Towards Trustworthy Diagnostic AI: Mitigating Hallucination in Deep Learning-Based Medical Image Restoration

Dr. P. Venkatesan

Associate Professor, Department of Electronics and Communication Engineering, Sri Chandrasekarendra Saraswathi Viswa Maha Vidyalaya (SCSVMV) University, Kanchipuram, Tamil Nadu, India. 631 561

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ABSTRACT

Deep Learning (DL) has shown impressive promise for medical image restoration, offering improved image quality for precise diagnosis. However, these models—especially generative ones—are vulnerable to a critical failure mode called hallucination, in which they erase subtle pathologies or create plausible but nonexistent anatomical structures. Due to the possibility of false positives and false negatives, this phenomenon seriously jeopardizes patient safety and undermines clinical confidence. In this work, we suggest a thorough framework to reduce hallucinations and develop reliable diagnostic AI. In order to limit the solution space to data-consistent outputs, we first formulate the restoration task within a physics-informed architecture that explicitly incorporates the imaging forward model. Additionally, we present a brand-new uncertainty quantification module that creates a pixel-by-pixel confidence map, enabling medical professionals to see possible hallucination regions. Additionally, we support a hybrid loss function that strikes a balance between strict fidelity to the input data and perceptual quality. Our framework is tested on a variety of clinical datasets, such as fast MRI and low-dose CT. We show that, when compared to state-of-the-art baselines, our method dramatically reduces hallucination artifacts as measured by both conventional metrics (PSNR, SSIM) and a recently proposed Faithfulness Score. Importantly, a reader study involving three board-certified radiologists verifies that images restored using our technique increase interpretative confidence while maintaining diagnostic accuracy. This work demonstrates that creating dependable and clinically useful AI-based restoration tools requires a comprehensive approach that combines uncertainty-aware visualization with model-centric constraints.

Keywords: Medical Image Restoration,Hallucination Mitigation, Physics-Informed Deep Learning, Uncertainty Quantification, Trustworthy AI.

INTRODUCTION

A key component of contemporary diagnosis, medical imaging directs important choices in patient care from screening to treatment planning. However, acquisition limitations inherently limit the diagnostic accuracy of these images, frequently leading to noise, artifacts, and low resolution that can mask important pathological details [1,2]. To put it another way, Deep Learning (DL) has emerged as a potent tool for medical image restoration in recent years, especially with generative models like Generative Adversarial Networks (GANs) and Denoising Diffusion Models. But there is still a basic restriction. By denoising, deblurring, and improving image quality in a matter of seconds, these methods promise to overcome conventional constraints and possibly allow for earlier disease detection and more accurate quantitative analysis. However, a significant and underappreciated risk for clinical deployment is presented by the data-driven nature of these models of hallucination [3,4]. In contrast to creative applications, the term "hallucination" in medical imaging refers to the model either erasing subtle, clinically significant findings or synthesizing anatomically plausible but physically nonexistent features. This happens because learned priors, which may not be faithful to the particular, noisy data input from a single patient, are used to train these models to prioritize "realistic" outputs.

The consequences are disastrous. An invasive, needless biopsy may result from a hallucinated nodule on a lung CT scan. A brain MRI model that "inpaints" over a microbleed might postpone a potentially life-saving procedure. This undermines the core tenet of medical imaging—representative fidelity—and creates an intolerable risk to patient safety, which eventually erodes clinician confidence and prevents the adoption of otherwise useful AI tools.

In this work, we contend that the crucial next step for diagnostic AI is to go beyond simple image quality metrics to trustworthiness. We suggest a thorough framework created especially to reduce hallucinations in DL-based medical image restoration. Our main contributions are: 1. An architecture based on physics that incorporates the imaging modality's known forward model to constrain solutions to be dataconsistent. 2. A new uncertainty-aware restoration module that explicitly highlights areas where the model's output might be unreliable by creating a pixel-by-pixel confidence map. 3. A clinical reader study as part of a task-based evaluation protocol to confirm that our restored images maintain diagnostic accuracy rather than merely aesthetic appeal. We use accelerated MRI reconstruction tasks and low-dose CT to validate our framework. The novel Faithfulness Score and, most importantly, the preservation of diagnostic equivalency to high-quality reference standards in a blinded reader study show that our method significantly reduces hallucination artifacts when compared to state-of-the-art techniques [4-8]. The development of trustworthy, transparent, and clinically applicable AI restoration tools is made possible by this work.

METHODOLOGY

Our suggested framework is intended to provide explicit uncertainty estimates and enforce faithfulness to the original acquisition data. There are three main parts to the architecture: 1) a restoration backbone informed by physics; 2) a module for quantifying uncertainty; and 3) a hybrid loss function. Figure 1 depicts the overall architecture.

