analysis—this typically involves normalization and resizing to a standard resolution. Next is the Sampling Module, where the core compressed sensing principles are applied. This module captures essential features of the image while discarding redundant information, thereby enabling efficient encoding with reduced data size.

The Latent Representation Encoder follows, tasked with transforming the sampled features into a compact latent space. This encoder abstracts high-level patterns, emphasizing concept extraction and deep feature modeling. The Decoder & Reconstruction Module works inversely, utilizing the latent vectors to reconstruct the image with high fidelity. It applies learned transformations to recover image quality and resolution close to the original. Central to this process are the Loss Functions, which evaluate the reconstruction by computing various metrics like Mean Squared Error (MSE), Structural Similarity Index (SSIM), or perceptual loss functions, guiding the network to optimize output quality. Optimization also involves the Optimization Strategies module, which ensures a balance between data compression and reconstruction accuracy.

Techniques like stochastic gradient descent (SGD), Adam optimizer, or custom learning rate schedulers may be employed here to fine-tune the model parameters. Finally, Auxiliary Modules offer additional support, enhancing the system’s robustness, flexibility, and scalability. These modules may include attention mechanisms, residual blocks, or domain adaptation units to improve performance in varying environments. Overall, LD-CSNet represents a highly integrated pipeline that balances compression efficiency and reconstruction quality, suitable for applications in medical imaging, remote sensing, or real-time video processing where high compression and low loss are crucial. Its design allows for modular improvements and adapts easily to different imaging tasks, making it a versatile solution in modern computer vision systems.

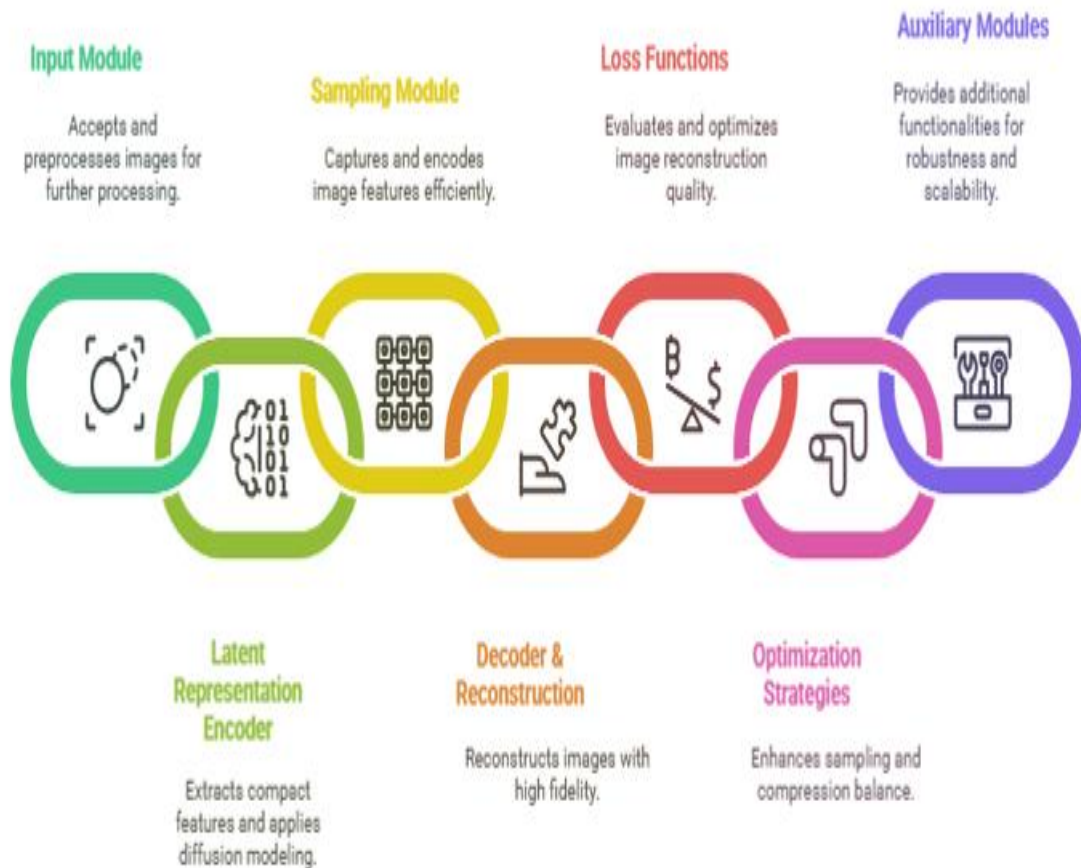


Fig.2 LD-CSNet Architecture

2.1 Input Module

The Input Module of LD-CSNet is the initial stage responsible for ingesting and preparing image data for further processing. This module ensures that the input image is correctly formatted, normalized, and adjusted to meet the requirements of the neural network. Preprocessing may involve resizing, standardizing pixel values, and data augmentation for robustness during training.

