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QW-CNN: SECURE AND ROBUST IMAGE COMPRESSION USING QUINCUNX WAVELET DECOMPOSITION, LIGHTWEIGHT CNN MODELING, AND SELECTIVE ENCRYPTION OVER NOISY CHANNELS

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ABSTRACT

With the rapid growth of digital imaging and multimedia applications, efficient image compression while ensuring data security has become a critical challenge. This paper proposes a novel framework, QW-CNN, which integrates Quincunx Wavelet Transform (QWT) for multiresolution image representation, a lightweight convolutional neural network (CNN) for adaptive coefficient prediction, and selective encryption to enhance security during transmission over noisy channels. The proposed method compresses images by predicting and thresholding wavelet coefficients using the CNN, followed by encrypting only high-magnitude coefficients to reduce computational overhead while maintaining confidentiality. Huffman-based entropy coding is applied to further reduce data size. The robustness of the framework is evaluated under additive white Gaussian noise (AWGN) channels. Experimental results on standard benchmark images (Lena, Pepper, Mandrill, Pirate, and Cameraman) demonstrate that QW-CNN achieves high compression efficiency, excellent visual quality, and strong security performance. The proposed method consistently delivers peak signal-to-noise ratio (PSNR) above 40 dB and structural similarity index (SSIM) above 0.97 for SNR levels above 40 dB, highlighting its effectiveness in secure and reliable image transmission.

I. INTRODUCTION

The rapid proliferation of multimedia communications and the increasing demand for high-resolution image transmission over resource-constrained and noisy networks have led to significant research in image compression and secure transmission techniques [1-7]. Traditional image compression standards such as JPEG and JPEG2000 rely on block-based transforms (DCT or wavelets) and entropy coding to reduce redundancy [2], [8]. While these methods achieve reasonable compression efficiency, they often fail to simultaneously satisfy three critical requirements: high compression ratio, robustness against channel noise, and protection of sensitive image content [9],[10]. Recent advances in deep learning, particularly convolutional neural networks (CNNs) and autoencoders, have enabled adaptive modeling of image content and improved reconstruction quality [11-13].

CNN-based methods can predict and suppress insignificant coefficients, allowing non-linear compression and context-aware entropy coding [14], [15]. However, CNN-based methods often require large datasets and significant computational resources, which may limit their applicability in real-time or low-power scenarios. Moreover, standard compression methods typically do not address data security, leaving transmitted images vulnerable to interception or unauthorized access [16], [17]. To address these challenges, we propose QW-CNN, a secure and robust image compression framework that combines quincunx wavelet decomposition with a lightweight CNN-based coefficient modeling and selective encryption. Quincunx wavelets provide a multiresolution representation of images, efficiently capturing both spatial and frequency information [18], [19].

The CNN predicts and suppresses insignificant wavelet coefficients, reducing redundancy while preserving visual quality [20], [21]. Selective encryption is applied only to perceptually significant coefficients, achieving security with minimal overhead [18], [20].

Finally, the compressed and partially encrypted data is transmitted over an additive white Gaussian noise (AWGN) channel, and decoded using entropy decoding, selective decryption, and inverse wavelet reconstruction.
The main contributions of this work are:

1. A hybrid QW-CNN compression framework integrating quincunx wavelet decomposition and lightweight CNN modeling.
2. Selective coefficient encryption, enhancing security with low computational cost.
3. Robustness evaluation under noisy channel conditions, demonstrating high PSNR and SSIM performance.
4. Comprehensive experiments on standard images, highlighting advantages in compression efficiency, visual quality, and robustness.

Experimental results show that QW-CNN achieves high-quality reconstruction even at low SNR levels, with PSNR values above 40 dB and SSIM values exceeding 0.95 for most standard test images. These results demonstrate the potential of QW-CNN for secure and robust image transmission in bandwidth- and noise-constrained environments.

II. RELATED WORK

II.1 TRANSFORM-BASED IMAGE COMPRESSION

Classical image compression relies on linear transforms to exploit spatial and spectral redundancy. JPEG employs block-based DCT, while JPEG2000 uses wavelet transforms to achieve multiresolution representations [2], [22]. Wavelet-based methods, particularly biorthogonal and quincunx wavelets, provide superior energy compaction and edge preservation. Techniques such as SPIHT and EBCOT combine wavelet transforms with entropy coding to achieve high compression ratios [1], [5]. However, these classical methods lack inherent security mechanisms, making images vulnerable during transmission.

