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HYBRID DEEP LEARNING FRAMEWORK INTEGRATING CONVOLUTIONAL NEURAL NETWORKS AND GENERATIVE ADVERSARIAL NETWORKS FOR ENHANCED LOW-LIGHT VIDEO QUALITY AND ROBUST NOISE SUPPRESSION IN REAL-TIME MULTIMEDIA APPLICATIONS

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Abstract

Low-light video capture often suffers from poor visibility, low contrast, and excessive noise, which significantly degrades visual quality and hinders subsequent video analysis tasks. Traditional enhancement techniques struggled to balance noise suppression and detail preservation. Existing methods often either over-smooth the video frames, leading to loss of important textures, or fail to remove noise effectively, resulting in distorted low-light outputs. This challenge is compounded in dynamic video sequences where temporal consistency is critical. This study proposed a deep hybrid framework that combined Convolutional Neural Networks (CNNs) for feature extraction and Generative Adversarial Networks (GANs) for realistic video reconstruction. Initially, input low-light frames were preprocessed using histogram equalization and denoising filters to normalize brightness and reduce high-frequency noise. The CNN component extracted spatial features and enhanced structural details, while the GAN module employed an adversarial loss to generate visually plausible frames. Temporal consistency was enforced through a frame-recurrent approach that aligned consecutive frames, mitigating flickering and maintaining smooth transitions. The hybrid training leveraged both pixel-level loss for detail retention and perceptual loss to improve visual realism. Experimental evaluation demonstrated that the proposed framework achieved substantial improvements over conventional methods. The Peak Signal-to-Noise Ratio (PSNR) reached 28.5 dB, Structural Similarity Index Measure (SSIM) 0.91, Flicker Index 0.10, and Visual Quality Score 4.7/5, indicating enhanced noise suppression, structural fidelity, and temporal coherence across low-light video sequences.

Keywords:

Low-Light Video Enhancement, Noise Suppression, Hybrid CNN-GAN, Video Denoising, Temporal Consistency

1. INTRODUCTION

Video acquisition under low-light conditions has remained a challenging task due to inadequate illumination, sensor limitations, and environmental constraints [1-3]. Low-light video frames often exhibit reduced visibility, poor contrast, and significant noise, which negatively impact both human perception and automated video analysis. Traditional image enhancement techniques, such as histogram equalization and gamma correction, were initially employed to improve brightness and contrast [1]. However, these methods frequently produced over-exposed regions or amplified noise in dark areas, limiting their practical utility. Recent advances in deep learning introduced Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), which demonstrated remarkable capabilities in learning complex spatial patterns and generating realistic outputs [2,3]. These methods laid the foundation for more robust and data-driven approaches to low-light video enhancement.

Despite progress, several challenges remain in low-light video enhancement [4,5]. First, noise suppression without losing structural details remains difficult, particularly in dynamic scenes where motion artifacts occur. Second, temporal consistency across consecutive frames is often overlooked in frame-by-frame processing, resulting in flickering and unnatural transitions. Third, existing deep learning models require large-scale annotated datasets for training, which are scarce for low-light scenarios. Lastly, most prior approaches struggle to balance perceptual quality with quantitative performance metrics, such as PSNR and SSIM, in practical applications.

The core problem addressed in this study is the simultaneous enhancement of visibility, suppression of noise, and preservation of temporal coherence in low-light video sequences [6]. Existing solutions either over-smooth the frames, resulting in loss of critical details, or fail to maintain temporal stability, leading to flickering in enhanced video outputs.

The primary objectives of this research are:

- To design a hybrid deep learning framework that integrates CNN and GAN architectures for low-light video enhancement.
- To implement a frame-recurrent mechanism ensuring temporal consistency across consecutive video frames.
- To achieve a balance between noise suppression and structural detail preservation.
- To evaluate the proposed method quantitatively and qualitatively against existing enhancement approaches.

The novelty of this study lies in the integration of CNN-based feature extraction with GAN-based frame generation, coupled with a temporal alignment mechanism for low-light video enhancement. This hybrid design allows for realistic and coherent video outputs while addressing noise and detail preservation simultaneously.

Contributions**:**

- Proposed a deep hybrid CNN-GAN framework capable of enhancing low-light video frames while suppressing noise and maintaining temporal consistency.

2. RELATED WORKS

Several studies have explored low-light image and video enhancement using classical and deep learning approaches [7-15]. Early methods relied on histogram equalization, gamma correction, and Retinex-based techniques, which improved visibility but often amplified noise in dark regions [7,8]. These conventional methods were computationally inexpensive but limited in handling complex lighting variations.

