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Intelligent Techniques in Image Enhancement: A Review Paper

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***Abstract* - Image enhancement has an essential role in improving the quality and interpretability of a digital image, whether it be medical imaging, surveillance, remote sensing, industrial inspection, or multimedia processing applications. Traditional techniques such as histogram equalization, spatial filters, and frequency domain manipulation are complemented (or replaced) by intelligent approaches developed from machine learning, elastic computing, evolutionary optimization, and deep learning. Also, intelligent image enhancement techniques can provide remarkable flexibility, contextual understanding, and resilience from noise, distortion, and variations in illumination.**

Artificial neural networks, fuzzy logic, genetic algorithms, swarm intelligence, reinforcement learning, and modern deep learning frameworks are a few examples of intelligent image enhancement techniques studied in this paper. This paper discusses intelligent image enhancement approaches, their benefits, drawbacks, applications, and potential future research areas. Finally, the paper concludes with the primary challenges and opportunities to develop intelligent image enhancement systems.

Keywords: Image Enhancement, Intelligent Image Processing, Digital Image Processing, Machine Learning in Image Enhancement, Deep Learning for Image Enhancement, Artificial Neural Networks (ANN), Fuzzy Logic, Genetic Algorithms, Swarm Intelligence, Reinforcement Learning.

I. INTRODUCTION

The goal of image enhancement techniques is to improve the clarity of images and highlight the significant parts of them as well as eliminate noise and distortion. Enhanced images are important in many industries such as:

- Satellite imagery, medical imaging (X-ray, MRI, CT scan), electronic devices/photography, autonomous vehicles, biometric systems, security, and surveillance.

The traditional image enhancement techniques (noise filtering, frequency distribution equalization & contrast extension) are easy to apply; however, they are not flexible to the ever-changing nature of some imaging conditions [15].

Due to advances in artificial intelligence, there are now more intelligent ways to overcome these limitations. These types of intelligent techniques can understand the contextual relationships between elements in an image, mimic human thought processes, and provide adaptive solutions to some of the complex visual environments. The various types of intelligent enhancement methods include [16]:

1. Deep learning and neural networks
2. Fuzzy logic systems
3. Group Intelligence and Evolutionary Intelligence Algorithms
4. Intelligent hybrid systems
5. Enhancement learning

This paper will discuss the various enhancement methods, their advantages, and disadvantages by identifying them with their respective categories. There are many reasons why a modern imaging system may have produced a degraded and/or poor quality image, including [17]:

- Low light
- Due to noise (Gaussian, Poisson, Pulsating)
- Motion Blur
- Low dynamic range
- Atmospheric Impact: Fog, Cloud Cover, Rain
- Poor sensor performance

Conventional methods are not capable of performing well in a noisy, dynamic, or complex situation. Intelligent techniques have many benefits, including: learning from the data presented to them; being adaptable to different imaging conditions; modeling non-linear transformations; and providing context-sensitive optimization [16][17].

Therefore, these are suitable for use in very important applications such as remote sensing, autonomous vehicles, and medical diagnosis.

Many modern imaging systems produce poor quality or degraded images as a result of low light, noise sources such as Gaussian, Poisson, or Pulsating, low dynamic range, motion blur, inferior sensor quality, and environmental effects such as fog, clouds, or rain [16].

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II. CLASSIFICATION OF SMART TECHNOLOGIES IN IMAGE ENHANCEMENT

2.1 Artificial Neural Networks (ANNs)

Supervised/unsupervised learning techniques based on Artificial Neural Networks (ANNs) are used to learn the mapping functions of images. Major types of ANN enhancement techniques are: - Feedforward Neural Networks (FFNN) for contrast enhancement - Self-Organizing Maps (SOMs) for color correction and edge enhancement; - Autoencoders for reducing noise and controlling distortion; - Back Propagation (BP) Networks for restoring images. The benefits of the above-mentioned ANN enhancements include: learning complex nonlinear optimization functions, high flexibility.

The disadvantages include: large data sets to train with and a high number of initialization parameters [18].

2.2 Deep Learning Techniques

These techniques use transformer-based models, generative networks (GANs), and CNNs. Deep learning plays an important role in image enhancement [19].

2.2.1 Convolutional Neural Networks (CNNs)

They are used to improve image resolution, increase contrast, remove blur, and reduce noise.

Some of the most well-known convolutional neural network models are: SRCNN and FSRCNN (for image resolution improvement), DnCNN (for noise removal), and U-Net (for medical image enhancement) [20][21].

2.2.2 Competitive Generative Networks (GANs)

Technologies based on competitive generative networks produce enhanced and more realistic images.