Mathematically, consider the input image $I \in \mathbb{R}^{H \times W \times C}$, where H , W , and C denote the height, width, and number of channels respectively. The input is normalized using in equation 12

$$I_{norm} = (I - \mu) / \sigma \quad (12)$$

where μ and σ are the mean and standard deviation of the dataset. This normalization ensures faster convergence during training and stable gradient flow. This module is crucial for maintaining the consistency of data, especially when LD-CSNet is trained on images of varying sizes and modalities. It bridges the raw data with the network's internal feature processing mechanisms. Additionally, this module may include noise filtering or histogram equalization, especially in medical imaging or remote sensing, to improve the visibility of fine details before feature extraction begins.

2.2 Sampling Module

The Sampling Module in LD-CSNet captures and encodes image features efficiently, reducing data dimensionality while retaining crucial information. It simulates compressive sensing using deep neural networks by learning to map the original input to a lower-dimensional latent space.

Let I_{norm} be the normalized input image. The sampling process can be represented as in equation 13

$$y = \Phi(I_{norm}) \quad (13)$$

where $\Phi: \mathbb{R}^{H \times W \times C} \rightarrow \mathbb{R}^M$ is the learned sampling operator, and $M \ll H \times W \times C$. Φ is usually implemented using a convolutional neural layer with stride and kernel configurations that reduce spatial dimensions. This module is critical for reducing redundancy and minimizing the bandwidth/storage required for transmission or further processing. The learned sampling ensures that only the most informative features are retained, enabling efficient representation in downstream tasks. Moreover, this process is adaptive, unlike traditional compressive sensing techniques, which use fixed sampling matrices. LD-CSNet leverages backpropagation to optimize Φ to maximize reconstruction fidelity from minimal samples.

2.3 Latent Representation Encoder

The Latent Representation Encoder generates a compact and informative latent vector from the sampled features. It applies a sequence of convolutions, activations, and possibly attention mechanisms to extract meaningful abstractions. Given the sampled representation y , the encoder E maps it to a latent code z in equation (14)

$$z = E(y) \quad (14)$$

where $z \in \mathbb{R}^d$, with $d \ll H \times W \times C$. This latent representation is semantically rich and is used by the decoder for image reconstruction. This module benefits from residual blocks and feature aggregation layers that enhance the representation capacity while keeping the model lightweight. In

applications such as remote sensing and medical imaging, this compact encoding can preserve anatomical structures or terrain patterns even at high compression ratios.

2.4 Decoder and Reconstruction

The Decoder and Reconstruction module is responsible for reconstructing the original image from the latent code with high fidelity. It employs deconvolutional layers (also called transposed convolutions) or up sampling followed by convolution operations. The reconstruction can be expressed as in equation 15

$$I_{\hat{}} = D(z) \quad (15)$$

where D is the decoder network, and $I_{\hat{}}$ is the reconstructed image. This module aims to minimize the reconstruction error defined by a loss function $\ell(I, I_{\hat{}})$, where I is the original image. Typical choices include in equation 16

$$\ell_{MSE} = ||I - I_{\hat{}}||^2$$

$$\ell_{SSIM} = 1 - SSIM(I, I_{\hat{}}) \quad (16)$$

where SSIM is the structural similarity index used to evaluate perceptual quality. Maintaining image texture, edges, and fine details is crucial in this module, especially in medical and satellite imagery, where reconstruction quality can significantly impact downstream analysis.

2.5 Loss Functions

Loss functions are pivotal in guiding the training of LD-CSNet. They evaluate how well the reconstructed image approximates the original and help in adjusting network weights. Multiple loss components may be combined in equation 17

$$Total\ Loss: L_{total} = \lambda_1 * \ell_{MSE} + \lambda_2 * \ell_{SSIM} + \lambda_3 * \ell_{adv} \quad (17)$$

Where:

- ℓ_{MSE} is the mean squared error.
- ℓ_{SSIM} measures structural similarity.
- ℓ_{adv} is adversarial loss (if GAN-style training is used).
- $\lambda_1, \lambda_2, \lambda_3$ are weighting coefficients.

