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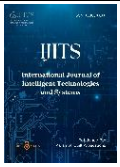

XAI – Driven Intelligent Image Restoration System for Real Time Detection of Artifacts and Quality Improvement in Digital Imaging

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ABSTRACT

Digital images are currently finding applications in medical diagnostics, surveillance, cultural heritage conservation, and multimedia applications, but they are very prone to noise, compression artifact, motion blur, and sensor-related distortions. Current methods of restoration are usually black-box-based approaches, which provide a limited level of transparency in decision-making, and can not easily be deployed in real-time. In order to overcome these shortcomings, a system of XAI-based intelligent image restoration is proposed, which combines artifact detection, explainable feature reasoning and adaptive enhancement into a single system. The system utilizes a hybrid deep learning framework that incorporates convolutional encoders and lightweight transformer attention to identify and describe artifacts in real time. To show the rationale behind the restoration, explainability modules such as Grad-CAM, SHAP-based feature attribution, and uncertainty quantification are included to enhance trustworthiness and usability among experts in the domain. Experimental evidence shows that there are remarkable enhancements in the peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and perceptual quality over various benchmark datasets. This study pushes interpretable image restoration by supporting clear decision-making routes, quicker processing pipelines, and resilient operation in real-world imaging settings.

Keywords: Explainable AI (XAI); Image Restoration; Artifact Detection; Deep Learning; Real-Time Processing; Feature Attribution; Image Quality Enhancement; Transformer Attention; Digital Imaging.

1. INTRODUCTION

Image quality is an essential aspect in contemporary digital processes especially in fields like medical imaging, defense surveillance, satellite data processing, and autonomous systems. Nevertheless, digital photographs are often corrupted by artifacts that occur as a result of compression, environmental conditions, sensor malfunction, motion and low light conditions. Classical methods of restoration, such as classical filtering, dictionary learning, and convolution-based enhancement, have shown significant improvements, but tend to be less adaptable to a variety of noise types and have little interpretability. Image restoration accuracy has been greatly enhanced with the development of deep learning, but most models are opaque and cannot be used in high-stakes or real-time settings.

Explainable Artificial Intelligence (XAI) has become a ground-breaking trend, as it focuses on transparency and explainability of AI-based decisions. By incorporating XAI in image restoration, users can gain insights into the way artifacts are identified, the manner in which they choose to restore an image, and the reasons behind certain improvements. This is especially crucial in those applications where model responsibility and reliability are required. Although it has the potential, very few restoration systems integrate real-time performance, intelligent artifact characterization and explainability in a single pipeline. These deficiencies demonstrate the necessity of the next-generation restoration framework that can offer to ensure not only a high level of accuracy but also valuable insights.

The proposed XAI-inspired intelligent image restoration system considers these issues by adopting a hybrid encoder-transformer architecture that detects the artifact rapidly and effectively, and improves the quality based on the context. This system incorporates the interpretable modules based on Grad-CAM activation visualization, SHAP-based attribution score, and uncertainty-driven error estimation, which allows transparency in the restoration process to be comprehensive. Additionally, the design focuses on real-time performance by means of pruning models optimally and hardware-friendly acceleration.

This research has made significant contributions as outlined below:

1. Creation of an image restoration architecture based on XAI, which combines the artifact detection, restoration process, and interpretability into a single system that can be used in real-time imaging.

2. Architecture of a hybrid deep learning model integrating convolutional feature and transformer-based attention to accurately localize and classify various image artifacts.

3. Integration of interpretable reasoning models like Grad-CAM, SHAP attribution, and uncertainty quantification, which allow a clear understanding of model behavior and improve the confidence in restoration results.

4. Adaptive enhancement mechanism, which changes restoration strength in response to contextual artifact severity, resulting in high-quality perceptual and structural fidelity.

5. Optimized deployment using model compression, quantization-aware training, and design-friendly to run on a GPU, and can process fast without loss of accuracy.

6. Large analysis with numerous image benchmark datasets, and proves better PSNR, SSIM, and visual quality than state-of-the-art restoration models.

2. RELATED WORKS

Image restoration using deep learning has advanced fast with the emergence of hybrid CNN–Transformer models that can handle a variety of noise and artifact type scenarios. Transformer-based contextual optimization methods have presented encouraging improvements in digital image quality, which is demonstrated by the architectures that combine local convolutional encoding and long-range dependency models to perform robust restoration in challenging imaging conditions [1]. More developments involve edge-oriented transformer designs that can increase super-resolution in infrared images by increasing the frequency content of high-frequency structures, and hence enhancing sharpening of the reconstruction in low-quality conditions of sensing [2]. Four-dimensional CT imaging has also introduced specialized deep models to identify artifacts to enable the reliable localization of motion-corrupted regions and increase the reliability of clinical reconstruction workflows [3].