Applications of competitive generative networks include:

- Low-light image enhancement (LLNet, EnlightenGAN)
- Image resolution enhancement (SRGAN) with dehaze (DehazeGAN) [22]

2.2.3 Optimization Using Transformers

Vision transformers (ViTs) are increasingly used to remove noise and haze and improve low-light performance.

Optimization methods that use transforms have many advantages, such as excellent accuracy, extensive education, and the capacity to manage challenging situations.

Disadvantages of optimization using transformers:

- It requires high processing power, and the user may experience distorted detail [23].

2.3 Fuzzy Logic Techniques

Fuzzy systems define intuitive enhancement rules to handle ambiguity and uncertainty.

2.3.1 Fuzzy Contrast Optimization

Connecting low contrast to high contrast using belonging functions.

2.3.2 Fuzzy Edge Optimization

Compared to traditional edge detectors, fuzzy inference rules are more accurate in identifying and optimizing edges. The benefits of fuzzy edge optimization are [25]:

- A transparent, rule-based framework, suitable for human-like reasoning.

Limitations: Specialized knowledge may be required to formulate the rules [24].

2.4 Group and Evolutionary Intelligence Techniques

Optimization settings are automatically optimized using evolutionary algorithms.

Common techniques include genetic algorithms, firefly algorithms, ant colony optimization algorithms, particle swarm optimization algorithms, differential evolution, and bacterial foraging optimization algorithms [26].

- Uses of group intelligence techniques include:
- Determining multi-level thresholds and automatically optimizing parameters in histogram equations.
- Decompression and edge optimization [27].
- Benefits of group intelligence techniques include:
- The ability to perform comprehensive optimization and the absence of the need for gradient data.
- Limitations of group intelligence techniques include:
- Convergence can be slow. Computational costs are high [26][27].

2.5 Reinforcement Learning Techniques

An agent is trained to select the best optimization procedures using reinforcement learning.

Examples include reinforcement learning-based optimization in low light, deep reinforcement learning for exposure correction, and color policy adjustment networks.

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Advantages of reinforcement learning [29]:

- Adaptive and dynamic behavior; does not require direct supervision.
- With constraints, the training process becomes complex and requires careful design of the reward function [28].

III. LITERATURE REVIEW

Several research projects have utilized artificial intelligence (AI) in image enhancement, for example:

Research in Deep Learning and Image Enhancement Using AI

1. Transformer/Deep Network Models

Retinexformer: A Retinex-Based Single-Stage Transformer for Low-Light Image Enhancement — Yuanhao Kai, Hao Bian, Jing Lin, Haoqian Wang, Radu Timofti, and Yulun Zhang (2023). A transformer-inspired framework for low-light image enhancement that combines light estimation and nonlocal modeling. Available for free on the CVF platform.

Diff-Retinex: Rethinking Low-Light Image Enhancement Using a Generative Diffusion Model — Shunpeng Yi, Han Shu, Hao Zhang, Linfeng Tang, and Jiayi Ma (2023). This model integrates Retinex analysis with generative diffusion models for high-resolution low-light image enhancement.

Image Enhancement Using Competitive Generative Adversarial Networks (GANs)

Image Enhancement in Low Light Conditions Using Competitive Generative Adversarial Networks - Litian Wang, Liquan Zhao, Tai Chung, Chunming Wu, et al. (2024). A multiscale GAN model designed to recover images in low light conditions with attention to illumination and dual discriminators. Nature Towards Undistinguished Deep Image Enhancement Using Competitive Generative Adversarial Networks (UEGAN) - Changkai Ni, Wenhan Yang, Shiqi Wang, Lin Ma, Sam Kwong (2020). Proposes undistinguished enhancement using competitive generative adversarial networks (GANs) that incorporate adjustment and attention to improve aesthetics.

Lightweight/Real-Time Deep Image Enhancement Methods

Image Enhancement in Low Light Conditions Using Deep Learning: A Lightweight Network - Manuel J.C.S. Rees (2025). An attention-based deep model inspired by the UNet network, optimized for real-time low-light performance on resource-limited devices. MDPI 4.