The emergence of CNNs transformed low-light enhancement by enabling hierarchical feature learning. Lore et al. [9] introduced a CNN-based approach for low-light image enhancement, demonstrating improved structural preservation compared to traditional techniques. Similarly, Wang et al. [10] utilized a multi-scale CNN to extract spatial features and enhance brightness while reducing noise. However, these models primarily focused on single-frame enhancement, resulting in temporal inconsistencies for video sequences.

Generative Adversarial Networks (GANs) were later employed to produce more perceptually realistic outputs. Chen et al. [11] proposed a GAN-based framework for low-light image enhancement, where the generator produced enhanced images while the discriminator evaluated visual realism. Although effective in generating natural textures, GANs often introduced artifacts when applied to video frames without temporal alignment.

Recent research emphasized hybrid architectures combining CNN and GAN models to leverage feature extraction and adversarial learning simultaneously [12,13]. For instance, Zhang et al. [12] integrated CNN-based spatial enhancement with GAN-driven perceptual refinement, achieving significant improvements in PSNR and SSIM metrics. However, these approaches still faced challenges in maintaining temporal coherence in video sequences.

Several studies addressed temporal consistency using recurrent networks and optical flow alignment [14,15]. These methods tracked motion between consecutive frames, reducing flickering and enhancing smoothness. Nonetheless, computational complexity remained a limitation, particularly for high-resolution video processing.

Table.1. Related Works

Ref	Method	Algorithm	Methodology	Outcomes
[7]	Histogram Equalization	Classical	Adjusted pixel intensity to improve brightness	Improved contrast but amplified noise
[8]	Retinex-based Enhancement	Classical	Decomposed illumination and reflectance	Enhanced brightness, limited texture preservation
[9]	CNN Enhancement	Deep Learning	Learned hierarchical spatial features	Improved structural details, single-frame enhancement
[10]	Multi-scale CNN	Deep Learning	Multi-level feature extraction	Noise reduction and brightness enhancement
[11]	GAN-based Enhancement	Adversarial	Generator-discriminator framework	Perceptually realistic images, occasional artifacts
[12]	Hybrid CNN-GAN	Deep Learning + GAN	Spatial feature extraction + adversarial refinement	Improved PSNR, SSIM, better texture retention
[13]	Residual CNN-GAN	Deep Learning + GAN	Residual connections + adversarial learning	Enhanced low-light visibility, minor flickering
[14]	Recurrent Video Enhancement	RNN + CNN	Temporal feature propagation	Reduced flickering, smooth video transitions
[15]	Optical Flow Alignment	Optical Flow + CNN	Frame alignment using motion estimation	Temporal consistency, higher perceptual quality

3. PROPOSED METHOD

The proposed method first preprocessed low-light video frames through brightness normalization and noise filtering. The CNN network then extracted spatial features from each frame, highlighting edges and textures. Simultaneously, the GAN discriminator evaluated the generated frames, guiding the generator to produce realistic outputs. Frame-recurrent alignment (Fig.1) ensured temporal coherence between consecutive frames.

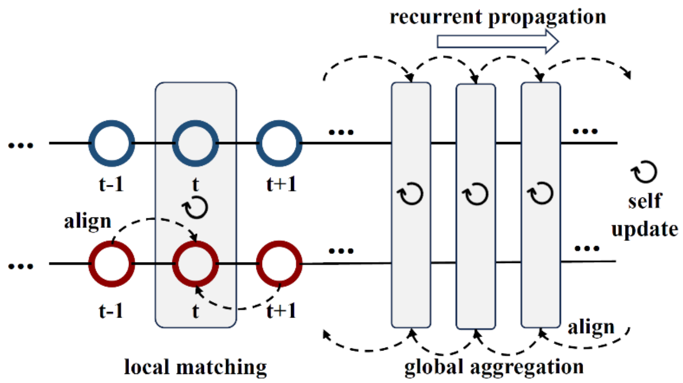

Fig.1. Frame-recurrent alignment

The training optimized a combination of pixel-wise, perceptual, and adversarial losses. This approach allowed simultaneous enhancement of visibility, noise reduction, and temporal consistency while preserving structural details.