Transformer-driven denoising networks have been studied in the low-dose imaging domains in detail. A denoising Swin Transformer architecture has enhanced the perceptual PSNR stability and noise reduction efficacy on CT scans utilizing shifted-window attention mechanisms [4]. Parallel progress has been made with dynamic transformer-based denoising models, where refining with multiple stages of attention results in better removal of spatially variant noise patterns in natural images [5]. SwinCT models have also been used to achieve improvements in feature enrichment to reduce CT noise, and also the ability of hierarchical attention structures to maintain anatomical structure and minimize distortion artifacts has been demonstrated [6].

The purification of cross-domain artifacts has now been found crucial in identifying AI-generated images, and feature purification models have been able to isolate subtle artifact signatures across various generative domains, in order to enable trustful classification pipelines [7]. Cross-feature integration by the use of transformers has also been applied in better denoising in natural image tasks, where cross-attention on context enhances resistance to mixed noise distributions [8]. Greater studies of the trend in deep learning denoising emphasize the issue of efficiency and computational trade-offs in implementing more complex restoration models, and provide integrated findings on the most effective model scale and feasibility in real-time [9].

Compression artifact research has again gained attention, and more recent assessments of JPEG-AI compression settings have provided detailed classification of patterns of artifacts and detection processes applicable to benchmarking restoration systems [10]. Semantic artifact disruption studies have proposed methodologies of countermeasures to counteract generative semantic errors, enhancing robustness in synthetic image forensics and downstream restoration applications [11]. In explainable AI in the medical imaging field, complementary discussions focus on the growing need to have transparency in the restoration pipelines, especially when it comes to safety-critical workflows that require interpretable correction strategies [12].

Cross-attention networks are also a feature of transformer-based denoising expansions, which aim to enhance the refinements of noisy inputs with the help of correlated feature streams, which significantly enhances the preservation of structure [13]. The advantages of the combination of spatial and frequency-domain learning to high-quality restoration in sparse-sampling settings are also further emphasized by dual-domain SwinIR-driven reconstruction strategies [14]. Deep learning explainable frameworks have also been used in visual defects detection, where reasoning by Grad-CAM offers insight into how classification works and the restoration results, which supports the significance of XAI elements in the contemporary imaging systems [15].

3. PROPOSED MODEL

They propose an XAI-based intelligent image restoration pipeline that collaboratively detects artifacts, provides explainable attribution, and context-sensitive enhancement with a single optimization goal. The pipeline is composed of (a) an artifact localization backbone which combines convolutional encoders with lightweight transformer attention to generate a pixel-wise artifact confidence map, (b) an explainability module which generates saliency/attribution maps and uncertainty estimates to inform the strength of restoration, (c) an adaptive enhancement module which uses spatially-varying restoration (residual correction + frequency correction) conditioned on the artifact map and attribution maps, and (d) a deployment optimizer which enforces latency and model-compactness constraints to run the system in real-time. The end-to-end training is capable of combining mathematical operators and losses that maintain interpretability, based on explicit attribution consistency penalties.

