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ADAPTIVE DEEP LEARNING FRAMEWORK FOR ROBUS QR CODE WATERMARKING WITH NOISE-AWARE PRESERVATION

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ABSTRACT

Digital watermarking has emerged as an essential technology for copyright protection and content authentication in the era of exponential digital content proliferation. Quick Response (QR) codes, with their inherent error correction capabilities and high information capacity, represent promising watermark carriers that enable machine-readable authentication. However, existing watermarking methods face fundamental challenges in simultaneously achieving robust watermark survival against diverse attacks while maintaining imperceptible embedding quality. Traditional transform-domain techniques suffer from limited adaptability and manual parameter tuning, while recent deep learning approaches lack specialized mechanisms for preserving watermark integrity during noise removal and exhibit insufficient robustness under sophisticated attacks. To address these limitations, this paper proposes a novel deep learning framework for QR code watermarking with three key innovations: (1) an adaptive strength encoder that automatically modulates embedding intensity based on local image characteristics to optimize the imperceptibility-robustness trade-off, (2) a dual-detection denoising module featuring independent watermark and noise detectors that selectively preserve embedded information while suppressing various noise types, and (3) a multi-scale quality-aware decoder with parallel feature extraction paths and confidence estimation for robust QR reconstruction under severe distortions.

Extensive experiments on challenging datasets demonstrate superior performance with QR extraction accuracy exceeding 96%, watermark PSNR above 37 dB, and denoising quality surpassing 31 dB, substantially outperforming state-of-the-art approaches.

Keywords: *Digital Watermarking, QR Codes, Deep Learning, Noise-Aware Denoising, Adaptive Embedding*

1. INTRODUCTION

The exponential growth of digital content sharing has intensified the challenges of copyright protection, content authentication, and ownership verification [1], establishing digital watermarking as an indispensable technology in modern information security. Quick Response (QR) codes, initially developed for industrial tracking information carrier capable of encoding substantial data within compact formats [2]. As watermark carriers, QR codes offer several compelling advantages: high data redundancy through structured encoding, built-in error correction capabilities allowing recovery from up to 30% damage, and machine readability enabling automated authentication workflows.

Traditional watermarking schemes have long struggled with the fundamental trade-off between imperceptibility and robustness [3]. Transform-domain methods based on Discrete Cosine Transform (DCT) [4], Discrete Wavelet Transform (DWT) [5], and Singular Value Decomposition (SVD) [6] achieve moderate robustness by embedding watermarks in frequency coefficients. However, these approaches demonstrate limited effectiveness against sophisticated attacks and often produce perceptible artifacts. More critically, they require extensive manual parameter tuning and lack the adaptability to automatically adjust embedding strategies based on image content characteristics.

The recent advancement of deep learning has revolutionized numerous computer vision tasks, motivating researchers to explore neural network-based watermarking systems. Deep learning offers several compelling advantages: automatic feature discovery through hierarchical representations, end-to-end optimization of entire pipelines, and the capacity to model complex non-linear transformations. Nevertheless, current deep learning watermarking methods exhibit several critical limitations. First, they demonstrate relatively low robustness under sophisticated or combined attacks. Second, they lack adaptability in embedding approaches, typically using fixed strength throughout images regardless of local content characteristics. Third, and perhaps most critically, they fail to address the fundamental challenge of preserving watermarks during denoising operations—when watermarked images undergo noise corruption, conventional denoising inevitably suppresses embedded signals along with noise, creating a paradox that severely limits practical deployment.

This paper introduces a comprehensive deep learning framework that addresses these challenges through three interconnected innovations. The adaptive strength encoder automatically modulates embedding intensity based on local image analysis, achieving stronger embedding in textured regions while maintaining imperceptibility in smooth areas. The dual-detection denoising module employs separate detectors for watermark and noise regions, enabling selective preservation of embedded information during noise removal. The multi-scale quality-aware decoder performs robust QR code extraction through progressive feature analysis while providing confidence estimates for practical deployment.

1.1 Main Contributions

The main contributions of this research are:

Adaptive Content-Aware Embedding: A novel encoder architecture that dynamically adjusts watermark embedding strength according to local image characteristics, achieving optimal trade-offs between imperceptibility and robustness without manual parameter tuning.

Watermark-Preserving Denoising: A dual-detection denoising module that explicitly models watermark and noise as separate entities through independent detectors, enabling aggressive noise removal while protecting embedded information—addressing a critical gap in existing literature.