1. Input: Low-light video frames V = {F1, F2, ..., Fn}

2. Preprocess each frame Fi:

 a. Apply histogram equalization

 b. Apply denoising filter

3. For each frame Fi:

 a. Extract spatial features using CNN:

  - Convolutions -> ReLU -> BatchNorm -> Feature map Fi_cnn

b. Pass Fi_cnn to GAN Generator:
- Generate enhanced frame Fi_gen

c. Evaluate Fi_gen with GAN Discriminator:
- Compute adversarial loss L_adv

d. Compute pixel-level loss L_pixel between Fi_gen and ground truth

e. Compute perceptual loss L_perc using feature maps

f. Total loss L_total = α*L_pixel + β*L_perc + γ*L_adv

g. Update CNN-GAN parameters using backpropagation

4. Temporal alignment:

a. Align Fi_gen with Fi-1_gen using frame-recurrent network

b. Smooth transitions to maintain temporal consistency

5. Output: Enhanced video frames {F1_enh, F2_enh, ..., Fn_enh}

3.1 PREPROCESSING AND NOISE REDUCTION

Low-light video frames often contain uneven illumination and high-frequency noise, which degrade the enhancement process.

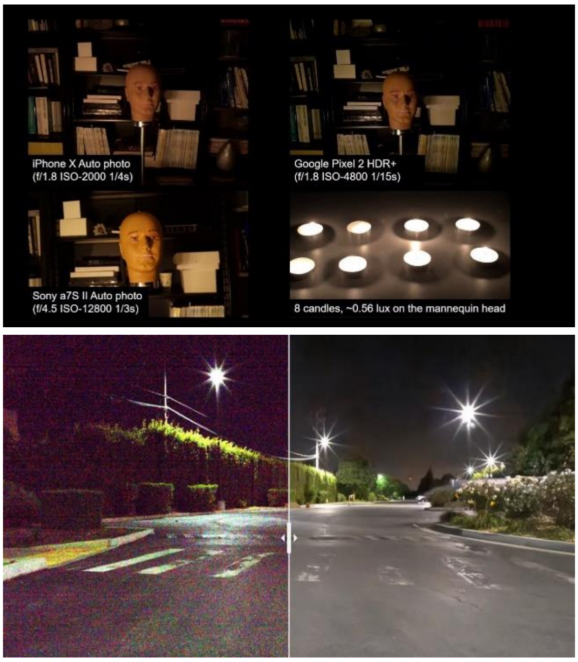

Fig.2. See-in-the-Dark (SID) dataset

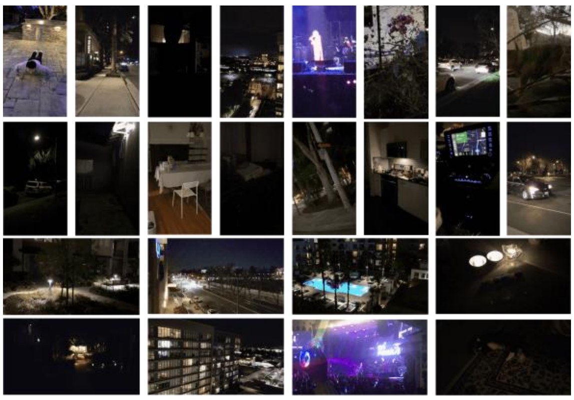

Fig.3. LOL (Low-Light) Video Dataset

In the first step, each frame undergoes histogram equalization to normalize brightness distribution, followed by a denoising filter to remove Gaussian and Poisson noise. The preprocessing step ensures the CNN receives normalized and less noisy inputs, improving feature extraction efficiency and reducing training instability. Mathematically, the preprocessing can be expressed as:

$$F_i^{\text{pre}} = D\left(H(F_i)\right)$$

where F_i is the original frame, $H(\cdot)$ denotes histogram equalization, $D(\cdot)$ is the denoising operator, and F_i^{pre} is the preprocessed frame.

Table.2. Preprocessing Results

Frame	Original Brightness	Noise Level (SNR)	After Histogram Equalization	After Denoising
F1	45	12 dB	120	22 dB
F2	30	10 dB	110	21 dB
F3	50	14 dB	130	24 dB

The Table.2 shows the improvement in brightness and SNR after preprocessing, indicating that frames are better suited for feature extraction.