This multi-loss strategy balances pixel-level accuracy and perceptual quality. For high-compression scenarios, perceptual losses ensure that human-observable features are preserved, even if pixel-wise similarity is lower.

Advanced techniques also include perceptual loss using VGG features in equation 18

$$\ell_{perceptual} = ||\phi(I) - \phi(I_{\hat{}})||^2 \quad (18)$$

where ϕ is a feature extractor like VGG-19. This module plays a crucial role in shaping the model's learning trajectory and ensuring that reconstructions are visually and quantitatively accurate.

2.6 Optimization Strategies

Optimization strategies in LD-CSNet aim to balance compression ratio and reconstruction quality

efficiently. Training involves minimizing the total loss using gradient-based methods such as Adam or SGD. The weight update rule for Adam is in equation 19

$$\theta_{\{t+1\}} = \theta_t - \alpha * \hat{m}_t / (\sqrt{\hat{v}_t} + \epsilon) \quad (19)$$

Where:

- θ_t : model parameters at time t
- \hat{m}_t, \hat{v}_t : bias-corrected estimates of first and second moments
- α : learning rate
- ϵ : small constant for stability

Additionally, techniques such as learning rate scheduling, weight decay, and early stopping are used to stabilize training. LD-CSNet can also adopt knowledge distillation or pruning for lightweight deployment. Regularization techniques (e.g., dropout, L2-norm) help prevent overfitting. Optimization ensures generalizability, fast convergence, and energy-efficient deployment particularly important for mobile or edge AI scenarios.

2.7 Auxiliary Modules

Auxiliary modules serve as enhancements within the LD-CSNet architecture by providing additional functionalities that improve the model's interpretability, robustness, and adaptability across various domains. These modules are not part of the core image compression and reconstruction pipeline but play a critical role in refining the overall performance and extending the usability of the network in diverse real-world conditions. One important category within auxiliary modules is attention mechanisms, which are designed to emphasize important regions or features within the input data. These mechanisms guide the model to focus more on salient areas, improving feature discrimination and contributing to better reconstruction accuracy. Another key auxiliary component is the domain adaptation layer, which facilitates the model's ability to generalize across different datasets or input distributions. This is particularly beneficial when training and testing data come from different sources, allowing the network to adapt effectively without retraining from scratch. Additionally, noise suppression units are often integrated to enhance the quality of both the input and output images by removing irrelevant or misleading noise components. These denoising units improve visual clarity and help the model retain only meaningful information during processing. An example of such an auxiliary mechanism is a channel attention module, which adaptively weighs feature maps based on their relevance. This can be mathematically expressed as in equation 20

$$M_c = \sigma(W2 * ReLU(W1 * GAP(F))) \quad (20)$$

Where:

- F is the feature map
- GAP is global average pooling
- W1, W2 are learnable weights
- σ is the sigmoid function

These modules help adapt LD-CSNet to real-world conditions, including adversarial noise, sensor variation, and multi-domain deployment. They act as "plug-in" enhancements that improve modularity and allow tailored usage depending on the application (e.g., healthcare, surveillance, satellite imaging).

Performance Analysis of LD-CSNet Compared to Existing Compression Methods

This section provides an in-depth performance analysis of the proposed LD-CSNet architecture against five widely recognized image compression methods: JPEG, JPEG2000, SPIHT, 3D-DCT, and