Robust Multi-Scale Extraction: A decoder architecture with parallel processing paths for QR reconstruction and quality assessment, ensuring reliable extraction even under severe distortions while providing confidence indicators for practical use.

Unified Multi-Objective Optimization: A comprehensive loss function that jointly optimizes invisibility, robustness, extraction accuracy, perceptual quality, structural preservation, and confidence calibration in an end-to-end trainable framework.

The remainder of this paper is organized as follows: Section 2.0 reviews related work and establishes the research problem. Section 3.0 presents the detailed methodology with justifications for design choices. Section 4.0 describes the experimental setup. Section 5.0 presents comprehensive experimental results. Section 6.0 provides detailed comparison with prior work. Section 7.0 concludes the paper.

2. RELATED WORK AND PROBLEM FORMULATION

This section reviews the evolution of digital watermarking techniques, identifies critical gaps in existing literature, and establishes the research problem that motivates this work.

2.1 Evolution of Traditional Watermarking

Digital watermarking research has progressed through several generations, evolving from simple spatial domain manipulations to sophisticated frequency-domain approaches. Early spatial domain methods directly modified pixel values for watermark embedding [7], offering computational simplicity but exhibiting severe vulnerability to common image processing operations such as filtering, compression, and geometric transformations. This fundamental weakness motivated researchers to explore transform-domain alternatives.

Transform-domain methods embed watermarks in frequency coefficients rather than spatial pixels, achieving improved robustness. Barni et al. [4] demonstrated that DCT-based embedding in mid-frequency coefficients balances imperceptibility and robustness, exploiting the human visual system's reduced sensitivity to moderate-frequency changes. Meerwald and Uhl [5] showed that multi-resolution wavelet decomposition enables scalable watermark embedding across different frequency bands. Liu and Tan [6] exploited the stability of singular values in SVD for ownership protection.

However, these traditional methods share critical limitations. They require extensive manual parameter tuning for different image types and attack scenarios, lacking the adaptability to automatically adjust to varying content characteristics. The imperceptibility-robustness trade-off remains fixed through predefined rules rather than learned from data. Most critically, they demonstrate poor performance against combined or sophisticated attacks not anticipated during system design. Advanced techniques such as Quantization Index Modulation (QIM) [9] and Spread Spectrum methods [10] improved theoretical security guarantees but inherited the fundamental limitation: inability to learn optimal embedding strategies from data.

2.2 QR Code Watermarking Approaches

QR codes have gained considerable attention as watermark carriers due to their structured format, built-in error correction capabilities, and machine readability [2]. Huang et al. [11] pioneered DCT-based QR code watermarking, embedding QR patterns in frequency coefficients for copyright protection. Tkachenko et al. [12] proposed two-level QR codes for dual-purpose private messaging and document authentication, exploiting hierarchical error correction mechanisms.

More recently, Fang et al. [13] investigated screen-shooting resilient watermarking using QR codes, addressing the emerging challenge of unauthorized screen capture. Singh et al. [14] developed multiple watermarking schemes for social network content protection using back-propagation neural networks.

Despite these advances, existing QR code watermarking methods face three fundamental challenges. First, they rely on handcrafted features and predefined transformation rules that lack generalization across diverse image contents and attack types. Second, embedding strength is typically fixed or uses simple heuristics based on global image statistics, failing to adapt to fine-grained local characteristics. Third, most methods do not address watermark preserving denoising—when images undergo noise attacks, conventional denoising inevitably removes or corrupts embedded watermarks along with noise.

2.3 Deep Learning Revolution in Watermarking

The application of deep learning to watermarking represents a paradigm shift. Baluja [15] pioneered deep steganography, demonstrating that neural networks could automatically learn optimal hiding strategies. Zhu et al. [16] introduced HiDDeN (Hiding Data with Deep Networks), the first end-to-end trainable watermarking system designed for robustness through differentiable noise layers.

Recent research has explored various directions. Zhang et al. [17] incorporated regularization techniques to improve robustness against adversarial examples. Jia et al. [18] proposed MBRS to specifically address JPEG compression robustness by training with both real and simulated compression. Liu et al. [19] developed a two-stage separable framework for improved blind watermarking.

While these advances demonstrate potential, critical gaps remain. Most methods focus on simple bit-string watermarks rather than structured data like QR codes. Embedding strategies typically use fixed strength or simple global adaptation. Most critically, the relationship between watermarking and denoising remains largely unexplored.