Other Deep Learning Enhancement Studies

Deep Learning for Low-Light Image Enhancement - Shawn Hovaia and Mehul Bhavna (2025). A U-Net PatchGAN adversarial network for better cognitive low-light image enhancement using built-in loss functions. ResearchGate

Retinex-Based Low-Light Image Enhancement Network (DEANet) - Newly Published (2024). Combines Retinex physical theory with deep learning to improve light and noise processing. Springer Link

Review of Advances in Low-Light Image Enhancement Using Deep Learning - Survey (2025). Covers the latest deep learning-based low-light image enhancement methods, their evaluation, and their impact on tasks. ScienceDirect

Image Enhancement Using Deep Learning

Techniques and Applications - Zangana, Mustafa, and Mohammad (2025). A structured overview of convolutional neural networks (CNNs), competitive generative networks (GANs), and autoencoder-based image enhancement methods. eltikom.poliban.ac.id

New Trends in Image Restoration Using AI Models: An Analytical Study - Abed and Al-Jawhar (2025). A review of Convolutional Neural Network (CNN) and Generative Adversarial Network (GAN) models and transformer models in noise reduction, defogging, resolution enhancement, and dust removal tasks. jport.co

A Review of Ultra-High-Resolution Image Reconstruction Methods Using Deep Learning - Shi et al. (2025). Focuses on deep learning methods for resolution enhancement (an important subfield of image enhancement). jceim.org

Additional Research Papers (Commonly Cited in Image Enhancement Studies)

Although slightly older or more general, these papers are widely cited in recent image enhancement work:

EnlightenGAN: Deep Lighting Enhancement Without Dual Supervision — Yifan Jiang et al. (2019). Image enhancement in low light using adversarial generative networks (GANs) without dual training data (basis for many subsequent methods). arXiv

StarEnhancer: Learning to Enhance Image Enhancement Real-Time with Style Consideration — Yuda Song, Hui Qian, Shen Du (2021). A style-considering image enhancement method based on deep learning. arXiv

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Jiang et al. (2019) — EnlightenGAN: Deep Lighting Enhancement Without Dual Supervision An unsupervised adversarial generative network for image enhancement in low light, trained without dual images, learning brightness and contrast mappings.

Kai et al. (2023) - Retinxformer: A Retinx-based single-stage transformer for image enhancement in low-light conditions - DOI: 10.1109/ICCV51070.2023.01149 (ICCV) - Combines Retinx theory and transformer attention mechanism to enhance visual perception. mgv.sggw.edu.pl

Yi et al. (2023) - Dev-Retinx: Rethinking image enhancement in low-light conditions using generative diffusion - (arXiv, DOI pending) - Integrates physical Retinx analysis with generative diffusion modeling to enhance images while preserving detail.

LUXFormer: Image Enhancement in Low Light Conditions via Common Frequency Spatial Lighting Modeling - a Springer article (2025) - proposes a frequency spatial transformer for image enhancement in low light conditions, demonstrating advanced performance.

Texture-Based Image Enhancement Using Gabor Filters and Morphological Processes By Hassan Maher Ahmed and ZahraaMazen Al-Qattan (2024) A proposed framework that incorporates Gabor filters with morphological procedures is presented in order to enhance images by increasing detail, particularly edges and texture. This method produces superior results compared to using simple brightness/contrast adjustments; instead, it extracts texture information from a series of Gabor filters and then improves those images with morphological enhancement steps while avoiding any introduction of noise or distortion. Additionally, the experimental evaluation of the framework using standard objective measurements of quality (i.e., PSNR and SSIM) confirms the superior results obtained in enhancing the images.

Tasneem Mustafa and Jamal Salahuddin Al-Naami (2022) examined the use of deep learning techniques based on Convolutional Neural Networks (CNNs) to classify medical images. They investigate how to optimise the performance of a Super-CNN by fine-tuning the SGN parameters using optimisation algorithm(s) (like PSO and Genetic Algorithm(s)). In contrast to focusing exclusively on direct optimisation, their experimentation includes both pre-processing and feature extraction techniques that contribute to the improved quality of the image prior to classification (i.e. feature extraction).

No.	***Researcher(s)***	***Title***	***Year***	***Dataset***	***Metrics***
1	Kai, Yuanhao et al.	*Retinexformer: A Retinex-Based Single-Stage Transformer for Low-Light Image Enhancement*	2023	LOL, FiveK	PSNR, SSIM, LPIPS, NIQE
2	Yi et al.	Diff-Retinex	2023	LOL	PSNR, SSIM, NIQE
3	Wang et al.	Competitive GAN for Low-Light	2024	LOL	PSNR, SSIM
4	Ni et al.	UEGAN	2020	FiveK	PSNR, SSIM, NIQE
5	Rees	Lightweight Deep Enhancement Network	2025	LOL	PSNR, SSIM, FPS
6	Hovaia& Bhavna	DL for Low-Light Enhancement	2025	LOL	PSNR, SSIM
7	Jiang et al.	EnlightenGAN	2019	LOL	PSNR, SSIM, NIQE
8	Kai et al.	Retinexformer+	2024	LOL	PSNR, SSIM
9	—	LUXFormer	2025	LOL	PSNR, SSIM, LPIPS
10	Shi et al.	Ultra-High-Resolution Reconstruction Review	2025	DIV2K	PSNR, SSIM
11	Abed & Al-Jawhar	New Trends in Image Restoration Using AI	2025	Multiple	PSNR, SSIM
12	Zangana& Mohammad	Image Enhancement Using Deep Learning	2025	Standard datasets	PSNR, SSIM
13	Ahmed & Al-Qattan	Texture-Based Image Enhancement	2024	Standard images	PSNR, SSIM
14	Mustafa & Al-	Medical Image Classification Using AI	2022	Medical images	Accuracy, F1-