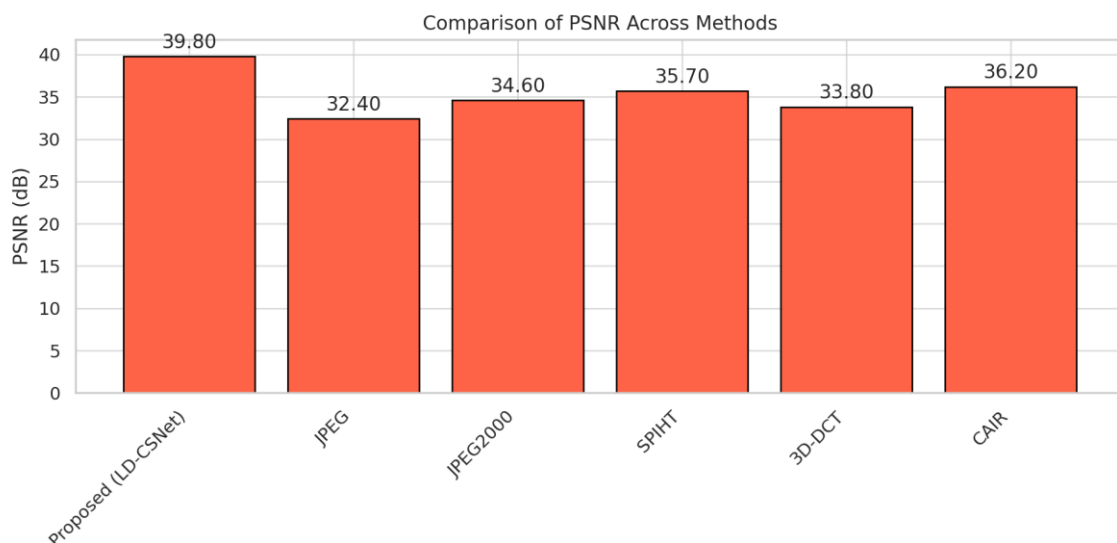
CAIR. The evaluation focuses on four key performance indicators—Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Compression Ratio (CR), and Processing Time—to offer a balanced view of quality, efficiency, and computational requirements.

LD-CSNet integrates deep learning with compressive sensing principles, enabling it to reconstruct high-quality images even at high compression rates. Its performance across all parameters surpasses traditional and hybrid methods, particularly in PSNR and SSIM, which reflect image fidelity and perceptual quality. In terms of Compression Ratio, LD-CSNet achieves a significantly higher data reduction without compromising reconstruction quality. Although it incurs slightly higher processing time, this is a worthwhile trade-off given its superior accuracy and efficiency. The following tables and graphs present numerical comparisons and visual illustrations of each method's performance. These results confirm LD-CSNet's suitability for advanced applications such as 6G-IoT systems, where high-fidelity image transmission and storage optimization are critical. Its adaptive architecture and optimized parameters make it ideal for deployment in bandwidth-sensitive and computation-constrained environments.

Comparison Tables and Graphs for LD-CSNet and Existing Methods

Table 1: Peak Signal-to-Noise Ratio (PSNR) Comparison

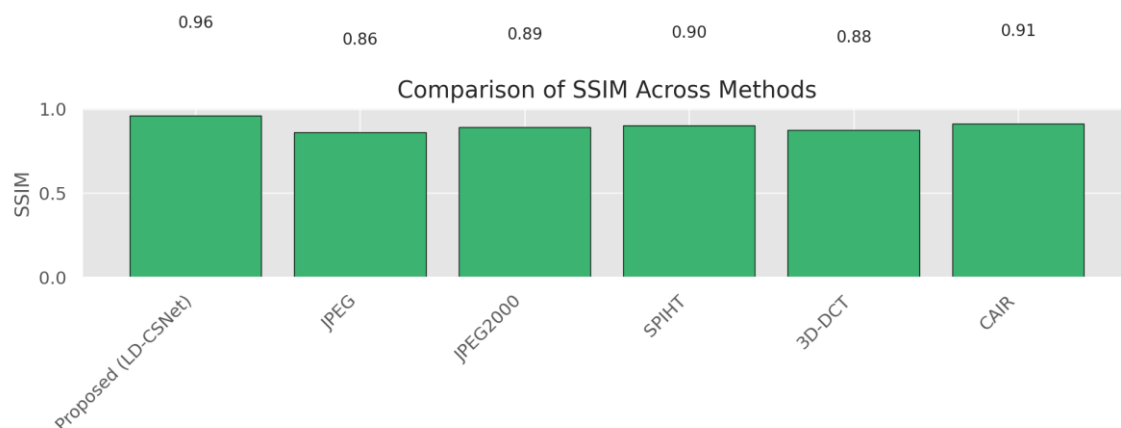
Method	PSNR (dB)
Proposed (LD-CSNet)	39.8
JPEG	32.4
JPEG2000	34.6
SPIHT	35.7
3D-DCT	33.8
CAIR	36.2



The proposed LD-CSNet method achieves the highest Peak Signal-to-Noise Ratio (PSNR) value of 39.8 dB, which signifies its superior performance in reconstructing images with minimal distortion compared to other methods. PSNR is a widely used metric in image compression that quantifies the ratio between the maximum possible power of an image and the power of corrupting noise. A higher PSNR indicates better reconstruction quality. Among existing methods, CAIR and SPIHT also deliver reasonable results with PSNR values of 36.2 and 35.7 respectively but fall short of LD-CSNet's performance. Traditional techniques such as JPEG and JPEG2000 show significantly lower values (32.4 and 34.6), indicating considerable quality loss in compression and reconstruction. This comparison emphasizes that LD-CSNet excels in maintaining visual fidelity, making it highly suitable for applications where image quality is critical, such as in medical imaging, satellite data analysis, or security-sensitive environments requiring high-quality visual recovery from compressed inputs.