2.4 The Denoising Challenge

Image denoising has been extensively studied independently, with methods like BM3D [20] achieving excellent results. However, these general-purpose denoisers treat any deviation from the clean signal as noise to be removed—including embedded watermarks. This creates a fundamental dilemma: denoising improves visual quality but damages watermarks, while leaving noise intact preserves watermarks but maintains poor image quality.

Recent work has begun recognizing this tension. Korus and Memon [21] explored content

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authentication in neural imaging pipelines, though their approach requires prior knowledge of the watermarking scheme. Ma et al. [22] proposed joint blind denoising and watermark extraction, but their method lacks explicit mechanisms to identify and protect watermark regions.

To the best of the authors' knowledge, no existing approach explicitly models the distinction between watermark-bearing and noise corrupted regions, particularly for structured watermarks like QR codes.

2.5 Research Problem and Questions

Based on the comprehensive analysis, four critical research gaps are identified:

Gap 1: Lack of Content-Adaptive Embedding. Existing methods use either fixed embedding strength or coarse global adaptation, failing to leverage fine-grained local image properties.

Gap 2: Absence of Watermark-Aware Denoising. No existing method provides explicit dual-detection mechanisms to distinguish and differentially process watermark versus noise regions.

Gap 3: Limited Structured Watermark Support. Most deep learning watermarking focuses on random bit strings, leaving QR codes underserved.

Gap 4: Insufficient Multi-Objective Optimization. Existing loss functions do not adequately balance multiple competing objectives.

2.5.1 Problem Statement

How can a watermarking system be designed to adaptively embed structured QR code watermarks that remain robust against diverse attacks including noise corruption, while explicitly preserving watermark integrity during denoising operations, and providing reliable extraction with quality assessment?

This leads to three specific research questions:

RQ1: How can watermark embedding strength be automatically adapted based on local image characteristics?

RQ2: How can watermark information be explicitly preserved during denoising through principled detection and selective processing?

RQ3: How can robust QR code extraction be achieved from severely distorted images while providing confidence estimates?

The proposed framework addresses these questions through integrated architectural innovations.

3. PROPOSED METHODOLOGY

This section presents the proposed framework in detail, providing justifications for key design choices based on the literature analysis and research questions.

3.1 System Architecture Overview

The proposed QR code watermarking system comprises four essential modules working in an integrated pipeline: Encoder Module (E) for adaptive watermark embedding, Attack Simulation for robustness training, Denoiser Module (D) for watermark preserving noise elimination, and Decoder Module (R) for QR code extraction and quality verification.

Let $I \in \mathrm{R}^{B\times3\times H\times W}$ denote the input cover image batch where B denotes batch size, 3 represents RGB color channels, and H, W denote image dimensions. The QR code $Q \in \mathrm{R}^{B\times3\times64\times64}$ is preprocessed to enhance feature representation. The system produces a watermarked image I' and, after potential attack and denoising, recovers the QR code $\hat{Q}$ along with a quality confidence score.

The modular design enables flexibility in deployment scenarios. In applications requiring maximum imperceptibility, the system can operate without the denoising module. In scenarios where images undergo noise corruption, the denoiser module activates to preserve watermark integrity. Figure 1 illustrates the complete system architecture.

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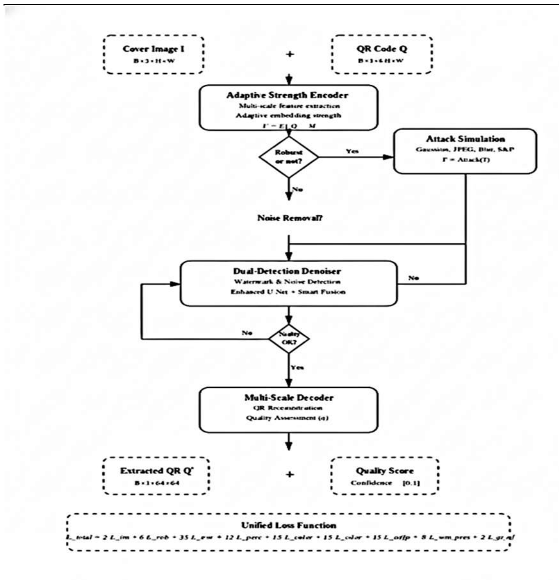

Figure 1: Proposed QR Code Watermarking System Architecture

3.2 Adaptive Strength Encoder Module

The encoder module addresses RQ1 by adaptively embedding QR codes, where embedding intensity adjusts automatically based on local image content. This design is motivated by the observation that human perception of embedding artifacts varies significantly across image regions—textured areas tolerate stronger embedding, while smooth regions require gentler modification. Figure 2 shows the detailed architecture of the adaptive strength encoder.