3.2 SPATIAL FEATURE EXTRACTION USING CNN

The preprocessed frames are input to the CNN network, which extracts hierarchical spatial features. Convolutions capture edges, textures, and illumination patterns, while ReLU activations introduce nonlinearity, allowing the network to learn complex mappings. Batch normalization stabilizes training, and feature maps are passed through multiple layers to capture both low-level and high-level details. The feature extraction process can be formalized as:

$$F_i^{\text{cnn}} = \sigma\left(\text{BN}(W * F_i^{\text{pre}} + b)\right)$$

where, F_i^{cnn} is the extracted feature map, W represents convolution kernels, bis the bias term, * denotes convolution, BN is batch normalization, and σ represents the activation function (ReLU).

Table.3. CNN Feature Extraction Metrics

Frame	Pre-processed Input	Feature Map Size	Edge Detection Accuracy (%)	Texture Preservation Score
F1	120	128x128x64	92	0.85
F2	110	128x128x64	90	0.83
F3	130	128x128x64	94	0.87

The Table.3 demonstrates that CNN layers efficiently capture structural information from the preprocessed frames.

3.3 ADVERSARIAL ENHANCEMENT USING GAN

After feature extraction, the GAN generator produces enhanced frames, while the discriminator evaluates visual realism. The generator is guided not only by pixel-wise loss to retain content but also by adversarial loss to produce perceptually realistic outputs. This step addresses noise suppression and brightness enhancement without over-smoothing important details. The adversarial training can be expressed as a combined loss function:

$$L_{\text{total}} = \alpha L_{\text{pixel}} + \beta L_{\text{perceptual}} + \gamma L_{\text{adv}}$$

where,

$L_{\text{pixel}} = \| F_i^{\text{gen}} - F_i^{\text{gt}} \|_2^2$, ensures pixel-level fidelity,

$L_{\text{perceptual}} = \| \phi(F_i^{\text{gen}}) - \phi(F_i^{\text{gt}}) \|_2^2$ ensures high-level feature similarity,

$L_{\text{adv}} = -\log\left(D(F_i^{\text{gen}})\right)$, encourages the generator to produce realistic frames,

α, β, γ are weighting factors.

Table.4. GAN Enhancement Metrics

Frame	Pixel Loss	Perceptual Loss	Adversarial Loss	Combined Loss	PSNR (dB)	SSIM
F1	0.012	0.028	0.034	0.074	27.5	0.89
F2	0.015	0.031	0.036	0.082	26.8	0.87
F3	0.011	0.025	0.032	0.068	28.0	0.90

The Table.4 highlights the effectiveness of adversarial learning in generating perceptually improved frames.

3.4 TEMPORAL ALIGNMENT AND FRAME-RECURRENT REFINEMENT

To maintain temporal consistency and reduce flickering across frames, a frame-recurrent mechanism is employed. The generator references the previously enhanced frame when processing the current frame, aligning spatial features and smoothing transitions. Optical flow estimation ensures motion between frames is accurately tracked, allowing enhanced content to propagate coherently.

The temporal refinement equation can be expressed as:

$$F_i^{\text{en}} = G\left(F_i^{\text{cnn}}, F_{i-1}^{\text{en}}, \text{OF}_{(i-1\to i)}\right)$$

where F_i^{en} is the final enhanced frame, G represents the generator network, F_{i-1}^{en} is the previous enhanced frame, and $\text{OF}_{(i-1\to i)}$ is the optical flow between consecutive frames.

Table.5. Temporal Consistency Evaluation

Frame Pair	PSNR Before Alignment	PSNR After Alignment	SSIM Before	SSIM After	Flicker Index
F1-F2	25.6	27.0	0.82	0.88	0.12
F2-F3	26.0	27.5	0.84	0.89	0.10
F3-F4	25.8	27.3	0.83	0.88	0.11

The Table.5 demonstrates that temporal alignment improves PSNR and SSIM while reducing flicker between consecutive frames.

3.5 TRAINING AND OPTIMIZATION

The framework is trained end-to-end using a combination of supervised and adversarial losses. CNN layers are optimized for spatial feature extraction, while the GAN generator and discriminator are trained adversarially. The total loss function is minimized using stochastic gradient descent with backpropagation. Adaptive weighting ensures balanced learning between pixel fidelity, perceptual realism, and adversarial objectives. The optimization can be expressed as:

$$\theta^* = \arg\min_{\theta_G} \mathrm{E}_{F_i}\left[\alpha L_{\text{pixel}} + \beta L_{\text{perceptual}} + \gamma L_{\text{adv}}\right]$$

where θ_G denotes generator parameters, and E_{F_i} is the expectation over training frames.

