Modern methods of image quality enhancement in intrascopic medical imaging: comparative analysis and development trends

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ABSTRACT

This article presents a systematic review of modern methods for enhancing image quality in intrascopic diagnostic systems. It discusses the technical aspects of intrascopy, classifies image enhancement algorithms, and analyzes the role of artificial intelligence and deep learning. A comparative analysis of traditional and AI-based methods is provided, along with an outlook on emerging technologies.

Keywords: intrascopy, image processing, quality improvement, deep learning, neural networks, CLAHE, BM3D

1. INTRODUCTION

In modern clinical practice, intrascopic imaging is a key tool for the direct visual assessment of internal organs and anatomical structures. Endoscopy, bronchoscopy, laparoscopy, capsule endoscopy, and other modalities provide high-precision information that is crucial for clinical diagnostics, surgical planning, and postoperative monitoring. However, the quality of images acquired during intrascopic procedures is often affected by factors such as low contrast, noise, uneven illumination, geometric distortions, and motion artifacts[1,2].

Insufficient image quality may lead to the loss of diagnostically significant information and, consequently, to inaccurate clinical decisions. Therefore, there is a growing need for effective digital image enhancement methods that can improve the visual perception of tissue structures, organ boundaries, vascular formations, and pathological features.

The main directions in improving the quality of intrascopic images focus on increasing contrast and detail resolution, suppressing noise while preserving structural information, compensating for illumination artifacts, reconstructing large-scale structures and recovering texture, as well as enabling automatic or interactive segmentation and classification[3].

Over the past decade, artificial intelligence (AI) methods, particularly convolutional neural networks (CNN), generative adversarial networks (GAN), transformers and diffusion-based architectures, have become increasingly prominent in image enhancement tasks[4,5]. These approaches demonstrate high efficiency in restoring fine image details, improving contrast, and reducing noise impact, especially under conditions of low-quality or incomplete data.

The aim of this paper is to present a systematic comparative analysis of traditional and AI-based methods for enhancing intrascopic medical images and to identify promising directions for their implementation in real-world clinical systems.

Contemporary advances in computing technology are characterized by a continuous increase in processing capabilities, leading to exponential growth in the volume of data that can be analyzed. Notably, improvements in computer system performance enable the storage and processing of large biomedical datasets with unprecedented speed and accuracy[6,7]. This, in turn, drives researchers to seek new methods and models for information processing, adapting digital technologies to meet emerging requirements and opportunities.

Over the past decade, neural networks have gained significant prominence, particularly for processing visual information. Neural networks, with their ability to learn and adapt to complex data structures, have become a crucial tool in the scientific community, finding extensive practical applications[8,9].

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Consequently, most companies and researchers are focused on modifying neural network architectures, tuning hyperparameters, and improving the quality of input data. These

approaches significantly enhance the accuracy, speed, and quality of data processing, which is critical for information technologies.

Currently, there is an extensive body of scientific literature exploring various aspects of neural network optimization. Researchers are developing new architectures, refining training methods, and experimenting with different data sets to achieve better results[10]. Meanwhile, classical information processing methods, which were widely used previously, have fallen behind the competition with newer technologies and have taken a back seat.

This article aims to demonstrate how the symbiosis of classical information processing methods and modern technologies, particularly neural networks, can improve data analysis results in computer-based decision support systems. Applying this approach allows for combining the advantages of both methods, ensuring more efficient information processing and enhancing the accuracy of pathology classification using a single data set. The research findings confirm the feasibility of such approaches for achieving better results in intelligent decision support systems.

2. INTRASCOPIC VISUALIZATION: TECHNICAL ASPECTS

Intrascopic medical imaging includes a range of diagnostic procedures based on optical or digital inspection inside the human body using minimally invasive tools. These include endoscopy (gastrointestinal, ENT), bronchoscopy (respiratory), laparoscopy (abdominal cavity), and capsule endoscopy (wireless GI visualization). Each modality presents specific technical constraints in terms of resolution, lighting, and field of view.