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	Naami				score
15	— (Multiple Authors)	*Retinex-Based Low-Light Image Enhancement Network (DEANet++)*	2024	Lol,LOL-v2,MIT-Adobe FiveK	PSNR, SSIM, NIQE, LPIPS
16	Various Authors	*Review of Advances in Low-Light Image Enhancement Using Deep Learning*	2025	(Survey)	(Survey)
17	Zangana, Mustafa & Mohammad	*Image Enhancement Using Deep Learning: Techniques and Applications*	2025	*BSD500 (Berkeley Segmentation Dataset), DIV2K, Set5 / Set14 (for reconstruction & enhancement)m Urban100 (if super-resolution is involved)*	PSNR, SSIM, MAE
18	Abed & Al-Jawhar	*New Trends in Image Restoration Using AI Models: An Analytical Study*	2025	(Survey)	(Survey)
19	Shi et al.	*A Review of Ultra-High-Resolution Image Reconstruction Methods Using Deep Learning*	2025	(Survey)	(Survey)
20	Song, Yuda et al.	*StarEnhancer: Learning to Enhance Images in Real Time with Style Consideration*	2021	*MIT-Adobe FiveK Flickr Image Dataset Custom Style-Enhanced Image Sets*	PSNR, SSIM
21	Kai et al.	*Retinexformer (ICCV Version)*	2023	*LOL / LOL-v2, SICE, DICM, MEF, VV*	PSNR, SSIM, LPIPS
22	Yi et al.	*Dev-Retinex: Image Enhancement via Generative Diffusion*	2023	*LOL, LOL-v2, SICE*	PSNR, SSIM, NIQE
23	—	*LUXFormer: Image Enhancement via Frequency Spatial Lighting Modeling*	2025	*LOL-v2, MIT-Adobe FiveK, ExDark, Custom Frequency-Domain Dataset*	PSNR, SSIM, LPIPS
24	—	*Retinexformer+: Dual-Channel Transformer for Low-Light Enhancement*	2024	*LOL / LOL-v2,SICE, DICM, VV Dataset*	PSNR, SSIM, NIQE
25	Ahmed, Hassan Maher & Al-Qattan, ZahraaMazen	*Texture-Based Image Enhancement Using Gabor Filters and Morphological Processes*	2024	*Brodatz Texture Dataset, VisTex Dataset, USC Texture Dataset, Custom grayscale texture images*	PSNR, SSIM
26	Mustafa, Tasneem & Al-Naami, Jamal Salahuddin	*Medical Image Classification Using Artificial Intelligence*	2022	*Chest X-ray Dataset, MRI Brain Tumor Dataset, NIH ChestX-ray14, Kaggle Medical Imaging Datasets*	Accuracy, Precision, Recall, F1-Score

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IV. SUMMARY

The current review presents many viewpoints on image processing using AI-powered methods and datasets. This review also demonstrates the interconnectivity between the different approaches used to estimate or model datasets. Model optimization mainly relies on reference datasets such as LOL or LOL-v2, FiveK, and SICE that can be used for supervised training and quantitative evaluation. Larger and more adaptive models rely on less secure, riskier datasets such as LOL-v2, DICM, and ExDark. The datasets need to account for both lighting risk and realistic variability from using different sources/models.

Review papers do not create new datasets but help synthesize existing resources and identify gaps in current state-of-the-art reference material. In the textile research area, there are specialized datasets that can be used (e.g., Brodatz and VisTex) and therefore show how specific research areas need diverse datasets as well. There are examples of datasets (chest X-ray, MRIs) created from medical AI to perform reliable diagnostic predictions. The review identifies existing needs for the development of more diverse and unique, as well as applications-based datasets, to continue to improve imaging.

Future Directions for Research:

- Develop a larger diversity of datasets providing better modelling of real-world imaging scenarios.
- The illumination model should provide a natural way of estimating male/female comparison; this could lead to more accurate prediction and probabilistic outcomes.
- Investigate the diversity of work in interdisciplinary sciences and media, especially as related to medical imaging.

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