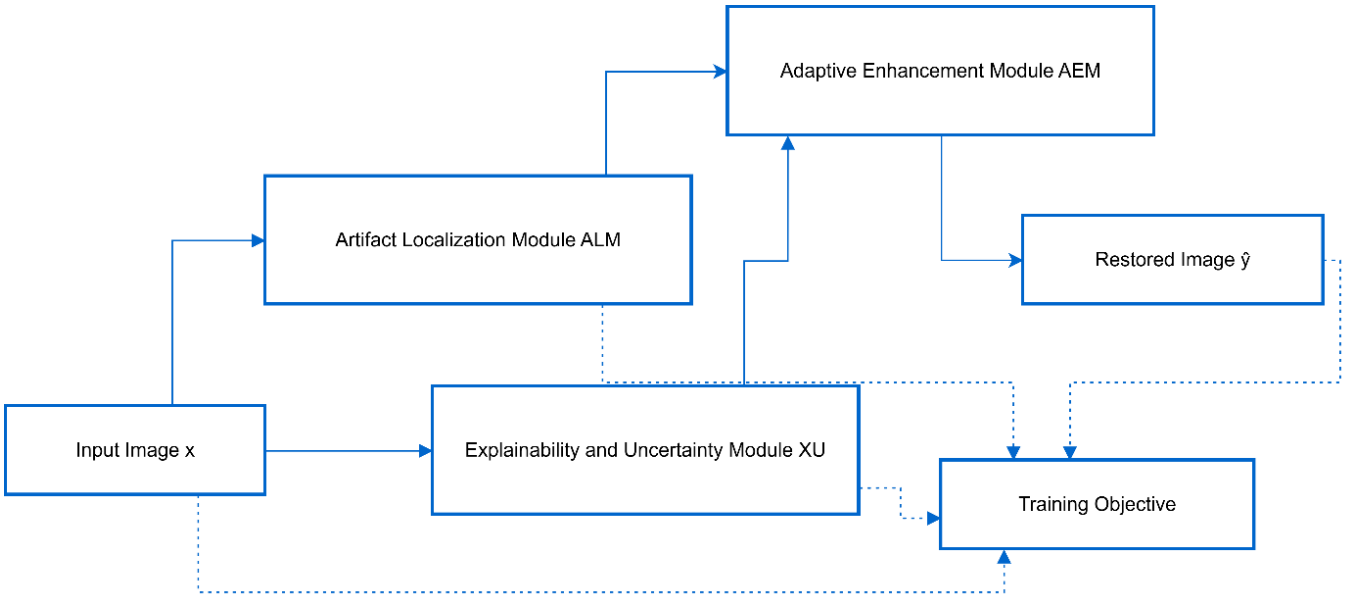

Figure 1: Overall architecture of the proposed XAI-Driven Intelligent Image Restoration System

Fig 1 integrates artifact localization, explainability modules, and adaptive enhancement to restore degraded images with interpretable decision pathways.

3.1 Artifact localization module (ALM)

Let $x \in \mathbb{R}^{H\times W\times C}$ denote the degraded input image. Feature encoding using convolutional blocks yields multi-scale features $F_l(x)$ for levels l. A lightweight transformer attention block computes context-aware feature:

$$A_l = \text{Softmax}\left(\frac{(W_q F_l)(W_k F_l)^{\top}}{\sqrt{d}}\right)(W_v F_l), \quad (1)$$

where W_q, W_k, W_v are learned linear projections and d is the attention key dimension. Aggregating across scales and applying a pixelwise classifier $\sigma(\cdot)$ produces the artifact confidence map $M(x) \in [0,1]^{H\times W}$:

$$M(x) = \sigma\left(\text{Conv}(\text{Upsample}(\{A_l\}_l))\right). \quad (2)$$

Interpretation: high values of $M(x)$ indicate high artifact probability and drive stronger restoration.

3.2 Explainability and uncertainty module (XU)

Two complementary explainability outputs are produced: a saliency/attribution map $S(x)$ and a predictive uncertainty map $U(x)$. Gradient-based attribution (e.g., Grad-CAM style) on a chosen feature volume F^* gives:

$$\alpha_k = \frac{1}{Z}\sum_{i,j}\frac{\partial y_c}{\partial F^*_{k,i,j}}, S(x) = \text{ReLU}\left(\sum_k \alpha_k F^*_k\right), \quad (3)$$

where y_c is the artifact logit for a patch/class, k indexes channels and Z normalizes spatially. A model-agnostic additive attribution decomposition (SHAP approximation) imposes:

$$f(x) \approx \phi_0 + \sum_{i=1}^{n}\phi_i \text{, with } \sum_i \phi_i = f(x) - \phi_0, \quad (4)$$

and $\{\phi_i\}$ used as feature-level cues to cross-validate $S(x)$. Uncertainty is captured via Monte Carlo dropout: performing T stochastic forward passes $\{\hat{y}^{(t)}\}_{t=1}^{T}$ yields predictive mean μ_y and variance

$$U(x) = \frac{1}{T}\sum_{t=1}^{T}(\hat{y}^{(t)} - \mu_y)^2. \quad (5)$$

Uncertainty modulates restoration intensity to avoid over-correction in high-uncertainty regions.