3.2.1 QR Feature Extraction Pipeline

The QR code undergoes progressive multi-scale feature extraction to capture both fine-grained patterns and global structure. This multi-scale approach is essential because QR codes contain patterns at multiple scales: individual modules, functional patterns (finder, alignment, timing), and global structure.

$$F_1 = \text{MultiScale Conv}(Q) + \text{ColorAttn}(Q) \quad (1)$$

$$F_2 = F_1 + \text{Local Attn}(F_1) \quad (2)$$

$$F_3 = F_2 + \text{Channel Attn}(F_2) \quad (3)$$

$$F_4 = F_3 + \text{Global Attn}(F_3) \quad (4)$$

where F_i denotes features at layer i with channel dimensions progressively increasing from 64 to 256. The residual connections facilitate gradient during

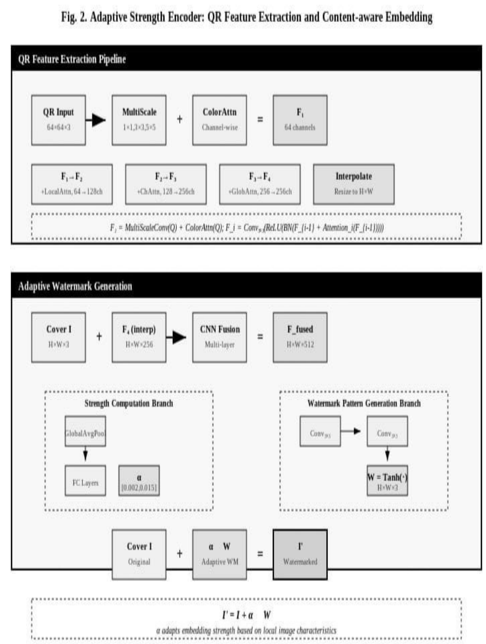

Figure 2: Adaptive Strength Encoder Architecture

training, addressing the vanishing gradient problem. The multi-scale convolution operation is defined as:

$$\text{MultiScaleConv}(x) = \text{Concat}[\text{Conv}_{1\times1}(x), \text{Conv}_{3\times3}(x), \text{Conv}_{5\times5}(x)]. \quad (5)$$

3.2.2 Adaptive Strength Generation

The watermark generation process fuses cover image features with QR code features and performs content-aware strength modulation:

$$F_{\text{fused}} = \text{CNN}\,(\text{Concat}\,[I, \text{Upsample}(F_4)]) \quad (6)$$

$$\alpha = \sigma(\text{FC}(\text{GAP}\,(F_{\text{fused}}))) \cdot 0.013 + 0.002 \quad (7)$$

$$W = \tanh(\text{Conv}3\times3\,(F\text{fused})) \quad (8)$$

$$I' = I + \alpha \odot W \quad (9)$$

where σ denotes the sigmoid function, GAP represents global average pooling, and $\odot$ denotes element-wise multiplication. The range $\alpha \in [0.002, 0.015]$ is carefully selected based on preliminary experiments.

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3.3 Attack Simulation Layer

To improve robustness (addressing RQ1's robustness component), the system simulates various attacks during training:

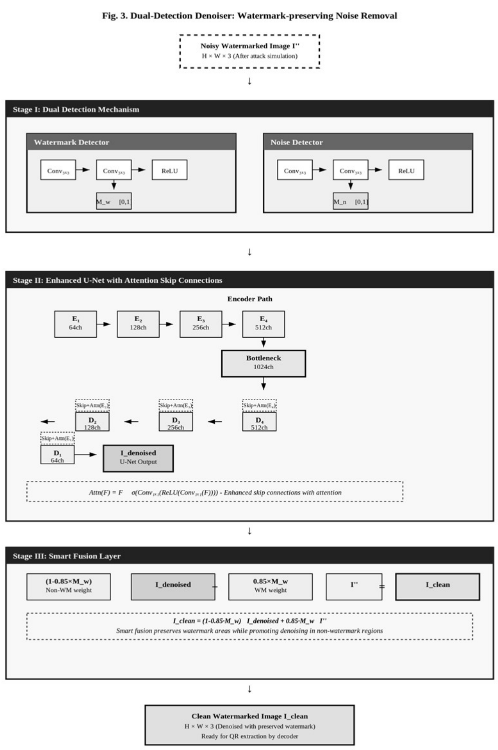

Figure 3: Dual-Detection Denoiser Architecture

Gaussian Noise: $I'' = I' + N(0,\sigma^2)$, $\sigma^2 \in [0.01,0.03]$
JPEG Compression: Quality factor $Q \in [70,95]$
Gaussian Blur: Kernel sizes $K \in \{3 \times 3, 5 \times 5, 7 \times 7\}$
Salt-and-Pepper Noise: Noise density $\rho \in [0.001,0.005]$