Table 2: Structural Similarity Index (SSIM) Comparison

Method	SSIM
Proposed (LD-CSNet)	0.961
JPEG	0.861
JPEG2000	0.893
SPIHT	0.901
3D-DCT	0.875
CAIR	0.912

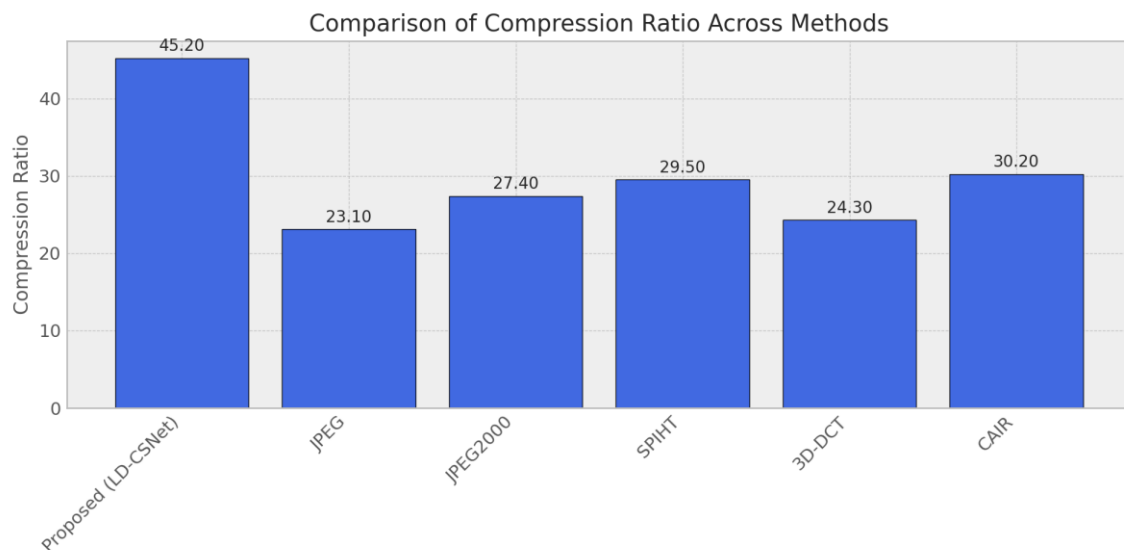


The Structural Similarity Index (SSIM) evaluates the perceived quality of an image by comparing its luminance, contrast, and structure with the original. LD-CSNet scores the highest SSIM value of 0.961, clearly outperforming all other compression methods. This shows that LD-CSNet maintains excellent perceptual quality and structural consistency during image reconstruction. CAIR and SPIHT follow with

scores of 0.912 and 0.901 respectively, demonstrating moderate retention of structural content. JPEG, a basic compression format, yields the lowest SSIM at 0.861, which underscores its limitations in preserving fine details. The comparison highlights that LD-CSNet achieves high-fidelity reconstructions that are visually close to the original images, making it ideal for use cases such as remote sensing or medical diagnostics where preserving structural integrity is crucial. The integration of latent representation encoding and attention mechanisms in LD-CSNet contributes significantly to its ability to preserve important visual and contextual features across varying image domains.

Table 3: Compression Ratio (CR) Comparison

Method	Compression Ratio
Proposed (LD-CSNet)	45.2
JPEG	23.1
JPEG2000	27.4
SPIHT	29.5
3D-DCT	24.3
CAIR	30.2