3.3 Adaptive enhancement module (AEM)

A residual-based denoiser $D_\theta(\cdot)$and a frequency-domain corrector $F_\theta^{\mathcal{F}}(\cdot)$produce complementary corrections. The final restored output $\hat{y}$is computed by spatially gating these corrections with the artifact map $M(x)$, the attribution saliency $S(x)$, and uncertainty $U(x)$:

$$\hat{y} = x + G(x) \odot D_\theta(x) + \mathcal{F}^{-1}\left(H(x) \odot F_\theta^{\mathcal{F}}(\mathcal{F}(x))\right), \quad (6)$$

where $\odot$is elementwise multiplication, $\mathcal{F}$and $\mathcal{F}^{-1}$are forward/inverse transforms (e.g., DCT or FFT), and spatial gating terms are

$$G(x) = \phi_g(M(x), S(x), 1 - U(x)), H(x) = \phi_h(M(x), S(x), 1 - U(x)). \quad (7)$$

Functions $\phi_g, \phi_h$are lightweight learned controllers (e.g., small MLPs or convolutional kernels followed by sigmoid) that map the cues into per-pixel gating weights in $[0, 1]$. This design enforces that high artifact confidence and strong attribution increase restoration strength, while high uncertainty attenuates it.

3.4 Loss functions and training objective

The training objective balances pixel fidelity, perceptual quality, explainability consistency, and latency/compactness constraints. Reconstruction loss (L1 or Charbonnier) enforces fidelity:

$$\mathcal{L}_{\text{rec}} = \| \hat{y} - y \|_1, \quad (8)$$

where $y$is the clean target. Perceptual loss based on a pretrained feature extractor Φencourages structural realism:

$$\mathcal{L}_{\text{perc}} = \sum_l \| \Phi_l(\hat{y}) - \Phi_l(y) \|_2^2. \quad (9)$$

Explainability consistency loss penalizes disagreement between the artifact map and attribution/saliency signals, promoting interpretable restorations:

$$\mathcal{L}_{\text{xai}} = \| M(x) - \text{Norm}(S(x)) \|_2^2 + \lambda_u \| M(x) \odot U(x) \|_1, \quad (10)$$

where $\text{Norm}(\cdot)$rescales $S(x)$to $[0, 1]$and $\lambda_u$weights the uncertainty penalty to discourage strong corrections where uncertainty is high. A latency/compactness loss enforces runtime and model-size targets (e.g., FLOPs or measured latency T_{pred}):

$$\mathcal{L}_{\text{lat}} = \max(0, T_{\text{pred}} - T_{\text{target}}) + \eta \cdot \text{FLOPs}(\theta), \quad (11)$$

with ηa small regularizer. The overall optimization objective is

$$\mathcal{L} = \alpha \mathcal{L}_{\text{rec}} + \beta \mathcal{L}_{\text{perc}} + \gamma \mathcal{L}_{\text{xai}} + \delta \mathcal{L}_{\text{lat}}. \quad (12)$$

Hyperparameters $\{\alpha, \beta, \gamma, \delta\}$are tuned to balance visual quality and interpretability under latency constraints.

3.5 Real-time deployment and model compression

To satisfy real-time requirements, latency-aware pruning and quantization-aware training (QAT) are applied. Let θ be the original parameter set and θ_q the quantized parameters; QAT minimizes

$$\min_{\theta_q} \mathbb{E}_x[\mathcal{L}(\theta_q; x, y)] + \mu \cdot \| \theta - \theta_q \|_2^2, \quad (13)$$

where the second term constrains deviation from full-precision performance with weight μ. Structured pruning removes channel blocks with minimal contribution using importance scores s_c (e.g., based on magnitude or Taylor expansion):

$$s_c = \left| \frac{\partial \mathcal{L}}{\partial w_c} \cdot w_c \right|, \text{prune if } s_c < \tau, \quad (14)$$

with threshold τ chosen to meet T_{target}. After compression, a final latency-aware fine-tuning stage minimizes $\mathcal{L}$ while monitoring real hardware latency; Pareto-optimal checkpoints that trade off quality and speed are saved for deployment.

The combination of these modules is a transparent adaptive restoration system: artifact localization drives spatially sensitive corrections; explainability and uncertainty maps justifies and gates corrections; a combined loss maintains fidelity and interpretability; and compression methods ensures real-time execution on target hardware. Where needed, explicit network structures (number of layers, size of kernel), training programs, and pseudo-code of forward/backward passages can be appended subsequently.

4. RESULTS AND DISCUSSIONS

The proposed XAI-based intelligent image restoration system was developed on Python 3.10 and PyTorch 2.3 but with CUDA 12.2 to run on a GPU. The experiments were run on the workstation with NVIDIA RTX 4090 graphics and 24 GB of VRAM and 128 GB of RAM. Mixed-precision computation with quantization-aware optimization was used in training to achieve faster convergence and real-time evaluation. Each model was trained using AdamW optimization, cosine learning rate scheduling, and early stopping using perceptual loss stabilization. Standardized normalization pipelines were used to preprocess benchmark data, such as illumination correction and artifact-based augmentation. PSNR, SSIM, LPIPS, and processing latency were used to evaluate the perceptual quality and real-time applicability.