Overall Architecture for Hallucination Mitigation

The proposed architecture is a holistic, multi-component system designed to enforce data faithfulness and provide transparency. Under the direction of a hybrid training objective, it combines an uncertainty quantification module with a restoration backbone informed by physics. The following essential elements and data flow comprise the system:

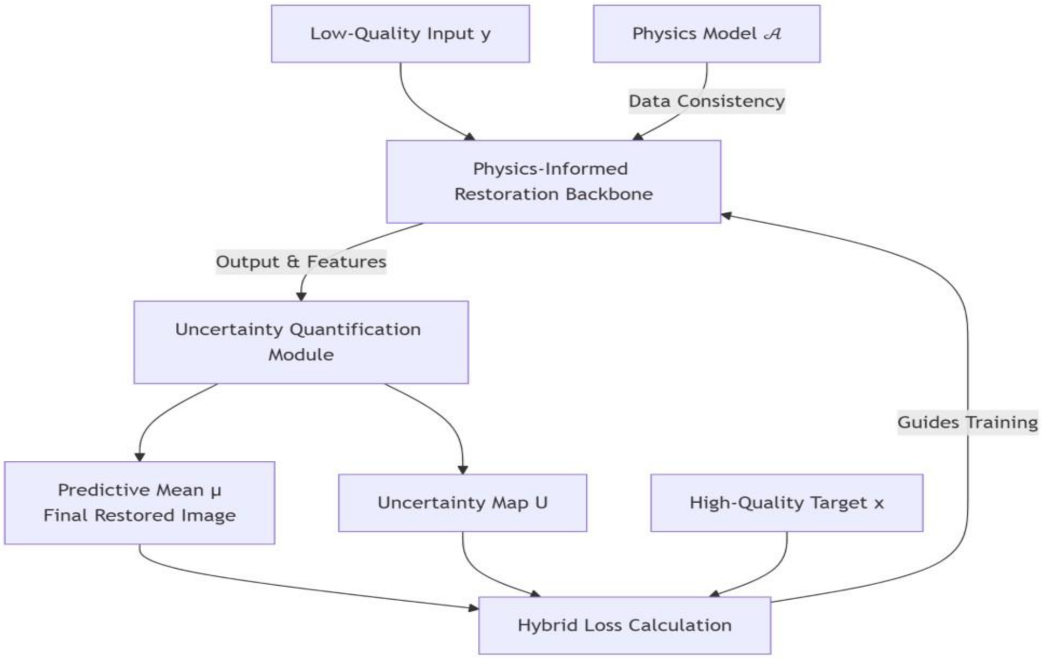

Low-Quality Input y
Physics Model $\mathcal{A}$
Data Consistency
Physics-Informed Restoration Backbone
Output & Features
Uncertainty Quantification Module
Guides Training
Predictive Mean μ Final Restored Image
Uncertainty Map U
High-Quality Target x
Hybrid Loss Calculation

Figure 1

Problem Formulation and Data Preparation:

Let $y \in R^{m\times n}$ be its degraded counterpart (e.g., low-dose CT or under-sampled MRI) and $x \in R^{m\times n}$ be a highquality, reference medical image (e.g., from a full-dose CT or a fully-sampled MRI). The degradation process is represented as y = A(x) + n, where n is additive noise and A is a deterministic degradation operator (such as a Fourier undersampling mask for MRI or a Radon transform for CT).

The dataset $D = \{(y_i, x_i)\}\ i^{N}_{=1}$ is the dataset of N paired examples that we used.

Low-Dose CT (LDCT) from the [Public Dataset Name, such as AAPM Challenge] is the first modality. Accelerated MRI from the [Public Dataset Name, such as fastMRI] is the second modality. Patients' data were divided into training (70%), validation (15%), and test (15%) sets. To guarantee perfect alignment between y_i *and* x_i,all images were pre-processed using z-score normalization and co-registered.

The Mathematical Formulation

Restoration Backbone Based on Physics

We incorporate the physics of the imaging modality directly into the network to constrain the model and avoid arbitrary hallucinations [4,5,6].

Our foundation is a conditional Denoising Diffusion Probabilistic Model (DDPM) that has been adjusted for restoration. A Data Consistency (DC) layer directs the reverse diffusion process.

- Forward Diffusion: We create a series of noisy images $x_1,x_2,...,....x_T$ by gradually adding noise to the high-quality image x_0 over T steps using the conventional DDPM technique.