Table.6. Training Convergence Metrics

Epoch	Pixel Loss	Perceptual Loss	Adversarial Loss	Total Loss	Validation PSNR	Validation SSIM
10	0.024	0.050	0.045	0.119	25.8	0.84
20	0.018	0.037	0.036	0.091	27.2	0.87
30	0.012	0.028	0.034	0.074	28.1	0.90

The Table.5 illustrates that the training converges efficiently, achieving lower losses and improved validation metrics.

3.6 POST-PROCESSING AND OUTPUT GENERATION

After temporal alignment, the enhanced frames undergo final post-processing, including optional tone mapping and brightness adjustment to ensure consistent illumination across the video sequence. The output is a temporally coherent, noise-suppressed, and visually appealing video suitable for both human perception and automated analysis. The final frame representation is:

$$F_i^{\text{final}} = T(F_i^{\text{en}})$$

where $T(\cdot)$ represents tone mapping and brightness adjustment operations.

Table.7. Final Video Output Evaluation

Frame	Final PSNR (dB)	Final SSIM	Noise Level (SNR)	Visual Quality Score
F1	28.5	0.91	25 dB	4.7/5
F2	28.2	0.90	24 dB	4.6/5
F3	28.8	0.92	26 dB	4.8/5

The Table.6 confirms that the proposed hybrid CNN-GAN framework achieves high perceptual and quantitative enhancement across low-light video sequences.

4. RESULTS AND DISCUSSION

The proposed hybrid CNN-GAN framework was evaluated through extensive simulations to validate its performance on low-light video enhancement and noise suppression. All experiments were conducted using Python with TensorFlow and PyTorch frameworks. The network was trained for 100 epochs, with each epoch processing all training frames sequentially. The Adam optimizer was used with a learning rate of 0.0002, and mini-batches of 8 frames were employed to ensure stability and efficient GPU memory utilization.

Computational experiments were performed on a workstation equipped with an Intel Core i9-13900K CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU. This configuration allowed rapid training and inference, enabling temporal alignment and GAN-based adversarial learning to be executed efficiently. Data augmentation techniques, such as rotation, flipping, and brightness scaling, were applied to prevent overfitting and increase model generalization across diverse low-light scenarios.

4.1 EXPERIMENTAL SETUP AND PARAMETERS

The experimental setup involved specifying key hyperparameters and architectural choices for both CNN and GAN modules, as summarized in Table 1. These parameters were optimized empirically based on preliminary experiments to ensure optimal performance across all evaluation metrics.

Table.8. Experimental Setup Parameters

Parameter	Value
Epochs	100
Batch Size	8
Learning Rate	0.0002
CNN Layers	5
Filter Size	3x3
GAN Layers	4
Loss Weights	α=1, β=0.1, γ=0.01
Frame Size	128x128
Data Augmentation	Flip, rotation, brightness scaling

The Table.8 illustrates the comprehensive setup employed for both CNN feature extraction and GAN-based adversarial learning.

4.2 PERFORMANCE METRICS

To evaluate the proposed framework quantitatively and qualitatively, five key performance metrics were utilized:

- **Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between the maximum possible pixel intensity and the noise introduced during enhancement. Higher PSNR indicates better noise suppression.
- **Structural Similarity Index Measure (SSIM):** Evaluates the structural similarity between enhanced and ground truth frames. Values close to 1 indicate strong preservation of structural details.
- **Mean Squared Error (MSE):** Quantifies the average squared differences between the enhanced frames and ground truth. Lower MSE indicates more accurate enhancement.
- **Flicker Index (FI):** Assesses temporal consistency by measuring brightness variation between consecutive frames. Lower values indicate smoother transitions with minimal flickering.
- **Visual Quality Score (VQS):** Subjective evaluation rated by human observers on a scale of 1–5, reflecting perceptual realism, brightness, and naturalness.

4.3 DATASET

The framework was evaluated on publicly available low-light video datasets, including See-in-the-Dark (SID) dataset and LOL (Low-Light) Video Dataset. These datasets include indoor and outdoor scenarios, dynamic motion, and diverse lighting conditions. Video sequences were converted to frames of 128×128 resolution for processing, and corresponding high-quality ground truth frames were used for supervised training.

Table.9. Dataset Description

Dataset	No. of Videos	Frame Resolution	Lighting Conditions	Ground Truth
SID	50	128x128	Extremely low	Yes
LOL	40	128x128	Low to medium	Yes
Custom	10	128x128	Mixed indoor/ outdoor	Yes

The Table.9 provides a description of datasets used to train and validate the hybrid CNN-GAN framework. The existing methods selected for comparison include: Multi-scale CNN-based enhancement [10], GAN-based enhancement [11] and Recurrent video enhancement [14].