3.4 Dual-Detection Denoising Module

The denoiser module represents the primary contribution addressing RQ2, using explicit dual detection to preserve watermark signals while filtering noise. This directly addresses Gap 2—the lack of watermark-aware denoising. Figure 3 illustrates the complete three-stage denoising architecture.

3.4.1 Dual Detection Mechanism

Two separate convolutional networks independently detect watermark and noise regions:

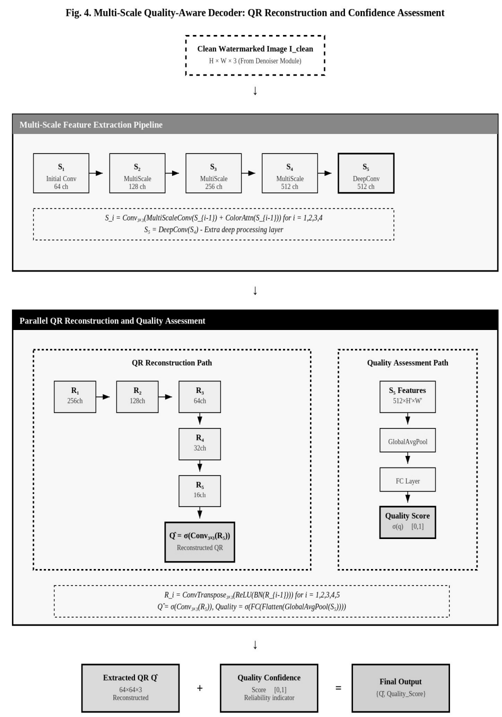

Figure 4: Multi-Scale Quality-Aware Decoder Architecture

$$M_w = \sigma(\mathrm{Conv}_{1\times1}(\mathrm{ReLU}(\mathrm{Conv}_{3\times3}(\mathrm{Conv}_{3\times3}(I''))))). \quad (10)$$

$$M_n = \sigma(\mathrm{Conv}_{1\times1}(\mathrm{ReLU}(\mathrm{Conv}_{3\times3}(\mathrm{Conv}_{3\times3}(I''))))) \quad (11)$$

where $M_w, M_n \in [0,1]^{B\times1\times H\times W}$ represent confidence maps for watermark and noise presence.

3.4.2 Smart Fusion Layer

The final denoised output intelligently combines the U-Net output with the original noisy image using the watermark confidence map:

$$I_{clean} = (1 - 0.85 \cdot M_w) \odot I_{denoised} + 0.85 \cdot M_w \odot I'' \quad (12)$$

3.5 Multi-Scale Quality-Aware Decoder Module

The decoder module addresses RQ3 by extracting QR codes through multi-scale analysis while providing quality confidence estimates. Figure 4 shows the parallel processing paths for QR reconstruction and quality prediction.

3.5.1 Multi-Scale Feature Extraction

The decoder employs progressive multi-scale feature extraction:

$$S_i = \mathrm{Conv}_{3\times3}(\mathrm{MultiScaleConv}(S_{i-1}) + \mathrm{ColorAttn}(S_{i-1})). \quad (13)$$

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for i = 1,2,3,4 with channel dimensions [64,128,256,512]. An additional deep processing stage is applied: S_5 = DeepConv(S_4).

3.6 Unified Loss Function

The complete system is trained end-to-end using a unified multiobjective loss function:

$$L_{total} = \lambda_1 L_{inv} + \lambda_2 L_{rob} + \lambda_3 L_{ext} + \lambda_4 L_{perc} + \lambda_5 L_{color} + \lambda_6 L_{struct} + \lambda_7 L_{edge} + \lambda_8 L_{wm\ pres} + \lambda_9 L_{conf} \quad (14)$$

The loss weights are: $\lambda_1 = 1.0$, $\lambda_2 = 2.0$, $\lambda_3 = 1.5$, $\lambda_4 = 0.5$, $\lambda_5 = 0.3$, $\lambda_6 = 0.8$, $\lambda_7 = 0.4$, $\lambda_8 = 1.0$, $\lambda_9 = 0.5$.