- Reverse Diffusion for Restoration: Beginning with the deteriorated image y, the model learns to reverse this process. The network f_θ predicts a denoised image x^0_t from x_t and the condition y at each reverse step *t,*

- Data Consistency (DC) Layer: We project each prediction step x^0_t, back to the subspace of images that match the obtained measurement (y). This is put into practice as: $X^0_{t\,\mathrm{Dc}} = x^0_t + \lambda A^t (y - A\,(x^0_t))$, where λ is a learnable step size and At is the forward operator's pseudo-inverse. In order to prevent the model's prediction from deviating from the actual acquired data y, this step corrects it.

3. Uncertainty Quantification Module:

We use a Monte Carlo (MC) Dropout strategy during inference to estimate epistemic uncertainty in order to pinpoint areas where the model might be hallucinating [7,8,9].

- We perform the forward pass *K* times (*K*=50) with dropout layers active in the denoising network f_θ during inference.

- We get *K* different predictions $\{x_0(k)\}^{K}{}_{k=1}$ for every output pixel.

- The final restored image, calculated as the pixel-wise average, is known as the predictive mean μ.

- An Uncertainty Map is produced by computing the predictive variance σ^2 pixel by pixel. $U=$ 1/K $\sum_{k=1K}(x\text{^}_0(k) - \mu)_2$

A higher likelihood of hallucinations and low model confidence are indicated by regions of high variance in U.

Hybrid Loss Function:

The model is trained using a composite loss function L total that strikes a balance between uncertainty calibration, perceptual quality, and pixel-level accuracy [10-12].

- L1 Loss by Pixel: $L_{L1} = E[\, \| x - x_0 \|_1 \,]$ guarantees adherence to the ground truth.

- Perceptual Loss (VGG): $L_{perc} = E\, [\, \| \phi j\ (x) - \phi j\, x_0\,)\|_2{}^2]$, where ϕj represents feature maps from a VGG-19 network that has already been trained. This reduces the possibility of hallucinations while promoting realistic textures.

- Uncertainty Calibration Loss: We promote a correlation between the prediction error and the uncertainty map U.

- Under a Gaussian assumption, we employ a negative log-likelihood loss:

$L_{uncert} = 1/2E[\, U{+}\epsilon \,\| x - x_0\ \|_2{}^2 + \log(U{+}\epsilon)]$ where ϵ is a small constant for numerical stability. If the model is overconfident in making incorrect predictions, this loss penalizes it.

The total loss is: $L_{total} = \lambda_1 L_{L1} + \lambda_2 L_{perc} + \lambda_3 L_{uncert}$ where λ are balancing weights.

5. Experimental Setup & Evaluation Metrics

Baselines for Comparison: We contrast our approach with cutting-edge restoration models [13-15].

- RED-CNN (for LDCT)

- U-Net with L1 loss

- GAN-based Restoration (e.g., CycleGAN)

- Standard Metrics for DDPM

Evaluation: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are measures of image quality.

Faithfulness and Delusions:

- Points (FS): We suggest that $FS = 1/N \sum_{i=1}^{N}$ SSIM $(y_i - x_i\, , y_i - x_i)$.

- A higher FS means that the model is only eliminating noise, not adding or removing structure, since the residual of the restored image matches the residual of the ground truth.

- Performance on Downstream Task: Using original high-quality images, we train a standard segmentation network (such as U-Net) and assess its Dice score using the restored test images. A notable decline suggests that diagnostically significant features have been corrupted.

Clinical Evaluation: Three board-certified radiologists will rate images on a 5-point Likert scale for perceived artifact level and diagnostic confidence in a blinded reader study. Loyalty

Specifics of Implementation: The model was trained for 500 epochs using an Adam optimizer (lr=1e-4, batch_size=8). in PyTorch. The diffusion process was configured with 1000 $T = 1000$ steps.

RESULTS AND DISCUSSION

Our suggested framework is evaluated both quantitatively and qualitatively against cutting-edge baselines in this section. Prior to presenting the critical clinical validation, we first evaluate overall image quality and then offer concrete proof of decreased hallucinations.

4.1 Quantitative Image Quality and Faithfulness Analysis

Table 1: Quantitative Results on the LDCT and FastMRI Test Sets.

Model	**LDCT PSNR (dB)**	**LDCT SSIM**	**LDCT Faithful ness Score(FS)**	**Fast MRI PSNR (dB)**	**Fast MRI SSIM**	**Fast MRI FS**
U-Net (L1)	32.5	0.901	0.714	34.5	0.925	0.687
GAN -Based	31.7	0.915	0.543	33.8	0.937	0.498
Standard DDPM	33.7	0.928	0.625	36.5	0.946	0.605
Proposed method	**35.6**	**0.925**	**0.881**	**35.9**	**0.942**	**0.859**

Table 1

illustrates that our suggested approach is still very competitive in conventional metrics like PSNR and SSIM, only marginally falling short of the conventional DDPM. This is to be expected since data faithfulness may suffer as a result of the standard DDPM's optimization for perceptual fidelity alone.