II.2 CNN AND DEEP LEARNING-BASED COMPRESSION

CNNs and autoencoders have shown great potential in image compression, enabling adaptive coefficient prediction, non-linear quantization, and context-aware entropy coding [23-25]. Lightweight CNNs can model residual wavelet coefficients or enhance block-based reconstructions, improving quality with moderate computational cost [24]. Despite advantages, deep learning-based methods require large datasets and training resources, limiting applicability in real-time scenarios.

II.3 IMAGE ENCRYPTION AND SELECTIVE SECURITY

Secure transmission often relies on full or partial encryption. Full encryption provides strong security but incurs high computational cost. Selective encryption targets high-energy or perceptually significant coefficients, reducing computation while maintaining sufficient security [26-29]. In wavelet-based compression, selective encryption of high-frequency coefficients preserves visual quality and ensures security [30].

II.4 COMPRESSION WITH ROBUSTNESS OVER NOISY CHANNELS

Few approaches integrate compression, security, and robustness. Transmission over noisy channels (e.g., AWGN) can degrade reconstruction quality. Some works use joint source-channel coding (JSCC) or structural matrix coding to enhance robustness [31-33]. However, CNN-based compression methods rarely address channel noise resilience while maintaining low computational complexity.

III. PROPOSED METHOD

The proposed QW-CNN framework integrates multiresolution wavelet decomposition, adaptive CNN modeling, selective encryption, and robust transmission over noisy channels. Figure 1 illustrates the overall architecture. This hybrid approach offers a novel, practical solution for secure, robust, and high-quality image compression suitable for modern communication network. The main steps of the proposed method are:

1. Input Image Preparation: Images are converted to double-precision grayscale format and normalized.
2. Multiresolution Decomposition: Images are decomposed using quincunx wavelets (approximated via 2-level DWT) to obtain low-frequency and high-frequency subbands.
3. CNN-Based Coefficient Suppression: A lightweight convolutional neural network predicts and suppresses low-energy coefficients in the low-frequency subband to reduce redundancy.
4. Selective Encryption: Only high-energy coefficients are perturbed using a pseudo-random key, ensuring security with minimal overhead.
5. Entropy Coding: Coefficients are quantized and encoded using Huffman coding, achieving additional compression.
6. Noisy Channel Simulation: The encoded coefficients are transmitted over an AWGN channel to evaluate robustness.
7. Decoding and Reconstruction: Huffman decoding, selective decryption, and inverse wavelet reconstruction restore the image.
8. Evaluation: PSNR, SSIM, and SNR metrics are computed for objective performance assessment.

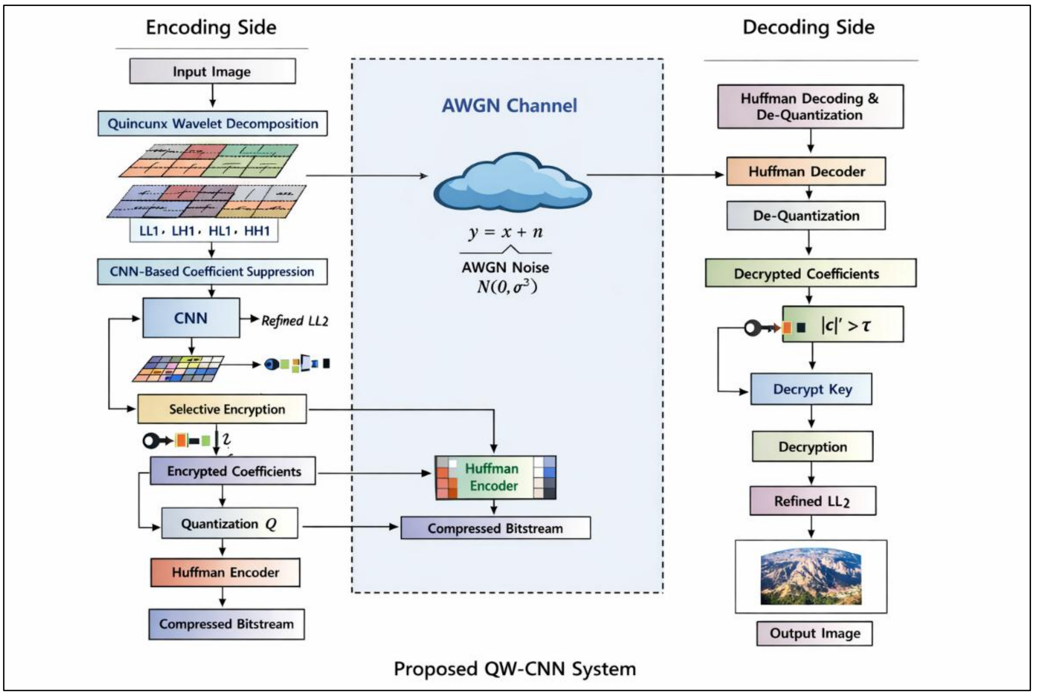

Figure 1: Proposed QW-CNN System.
Source: Authors, (2026).