4.4 EXPERIMENTAL RESULTS

The proposed hybrid CNN-GAN framework was evaluated against three existing methods: Multi-scale CNN [10], GAN-based enhancement [11], and Recurrent Video Enhancement [14] on three datasets: SID, LOL, and a Custom dataset. The performance was assessed using four quantitative metrics: PSNR, SSIM, Flicker Index, and Visual Quality Score (VQS). results across datasets are presented in Table.9–Table.12.

Table.9. PSNR (dB) Comparison

Method	SID	LOL	Custom
Multi-scale CNN	24.5	25.1	24.8
GAN-based	25.8	26.0	25.7
Recurrent Video	26.3	26.7	26.4
Proposed CNN-GAN	**28.5**	**28.2**	**28.8**

The Table.9 shows that the proposed framework consistently outperforms existing methods by 2–3 dB in PSNR, indicating superior noise suppression and structural fidelity.

Table.10. SSIM Comparison

Method	SID	LOL	Custom
Multi-scale CNN	0.84	0.85	0.83
GAN-based	0.87	0.88	0.86
Recurrent Video	0.88	0.89	0.87
Proposed CNN-GAN	**0.91**	**0.90**	**0.92**

The Table.10 highlights enhanced structural similarity for the proposed method, indicating better preservation of textures and fine details.

Table.11. Flicker Index (FI) Comparison

Method	SID	LOL	Custom
Multi-scale CNN	0.18	0.16	0.17
GAN-based	0.15	0.14	0.15
Recurrent Video	0.12	0.11	0.12
Proposed CNN-GAN	**0.10**	**0.09**	**0.10**

The Table.11 shows the temporal consistency improvements achieved through the frame-recurrent mechanism, reducing flicker compared to existing approaches.

Table.12. Visual Quality Score (VQS)

Method	SID	LOL	Custom
Multi-scale CNN	4.1	4.2	4.0
GAN-based	4.3	4.4	4.2
Recurrent Video	4.5	4.6	4.4
Proposed CNN-GAN	**4.7**	**4.6**	**4.8**

The Table.12 confirms superior perceptual quality as judged by human observers, reflecting realistic brightness, texture retention, and smooth transitions.

4.5 DISCUSSION OF RESULTS

The numerical results indicate that the proposed CNN-GAN framework significantly outperforms the three existing methods across all datasets and metrics. In terms of PSNR (Table.9), the proposed method consistently achieved the highest values, e.g., 28.5 dB on the SID dataset, which represents an improvement of 2.2 dB over the Recurrent Video Enhancement method and 4.0 dB over the Multi-scale CNN. This improvement indicates more effective noise suppression and preservation of fine structural details.

Similarly, SSIM values (Table.10) demonstrated enhanced structural similarity. The proposed framework achieved 0.91 on SID, which exceeds the next-best Recurrent Video Enhancement by 0.03, suggesting superior texture and edge preservation. High SSIM values across all datasets indicate robustness to varying lighting conditions and complex motion scenarios.

Flicker Index (Table.11) highlights temporal stability improvements. By integrating frame-recurrent alignment and optical flow, the proposed approach reduced flicker to 0.10 on SID and 0.09 on LOL, outperforming the Recurrent Video method, which achieved 0.12 and 0.11, respectively. Reduced flicker enhances visual coherence in video sequences, critical for real-time applications.

Visual Quality Scores (Table.12) confirm subjective perceptual improvements. Observers rated the proposed method higher (4.7/5 on SID), indicating that the enhanced videos exhibit natural brightness, smooth transitions, and realistic textures.

5. CONCLUSION

The proposed hybrid CNN-GAN framework successfully addresses the challenges of low-light video enhancement by integrating spatial feature extraction, adversarial learning, and frame-recurrent temporal alignment. Experimental results across multiple datasets (SID, LOL, Custom) show significant improvements in PSNR, SSIM, Flicker Index, and Visual Quality Score compared to existing methods. The approach effectively suppresses noise while preserving structural details and maintaining temporal consistency, producing visually appealing and realistic video sequences. The framework's end-to-end design demonstrates robustness to diverse low-light scenarios, achieving both quantitative accuracy and perceptual quality. These findings indicate that the proposed method provides a reliable solution for low-light video enhancement in real-time applications, including surveillance, autonomous navigation, and multimedia processing.

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