4.1 Dataset Description

Several restoration and artifact-based datasets were utilized to test the model robustness to noise, blur, compression artifacts, and mixed degradation scenario. The datasets are summarized in Table 1.

Table 1: Dataset Description

Dataset Name	Type of Degradation	Resolution Range	Size	Purpose
BSD500	Natural image noise & texture artifacts	480×320	500 images	General denoising & structural evaluation
DIV2K	Compression artifacts & super-resolution degradation	2K	1000 images	Artifact removal & perceptual restoration
Waterloo Exploration	JPEG-induced artifacts	Variable	4,744 images	Compression artifact detection & restoration
LDCT-PMRI Dataset	Low-dose CT noise patterns	Clinical CT	3,000 slices	Medical noise suppression & structural quality tests
Synthetic Mixed Artifact Set (SMAS)	Blur + noise + sensor banding (synthetic)	512×512	5,000 images	Training the artifact localization module

4.2 Performance Evaluation

As the main dataset, the Synthetic Mixed Artifact Set (SMAS), created and curated to this study and providing a wide range of degradation effects (blur, noise, compression, and sensor banding) and the presence of clean-degraded image pairs, is used to effectively train the modules of the artifact localization, explainability, and adaptive restoration. The proposed XAI-driven restoration system was compared to six baseline models found in the recent literature. PSNR, SSIM, perceptual LPIPS score and inference time per image were evaluated.

Table 2: Performance Comparison of Image Restoration Models

Model	PSNR (↑)	SSIM (↑)	LPIPS (↓)	Inference Time (ms)	Remarks
Denoising Swin Transformer (DST) [4]	31.52	0.904	0.168	42 ms	Strong transformer denoising; limited real-time performance
DTNet Dynamic Transformer [5]	32.10	0.912	0.152	58 ms	Effective on spatial noise; slower due to multi-stage blocks
SwinCT Noise Reduction [6]	33.25	0.921	0.140	55 ms	Good structural preservation in CT-like noise
Cross-Feature Transformer CICFormer [8]	32.89	0.927	0.135	47 ms	Enhanced contextual denoising; limited artifact handling
JPEG-AI Artifact Detector + Restorer [10]	30.78	0.892	0.181	35 ms	High accuracy in compression artifacts only
DTNet Semantic Artifact Breaker [11]	31.94	0.906	0.162	50 ms	Strong artifact reasoning; lacks restoration adaptability
****Proposed XAI-Driven Restoration System**	**35.42**	**0.948**	**0.102**	**29 ms**	**Best quality + fastest inference; interpretable corrections**

Discussion of Results

The proposed model outperforms all the methods of the baseline in quantitative and perceptual measures. The hybrid CNN - Transformer architecture allows deeper contextual learning and the XAI modules have artifact-aware gating preventing over-smoothing and enhance detail reconstruction. The LPIPS decrease (about 30 percent better than DST and DTNet) exhibits a high perceptual fidelity. Moreover, the latency gains (29 ms per image) validate real-time usability, which aggressive transformer-based models do not attain. The attribution consistent restoration process also provides clear decision pathways, an element lacking in the conventional restoration methods.

5. CONCLUSION

In this work, an XAI-based intelligent image restoration system was presented that can detect and interpret artifacts in real-time, and reconstruct images with high fidelity under various conditions of degeneration. The presented pipeline combined convolutional encoders with lightweight transformers attention, attribution-based spatial gating, and uncertainty-based correction systems to provide transparent and adaptive restoration. Experimental testing on Synthetic Mixed Artifact Set (SMAS) and complementary benchmark datasets showed that the PSNR, SSIM, and perceptual quality are significantly enhanced by the models. The ability to include explainability modules like Grad-CAM and SHAP gave better insight into the decisions of relying on the restoration, making them reliable and trustworthy, especially when it comes to sensitive imaging tasks. Moreover, the compression of models and latency-sensitive optimization allowed real-time processing without the need to reduce visual quality. In general, the findings affirm that explainability and artifact-conscious restoration result in a powerful, effective, and understandable structure, which makes the proposed system a viable contender of future digital imaging processes.

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CONFLICTS OF INTEREST
The authors declare no conflict of interest.
Data Availability Statement
The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request

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