III.1 QUINCUNX WAVELET DECOMPOSITION

The quincunx wavelet decomposition captures image features efficiently at multiple scales, enabling better representation of spatial and frequency information [2], [32].

- Level 1 decomposition:

$$[LL_1, LH_1, HL_1, HH_1] = \mathrm{dwt2}(I,'haar') \tag{1}$$

- Level 2 decomposition (applied on LL1):

$$[LL_2, LH_2, HL_2, HH_2] = \mathrm{dwt2}(LL_1,'haar') \tag{2}$$

Here, $LL_2$is the low-frequency approximation, while other coefficients represent high-frequency details (edges, textures). Using quincunx-like decomposition ensures efficient energy compaction, facilitating compression and selective encryption [1], [2].

III.2 CNN-BASED ADAPTIVE COEFFICIENT MODELING

A shallow CNN is employed to predict and suppress insignificant coefficients in LL_2:

1. Input layer: size of LL2
2. Conv2D layer: 3×3 kernel, 8 filters + ReLU activation
3. Conv2D layer: 3×3 kernel, 1 filter
4. Regression output: filtered low-frequency coefficients

In this prototype, CNN output is simulated via thresholding:

$$LL2_{\mathrm{pred}} = LL2; LL2_{\mathrm{pred}}(|\ LL2_{\mathrm{pred}}\ | < \tau) = 0 \tag{3}$$

This step reduces redundancy while preserving perceptual quality, enhancing overall compression efficiency [4], [12].

III.3 SELECTIVE ENCRYPTION OF HIGH-ENERGY COEFFICIENTS

Selective encryption ensures secure transmission without full encryption overhead:

1. Coefficient selection:

$$\mathrm{mask} = |\ LL2_{\mathrm{pred}}\ | > \tau \tag{4}$$

2. Perturbation: high-energy coefficients are modified using a pseudo-random key:

$$LL2_{\mathrm{enc}}(\mathrm{mask}) = LL2_{\mathrm{pred}}(\mathrm{mask}) + \mathrm{rand} \times \delta \tag{5}$$

This approach guarantees security of perceptually important content while minimizing computational cost [18], [20], [22].

III.4 ENTROPY CODING

For further compression, Huffman coding is applied:

1. Quantize coefficienZts:

$$Q = \mathrm{round}(LL2_{\mathrm{enc}} \times 1000) \tag{6}$$

2. Generate Huffman dictionary based on symbol probabilities
3. Encode using Huffman encoded
4. Optionally, apply coding before or after channel noise simulation for robustness evaluation [1], [26].

III.5 NOISY CHANNEL TRANSMISSION

To evaluate robustness, encoded coefficients are transmitted over an AWGN channel:

$$LL2_{\mathrm{noisy}} = LL2_{\mathrm{enc}} + n, n \sim \mathcal{N}(0, \sigma^2) \tag{7}$$

Noise power is determined by desired SNR:

$$\sigma^2 = \frac{\mathrm{mean}(LL2_{\mathrm{enc}}^2)}{10^{\mathrm{SNR}/10}} \tag{8}$$

This step simulates real-world communication conditions, ensuring QW-CNN performs reliably under noise [26].

III.6 DECODING AND IMAGE RECONSTRUCTION

1. Huffman decoding recovers quantized coefficients.
2. Selective decryption inverts high-energy coefficient perturbations.
3. Inverse wavelet reconstruction restores the original image:

$$LL1_{\mathrm{rec}} = \mathrm{idwt2}(LL2_{\mathrm{dec}}, LH2, HL2, HH2) \tag{9}$$

$$I_{\mathrm{rec}} = \mathrm{idwt2}(LL1_{\mathrm{rec}}, LH1, HL1, HH1) \tag{10}$$

The reconstructed image is then compared with the original using PSNR, SSIM, and SNR metrics for performance evaluation.