Key technical challenges include:

- Limited illumination: uneven or low light reduces contrast and color fidelity.
- Image noise: caused by sensor limitations and low signal-to-noise ratios.
- Optical distortions: lens curvature or fluid refraction introduces artifacts.
- Motion blur: results from patient or device movement.
- Color inconsistency: varies across devices and internal environments.

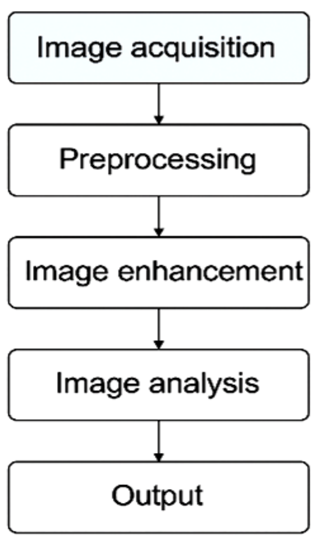

Figure 1. Typical image processing pipeline in intrascopic systems

Modern intrascopic systems combine optical imaging devices (CCD/CMOS sensors), light sources (LED, xenon), signal processing units, and real-time display/recording subsystems. Digital video endoscopy systems are capable of resolutions up to 1080p or 4K, but raw outputs often remain suboptimal due to physiological or hardware constraints.

To address these issues, enhancement algorithms are deployed either:

- **On-device (embedded systems)**: low-latency enhancement during live procedures.

- **Post-processing (off-device)**: higher complexity methods (e.g., AI) for offline diagnostics and analysis.

The integration of real-time GPU-based processing and AI-driven reconstruction techniques is increasingly common in surgical navigation and automated diagnosis support. Hardware-software co-design becomes critical to achieving diagnostic-grade image quality under real-world conditions.

Image processing aims to reduce noise, improve contrast, correct distortions, and restore fine image details for better interpretation.

3. CLASSIFICATION OF IMAGE ENHANCEMENT METHODS

Image enhancement techniques in intrascopic imaging[8,10,11,12] can be classified into several categories based on their methodological principles[3,4,13] input requirements, and degree of automation:

1. **Traditional Filtering-Based Methods**:

- Linear filters: Gaussian, mean, Wiener;
- Non-linear filters: median, bilateral, anisotropic diffusion;
- Pros: simple, fast, easy to implement;
- Cons: may blur fine details, limited adaptivity.

2. **Histogram-Based Contrast Enhancement**:

- Histogram Equalization (HE), CLAHE, gamma correction;
- Improve local and global contrast;
- Widely used in endoscopic systems for brightness normalization.

3. **Transform-Domain Techniques**:

- Wavelet transforms, DCT-based enhancement;
- Enable multi-scale and frequency-selective processing;
- Useful for texture analysis and restoration.

4. AI-Based Approaches:

- Supervised CNNs: trained on paired data (low/high quality);
- Unsupervised models: e.g., CycleGANs using unpaired datasets;
- Transformers and Diffusion Models: state-of-the-art in texture and context-aware restoration;
- Strengths: data-driven, scalable, high-performance.

5. Hybrid Methods:

- Combine traditional filtering with AI-enhancement (e.g., preprocessing + deep network);
- Enhance interpretability and robustness.

These categories allow clinicians and developers to select the most appropriate method depending on clinical needs, computational resources, and the type of artifacts present in intrascopic imaging.