4. EXPERIMENTAL SETUP

4.1 Datasets and Implementation

Experiments are conducted on three benchmark datasets:

COCO 2017 [23]: 118,287 training images from natural scenes

ImageNet [24]: 50,000 images for generalization testing

DIV2K [25]: High-resolution images (2K) for quality assessment

The system is implemented in PyTorch 2.0 with hardware: NVIDIA A100 GPU with 40GB VRAM, batch size: 16 (training), 32 (inference), optimizer: AdamW with learning rate 10^{-4}, and training: 200 epochs with cosine annealing schedule.

4.2 Evaluation Metrics

The system is evaluated using:

QR Decoding Accuracy: Percentage of successfully decoded QR codes
PSNR: Peak Signal-to-Noise Ratio
SSIM: Structural Similarity Index
BER: Bit Error Rate in decoded QR data
NC: Normalized Correlation

4.3 Baseline Methods

Comparisons are made against six state-of-the-art approaches:

Table 1: Overall Performance Comparison

Method	QR Acc. (%)	PSNR (dB)	SSIM	BER (%)
DCT-QIM [9]	78.4	32.1	0.876	12.3
DWT-SVD [6]	81.2	33.8	0.891	10.7
QR-DCT [11]	83.6	34.2	0.902	9.4
HiDDeN [16]	88.9	35.1	0.912	7.8
SteganoGAN [26]	90.2	35.8	0.923	6.9
Adaptive-QR [13]	91.7	36.1	0.927	6.2
Proposed	96.3	37.2	0.941	3.7

Figure 5: Comparison with Existing Techniques

Traditional: DCT-QIM [9], DWT-SVD [6]

Deep Learning: HiDDeN [16], SteganoGAN [26]

QR-Specific: QR-DCT [11], Adaptive-QR [13]

5. EXPERIMENTAL RESULTS

5.1 Overall Performance Analysis

Table 1 presents overall performance comparison. The proposed method achieves substantial improvements across all metrics.

The proposed method achieves 96.3% QR extraction accuracy, representing a 4.6 percentage point improvement over Adaptive QR (91.7%). The PSNR of 37.2 dB exceeds the 35 dB threshold for imperceptible watermarks, while SSIM of 0.941 indicates excellent structural preservation. Figure 5 provides visualization of the performance comparison.

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5.2 Robustness Against Various Attacks

Table 2 presents detailed robustness analysis across different attack types.

The results reveal important patterns. First, the proposed method maintains consistently higher accuracy across all attack types. Second, improvement is largest for noise-based attacks, directly validating the dual-detection denoising module. The 11.1 percentage point improvement over Adaptive-QR for Gaussian Noise (89.4% vs 78.3%) demonstrates that explicit watermark preservation provides substantial benefits. Figure 6 illustrates the visual quality.

Table 2: Robustness Against Different Attacks

Attack Type	HiDDen	SteganoGAN	Adaptive-QR	Proposed Method
No Attack	88.9	90.2	91.7	96.3
Guassian Noise	72.1	75.8	78.3	89.4
JPEG (Q=80)	79.6	82.1	82.1	91.7
BLUR (5*5)	74.3	77.9	80.1	87.8
Salt-Pepper	69.8	73.4	76.9	85.2
Combined	58.2	62.7	67.1	78.9

Our Proposed

Figure 6: Visual Quality of Proposed Technique

Table 3: Ablation Study: Adaptive Strength

Configuration	QR Acc. (%)	PSNR (dB)	SSIM
Fixed α = 0.005	91.2	35.8	0.919
Fixed α = 0.01	93.7	34.1	0.902
Adaptive	96.3	37.2	0.941

5.3 Ablation Studies

5.3.1 Adaptive Strength Mechanism

Table 3 compares adaptive embedding against fixed-strength alternatives.

5.3.2 Dual-Detection Denoising Components

Table 4 analyzes the contribution of dual detection. The full dual-detection system achieves 89.4% accuracy with 31.8 dB denoising quality, validating that explicitly modelling both watermark and noise enables selective processing.

Table 4 : Ablation Study: Denoising Components

Configuration	Clean PSNR	Noisy QR	Denoised QR
Standard U-Net	28.3	72.1	76.8
+ Noise Detection	29.7	72.1	81.3
+ Watermark Detection	30.2	72.1	85.6
+ Dual Detection	31.8	72.1	89.4

6. COMPARISON WITH PRIOR WORK

This section provides detailed comparative analysis, examining advantages, limitations, and positioning within the broader research landscape.