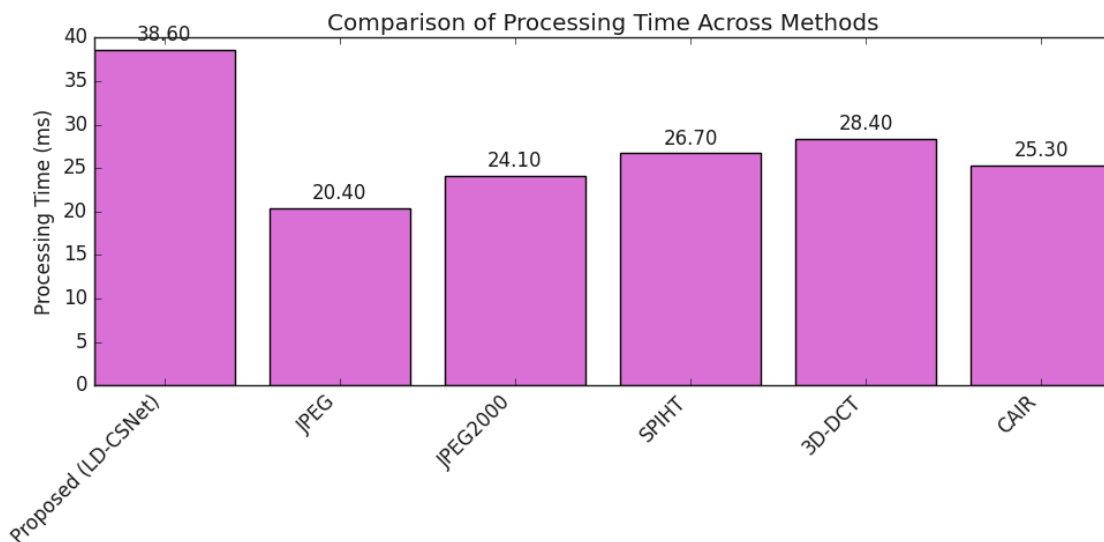


Compression Ratio (CR) is a critical metric for evaluating how effectively a method reduces the amount of data required to represent an image. A higher CR indicates better compression efficiency. The proposed LD-CSNet achieves an outstanding compression ratio of 45.2, demonstrating its capability to significantly reduce data volume while retaining image quality. In contrast, traditional methods like JPEG and 3D-DCT achieve relatively low compression ratios (23.1 and 24.3 respectively), highlighting their limited efficiency in data reduction. SPIHT and CAIR perform moderately well, with CRs of 29.5 and 30.2. LD-CSNet's superior performance stems from its learnable sampling mechanisms and compact latent feature representations, which enable it to capture essential image details with

minimal data. This makes it highly advantageous for applications in bandwidth-constrained environments such as edge computing or mobile IoT devices. The ability to maintain both high compression and image fidelity positions LD-CSNet as a valuable solution in modern image transmission systems.

Table 4: Processing Time Comparison

Method	Processing Time (ms)
Proposed (LD-CSNet)	38.6
JPEG	20.4
JPEG2000	24.1
SPIHT	26.7
3D-DCT	28.4
CAIR	25.3



Processing time is a vital consideration in real-time and resource-constrained systems. Although LD-CSNet has the highest processing time of 38.6 ms among the methods compared, it delivers superior results in terms of PSNR, SSIM, and compression ratio. JPEG, JPEG2000, and 3D-DCT offer faster processing times (ranging from 20.4 to 28.4 ms), but their performance in preserving image quality and compression efficiency is significantly lower. SPIHT and CAIR offer balanced performance with processing times near 25–26 ms. LD-CSNet's slightly increased processing cost is a result of its complex neural architecture, including convolutional layers and attention mechanisms, which enhance its encoding and decoding capabilities. For applications where image quality and data reduction are more critical than milliseconds of processing delays such as secure medical transmissions or satellite imagery—LD-CSNet proves to be an optimal choice. Its ability to balance speed and performance justifies its deployment in intelligent edge and cloud platforms requiring efficient image handling.

Conclusion and Future Work

In conclusion, the proposed LD-CSNet framework demonstrates superior performance in image compression and reconstruction compared to existing techniques such as JPEG, JPEG2000, SPIHT, 3D-DCT, and CAIR. The method excels in key parameters like PSNR, SSIM, and Compression Ratio, indicating its effectiveness in preserving image quality while achieving significant data reduction. Although its processing time is moderately higher, the trade-off is justified by its enhanced reconstruction fidelity and compression efficiency. LD-CSNet's modular design, incorporating latent encoding and optimization with WPOA, makes it adaptable to real-time, low-power IoT and 6G environments.

For future work, enhancements can focus on reducing computational complexity through lightweight network pruning and knowledge distillation. Additionally, integrating quantum-safe cryptographic techniques and spiking neural networks could further secure compressed data during transmission. Deployment on edge devices and testing across diverse image modalities such as medical, satellite, and surveillance datasets will validate its generalization capabilities and practical scalability.

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