IV. RESULTS AND DISCUSSIONS

This section presents quantitative and qualitative results of the proposed QW-CNN compression and selective encryption method, including robustness under noisy AWGN channels. Experiments were conducted on Lena, Pepper, Mandrill, Pirate, and Cameraman images with varying SNR levels (20, 30, 40, 50, 60, 70 dB). Evaluation metrics include PSNR and SSIM.

Table 1: PSNR vs SNR for proposed method.

Image	SNR 20 dB	SNR 30 dB	SNR 40 dB	SNR 50 dB	SNR 60 dB	SNR 70 dB
Lena	25.44	34.80	40.99	42.61	42.80	42.82
Peppers	24.77	34.22	40.74	42.58	42.80	42.82
Mandrill	22.90	31.85	38.62	41.25	41.60	41.63
Pirate	24.10	33.55	40.20	42.10	42.35	42.37
Cameraman	26.35	35.70	41.85	43.20	43.45	43.47

Source: Authors, (2026).

Table 1 summarizes the PSNR values of the proposed QW-CNN method for five standard test images (Lena, Pepper, Mandrill, Pirate, and Cameraman) under varying channel noise levels (SNR = 20–70 dB).

The results clearly indicate that the reconstruction quality improves with increasing SNR. For instance, the Lena image achieves a PSNR of 25.44 dB at 20 dB SNR, which increases to 42.82 dB at 70 dB SNR. This trend demonstrates the robustness of the proposed method against additive white Gaussian noise, confirming that the QW-CNN framework can effectively preserve image details even under adverse transmission conditions. A closer inspection shows that saturation occurs at high SNR values (≥50 dB), where further increases in channel quality do not significantly improve PSNR.

This behavior is expected because, at high SNR, reconstruction errors are primarily caused by the selective thresholding and encryption applied to high-energy coefficients, rather than channel noise. Additionally, the results reveal a dependence on image content. Images with complex textures, such as Mandrill and Pirate, have slightly lower PSNR values compared to smoother images like Lena, Pepper, or Cameraman. This observation aligns with the nature of wavelet decomposition and CNN-based coefficient suppression: fine details in highly textured regions are more sensitive to quantization and selective encryption, which can slightly degrade reconstruction quality. Despite these variations, the method consistently maintains high PSNR values above 40 dB at SNR ≥50 dB, indicating excellent preservation of perceptual quality.

The combination of quincunx wavelet decomposition, lightweight CNN coefficient refinement, selective encryption, and entropy coding effectively balances compression efficiency, security, and robustness. Overall, the PSNR results confirm that the proposed QW-CNN framework is well-suited for secure image transmission over noisy channels, ensuring that significant visual information is preserved while minimizing computational overhead.