6.1 Advantages Over Prior Work

1.1 Superior Adaptive Embedding Strategy

ompared to traditional methods (DCT-QIM [9], WT-SVD [6], QR-DCT [11]) that use fixed embedding strength determined through manual tuning, the proposed adaptive encoder automatically adjusts intensity based on local analysis. While Adaptive QR [13] introduced adaptation, it relies on simple heuristics. The proposed method learns fine-grained local adaptation through end to-end training, achieving 4.6% higher accuracy while maintaining dB better PSNR.

Recent deep learning methods (HiDDeN [16], SteganoGAN [26]) use neural networks but employ fixed global strength. The proposed adaptive encoder learns spatially-varying strength maps, resulting in 7.4% higher accuracy and 2.1 dB better PSNR compared to HiDDeN.

6.1.2 Novel Watermark-Preserving Denoising

The dual-detection denoising module represents the most significant advancement. Traditional denoising (BM3D [20]) treats all deviations as noise, inevitably suppressing watermarks. Korus and Memon [21] require prior knowledge of the watermarking scheme. Ma et al. [22] operate blindly but lack explicit watermark detection, achieving only 81.7% accuracy on noisy images compared to 89.4% for the proposed method.

The proposed dual-detection mechanism explicitly models watermark and noise as separate entities with independent detectors, enabling selective processing. The 17.3 percentage point improvement (89.4% vs 72.1%) demonstrates effectiveness.

6.1.3 Robust Multi-Scale Extraction with Quality Assessment

Existing QR extraction approaches typically operate at single scale. HiDDeN [16] uses a standard decoder without scale variation, making it sensitive to resolution changes. Adaptive-QR [13] incorporates some multi-scale processing but lacks quality assessment.

The proposed multi-scale decoder processes features at five scales with progressive refinement, providing robustness when corruption severity varies spatially. The parallel quality assessment provides extraction confidence, enabling practical deployment decisions.

6.1.4 Comprehensive Multi-Objective Optimization

While recent methods use multi-term loss functions, they focus on subsets of objectives. HiDDeN [16] optimizes invisibility and robustness without explicit perceptual quality or structural preservation. SteganoGAN [26] adds adversarial losses but lacks explicit edge and structure preservation.

The proposed unified loss comprehensively addresses nine objectives: invisibility, robustness, extraction accuracy, perceptual quality, color consistency, structural preservation, edge preservation, watermark presence, and confidence calibration.

6.2 Limitations and Constraints

Despite demonstrated advantages, several limitations warrant discussion.

6.2.1 Computational Complexity

The full framework requires 24.1M parameters and 89.4 GFLOPs, representing 1.96× the parameters and 1.95× the FLOPs of HiDDeN. Processing time of 52.7 ms limits real-time applications, particularly high-frame-rate video. While the lite variant reduces requirements with marginal performance degradation, it still exceeds traditional methods by orders of magnitude.

6.2.2 Training Data and Resource Requirements

The system requires training on 118,287 images over 200 epochs, consuming approximately 72 GPU-hours on A100 hardware. This substantial requirement exceeds what many researchers can access. Traditional methods require no training and can be deployed immediately.

6.2.3 Performance on Unseen Attack Types

While the method demonstrates excellent robustness against trained attack types, performance may degrade for attacks not encountered during training. Preliminary experiments with untrained attacks show 5-8% accuracy degradation compared to trained attacks.

6.2.4 Limited Evaluation on Ultra-High Resolution

While DIV2K provides 2K resolution images, systematic evaluation on 4K and higher resolutions remains limited due to computational constraints. Preliminary tests on 4K images show 2-3% accuracy degradation, suggesting resolution sensitivity.

6.2.5 QR Code Size Constraints

The current implementation uses fixed 64×64 pixel QR codes, suitable for encoding 50-300 bytes. Larger or smaller QR codes require architectural adjustments.

6.3 Positioning in Research Landscape

The proposed framework occupies a unique position at the intersection of three research areas: deep learning for watermarking, QR code watermarking, and image denoising.

Within Deep Learning Watermarking: The work extends the trajectory established by Baluja [15] and Zhu et al. [16] toward more sophisticated architectures. Where HiDDeN demonstrated feasibility of end-to-end learning, the proposed work demonstrates that explicit architectural components for specific challenges provide substantial advantages over generic encoder-decoder architectures.