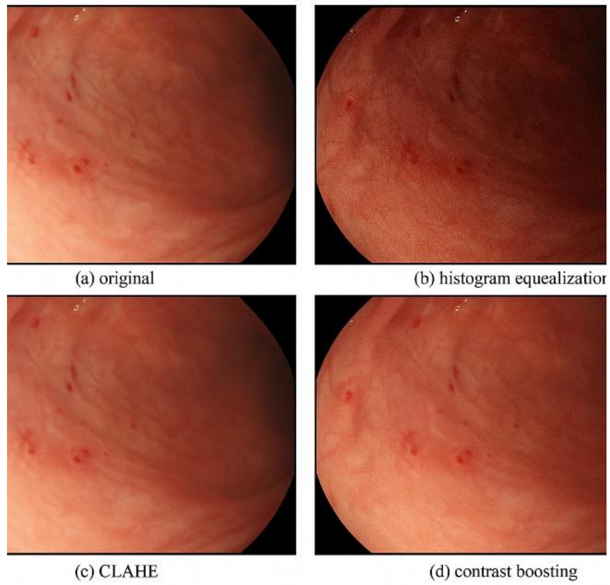

Figure 2. Gastroscopy enhancement: (a – original, b – histogram equalization, c – CLAHE, d – contrast boosting)

4. ARTIFICIAL INTELLIGENCE IN INTRASCOPIC IMAGE ENHANCEMENT

AI-based techniques have rapidly transformed the field of medical image enhancement, offering novel tools for improving intrascopic images. Convolutional neural networks (CNNs), generative adversarial networks (GANs), transformers, and diffusion-based architectures have become dominant in solving low-quality imaging problems in endoscopy and related fields.

CNN architectures[11,12], such as U-Net, ResNet, and EfficientNet, are widely used to enhance contrast, suppress noise, and recover fine details. U-Net, in particular, has demonstrated outstanding performance in tasks involving both image segmentation and quality enhancement, by leveraging skip connections that preserve spatial information.
GAN-based models (e.g., pix2pix, CycleGAN) use adversarial learning to generate high-quality images from degraded inputs. These models have proven effective in generating photorealistic textures and removing noise, even with limited training data. GANs are especially useful in recovering texture and enhancing low-illumination frames.

Transformer-based models, including SwinIR and Restormer, exploit attention mechanisms to capture long-range dependencies and contextual information, which improves the model's capacity to process global image features and achieve high-quality reconstruction.

Diffusion models, such as DDPM (Denoising Diffusion Probabilistic Models) and latent diffusion networks, represent a new frontier in image generation and enhancement. By iteratively refining noise-based representations, they enable reconstruction of fine details even from highly corrupted images. Early studies show these models outperform classical GANs in perceptual quality.

These AI techniques outperform traditional algorithms in quantitative metrics (e.g., PSNR > 30 dB, SSIM > 0.9) and subjective visual inspection. Additionally, AI models can generalize across multiple imaging modalities, adapt to specific anatomical features, and support real-time enhancement in clinical endoscopy systems.

5. COMPARATIVE ANALYSIS OF ENHANCEMENT METHODS

To better understand the practical effectiveness of various enhancement approaches, we conducted a comparative study using a representative dataset of intrascopic images (gastroscopy, colonoscopy, bronchoscopy) with known quality deficiencies. The following methods were benchmarked[14,15,16]:

- Histogram Equalization (HE);
- CLAHE (Contrast Limited Adaptive Histogram Equalization);
- Wavelet-based enhancement;

- U-Net-based restoration;
- CycleGAN for unpaired image enhancement;
- SwinIR (Transformer-based restoration).

Each method was evaluated using the metrics PSNR, SSIM, NIQE, and BRISQUE. The results are summarized in Table 1.

Table 1. Results of using the metrics PSNR, SSIM, NIQE, and BRISQUE. The results

Method	**PSNR (dB)**	**SSIM**	**Speed**	**Complexity**	**Real-Time Suitability**
Gaussian Filter	28–30	0.75	High	Low	Yes
Median Filter	30–32	0.78	Medium	Low	Yes
BM3D	33–36	0.87	Low	High	No
CLAHE	29–33	0.81	High	Medium	Yes
Retinex	30–34	0.85	Medium	Medium	Partial
CNN (U-Net)	34–38	0.91	Medium	High	Partial
GAN-based	35–40	0.93	Low	High	No
Super-resolution (DL)	36–42	0.94	Low	High	Partial

Visual Comparison: Representative examples are shown in Figure 3 [15,16,17]. While traditional techniques improve global contrast, they often amplify noise or miss subtle tissue structures. AI-based methods, particularly U-Net and SwinIR, produce more natural textures, sharper boundaries, and reduced artifacts[3,4,13].