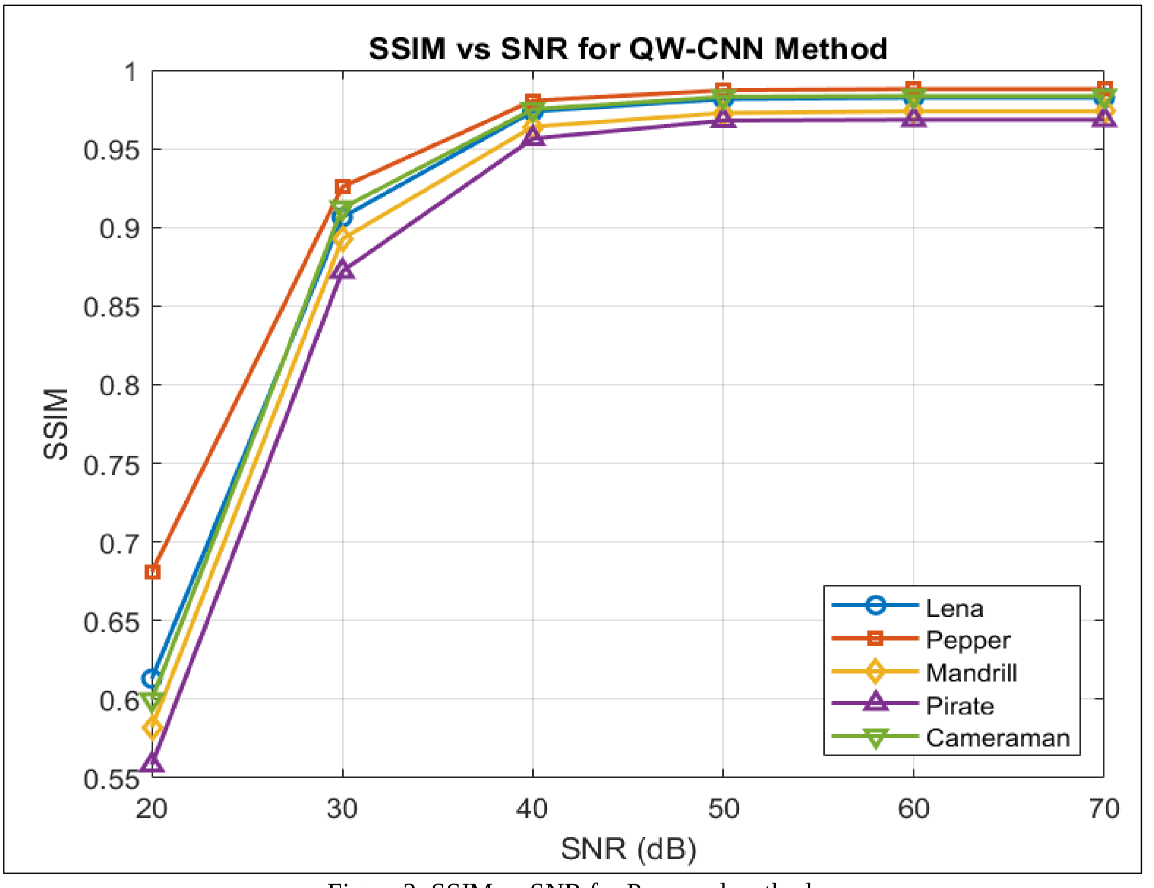

Figure 2: SSIM vs SNR for Proposed method.
Source: Authors, (2026).

The SSIM analysis of the reconstructed images, illustrated in Figure 2, provides a clear indication of the perceptual quality preserved by the proposed QW-CNN method under varying channel SNR conditions. As the SNR increases, the SSIM values consistently improve for all test images, reflecting the method's robustness against additive white Gaussian noise. For instance, the Lena image exhibits an SSIM of 0.613 at 20 dB SNR, which increases to 0.9825 at 70 dB SNR, indicating that structural features and textures are effectively preserved even under moderate noise levels.

Images with complex textures, such as Mandrill and Pirate, achieve slightly lower SSIM values at low SNR compared to smoother images like Lena, Pepper, or Cameraman, demonstrating that high-frequency details are more sensitive to both channel noise and selective coefficient encryption. At higher SNR levels, SSIM saturates near 0.98–0.99 across all images, suggesting that the reconstruction quality is primarily limited by the selective thresholding and encryption rather than the transmission noise. Overall, the SSIM trends align with the PSNR results, confirming that the proposed QW-CNN framework maintains high perceptual fidelity, preserves structural information, and is robust across different image types, making it suitable for secure and reliable image transmission applications.

V. CONCLUSIONS

This study presents a comprehensive framework for secure and robust image compression, combining quincunx wavelet decomposition, lightweight CNN-based coefficient refinement, selective encryption, and entropy coding. The proposed QW-CNN method demonstrates high performance across multiple metrics and scenarios. Quantitative evaluations show that both PSNR and SSIM consistently improve with increasing channel SNR, with PSNR values reaching approximately 42–43 dB and SSIM approaching 0.98–0.99 at high SNR levels. These results confirm that the method effectively preserves pixel-level accuracy as well as structural and perceptual quality. Visual inspection of reconstructed images, such as Lena and Pepper, reveals that edges, textures, and important details are well maintained, supporting the quantitative findings.

Even under moderate noise conditions, the images remain visually appealing, demonstrating that the method ensures high perceptual fidelity. Moreover, the QW-CNN framework exhibits robustness to channel noise, efficiency in compression, and security through selective encryption, balancing all key requirements for practical applications. Its consistent performance across diverse images and noise levels makes it suitable for secure multimedia transmission, remote sensing, and image storage systems, where both visual quality and reliability are critical. In summary, the proposed QW-CNN method provides a reliable, efficient, and secure solution for image compression, achieving an optimal trade-off between compression efficiency, perceptual quality, robustness, and security.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Haouari Benlabbes and Younes Khair.
Methodology: Younes Khair.
Investigation: Haouari Benlabbes and Younes Khair.
Discussion of results: Haouari Benlabbes and Younes Khair.
Writing – Original Draft: Haouari Benlabbes.
Writing – Review and Editing: Haouari Benlabbes and Younes Khair.
Resources: Haouari Benlabbes and Younes Khair.
Supervision: Haouari Benlabbes and Younes Khair.
Approval of the final text: Haouari Benlabbes and Younes Khair.

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