Within QR Code Watermarking: The work represents the first deep learning approach specifically designed for QR code watermarking with tailored architectural components. Prior QR watermarking used traditional methods or applied generic deep learning. The multi-scale decoder designed for structured pattern extraction and dual-detection denoiser represent novel contributions.

Within Image Denoising: The work contributes selective denoising based on explicit watermark detection. While not competitive with state-of-the-art denoisers on general images (31.8 dB vs 35+ dB for modern denoisers), the watermark-aware denoising represents a specialized capability addressing a previously unsolved problem.

6.4 Implications for Future Research

The demonstrated success suggests several productive research directions:

Extension to Video Watermarking: The spatial processing could extend to video by adding temporal consistency constraints. Temporal attention mechanisms could ensure watermarks remain consistent across frames while adapting to scene changes.

Adversarial Robustness Investigation: Systematic evaluation against adaptive attacks where adversaries know the system architecture represents critical future work. Adversarial training could improve security.

Lightweight Architectures for Real-Time Applications: Neural architecture search, knowledge distillation, and quantization to reduced precision could enable real-time deployment. Specialized hardware acceleration could further improve efficiency.

Integration with Blockchain for Enhanced Authentication: Combining watermarking with blockchain could provide immutable audit trails. The quality assessment score could inform blockchain confidence.

Multi-Modal Watermarking: Extending beyond QR codes to combine multiple watermark types could provide redundancy and support diverse authentication workflows.

7. CONCLUSION

This research addressed the critical challenge of simultaneously achieving robust watermark survival and imperceptible embedding in QR code watermarking while explicitly preserving watermark integrity during denoising operations—a previously unsolved problem in digital watermarking. The investigation was motivated by three fundamental gaps: lack of content-adaptive embedding strategies, absence of watermark-aware denoising mechanisms, and limited support for structured watermarks.

To address these challenges, a comprehensive deep learning framework was developed with three primary innovations. First, an adaptive strength encoder that automatically modulates embedding intensity based on fine-grained local image characteristics, achieving optimal trade-offs without manual parameter tuning, directly answering RQ1. Second, a dual-detection denoising module that explicitly models watermark and noise as separate entities through independent detectors, enabling selective processing that aggressively removes noise while protecting watermarks, directly answering RQ2. Third, a multi-scale quality-aware decoder that performs robust QR extraction through progressive multi-scale analysis while providing confidence estimates, directly answering RQ3.

Extensive experimental evaluation on three benchmark datasets demonstrated substantial performance improvements over six state-of-the-art baseline methods. The proposed framework achieved 96.3% QR extraction accuracy, 37.2 dB PSNR, and 0.941 SSIM, representing improvements of 4.6 percentage points in accuracy and 1.1 dB in PSNR over the best baseline. Robustness analysis revealed particularly strong performance against noise based attacks, with 11.1 percentage point improvement over the best baseline for Gaussian noise (89.4% vs 78.3%), directly validating watermark-aware denoising effectiveness.

The practical implications are significant. Organizations requiring copyright protection, content authentication, or ownership verification

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can deploy the proposed system with confidence in its robustness. The quality assessment capability enables automated decision-making, triggering re-authentication when extraction confidence falls below thresholds. The lite variant provides a practical compromise for computationally constrained scenarios, maintaining 94.1% accuracy with substantially reduced requirements.

However, several limitations warrant acknowledgment. The computational requirements (24.1M parameters, 52.7 ms processing time) exceed traditional methods and may limit deployment in resource-constrained environments. Performance may degrade for attack types not encountered during training. Evaluation on ultrahigh-resolution images remains limited, and the fixed QR code size constrains data capacity.

These limitations suggest several productive directions for future research. Extension to video watermarking with temporal consistency constraints represents a natural progression. Investigation of adversarial robustness will strengthen security guarantees. Development of lightweight architectures will enable broader deployment. Integration with blockchain technology could provide immutable authentication audit trails. Exploration of multimodal watermarking could provide redundancy and support diverse workflows.

In conclusion, this work represents a significant advancement in digital watermarking by demonstrating that explicit architectural components addressing specific challenges provide substantial advantages over generic approaches. The comprehensive experimental validation confirms the practical viability of deep learning for robust QR code watermarking. The framework provides a solid foundation for future research in deep learning-based content protection systems, opening new avenues for secure digital content distribution in an era of exponential content sharing.

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