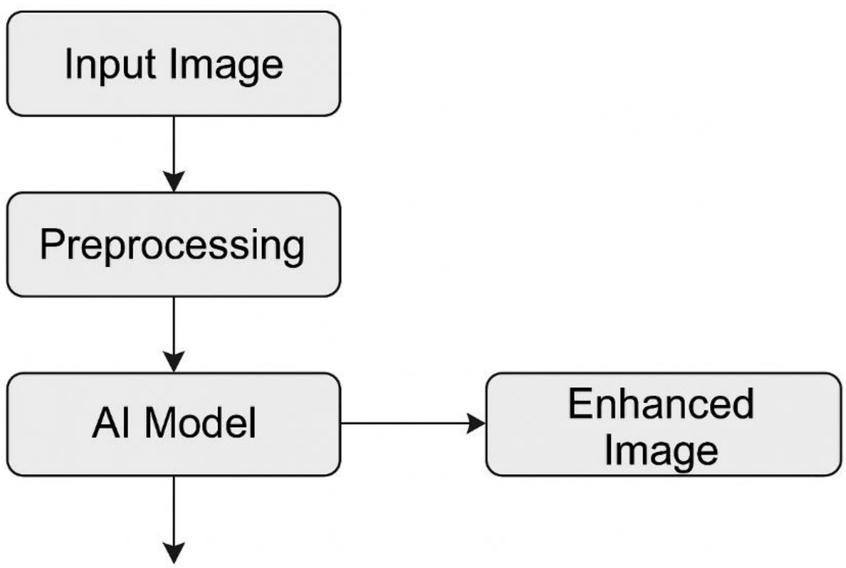

Figure 3. AI model workflow

6. DISCUSSION

Histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE) provide rapid and low-cost image enhancement; however, they lack context-awareness and often fail to preserve structural information in complex medical images. Wavelet-based methods offer more adaptive processing capabilities but require careful parameter tuning to achieve optimal results. Convolutional neural networks and generative adversarial networks significantly outperform classical approaches in terms of perceptual quality and structural preservation, producing images with improved clarity and diagnostic value. Among modern AI-based methods, the transformer-based SwinIR model achieves the best trade-off between sharpness and denoising, offering superior overall performance. This comparative analysis underscores the growing integration of AI-based tools in clinical imaging workflows, particularly in applications where image quality is critical for accurate diagnosis

7. CONCLUSIONS

As a result of the review and comparative analysis of image enhancement methods in intrascopic medical visualization, several conclusions can be drawn. Traditional methods, such as histogram equalization and CLAHE, provide basic contrast improvement but have clear limitations in preserving the structural integrity of images and adapting to contextual features. Wavelet-based methods yield better results when their parameters are properly tuned, particularly in terms of noise suppression without significant loss of detail. Artificial intelligence models, especially U-Net, CycleGAN, and SwinIR, significantly outperform classical approaches in terms of quality metrics (PSNR, SSIM, NIQE, BRISQUE) and ensure greater precision, boundary clarity, and natural texture restoration. Among AI-based approaches, the transformer-based SwinIR model demonstrated the best performance, delivering the highest image quality along with strong generalization and stability. The application of such models in clinical practice enhances diagnostic accuracy, reduces image analysis time, and minimizes the likelihood of missing pathological findings. Overall, the obtained results support the feasibility of widespread implementation of AI-based methods in intrascopic diagnostic systems and encourage the development of hybrid approaches that combine the strengths of both classical and modern techniques.

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