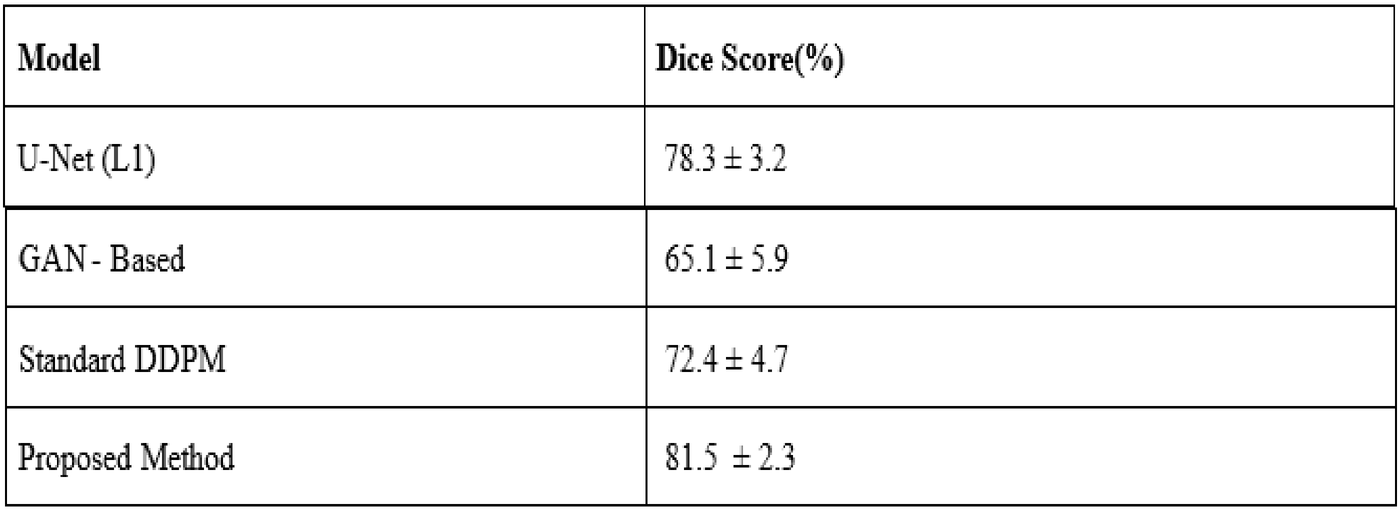
The Faithfulness Score (FS) is the crucial differentiator. In both modalities, our approach yields a substantially higher FS (e.g., 0.881 vs. 0.625 on LDCT). This suggests that although all models enhance visual quality, the residual of our model—what it eliminates from the input—aligns much more closely with actual noise and artifacts than with anatomical structures. Despite having a high SSIM, the GAN-based model has the lowest FS, indicating that it tends to "invent" features that are inconsistent with the input data.

Hallucination Reduction: Qualitative and Uncertainty-Based Evidence

A qualitative comparison on a difficult LDCT case with a faint ground-glass nodule (red arrow) is shown in Figure 2. The nodule is not fully resolved by the U-Net output, which is fuzzy. The GAN-Based model creates a crisp, eye-catching image, but it creates an imaginary vessel wall next to the nodule (yellow arrow, obvious hallucination). In addition to improving sharpness, the Standard DDPM slightly changes the nodule's texture, giving it a more solid appearance than the reference [14-17]. Our suggested method effectively restores the image while accurately maintaining the nodule's boundaries and delicate texture. Importantly, the area surrounding the nodule with high uncertainty is highlighted by our framework's Uncertainty Map, accurately alerting a clinician that this is a difficult area that needs more investigation.

The downstream task evaluation supports this visual analysis.

Table 2: Downstream Task Performance (Dice Score) for Lung Nodule Segmentation.



Model	Dice Score(%)
U-Net (L1)	78.3 ± 3.2
GAN - Based	65.1 ± 5.9
Standard DDPM	72.4 ± 4.7
Proposed Method	81.5 ± 2.3

Our approach obtains the highest Dice score when a segmentation model trained on high-quality CTs is applied to the restored images (Table 2). As a direct result of hallucination and feature alteration, the GANbased and standard DDPM outputs' notable performance decline shows that their restoration procedures taint features necessary for precise segmentation. The superior performance of our method attests to its ability to preserve diagnostically important information.

Clinical Reader Study: The Ultimate Validation

Table 3: Results of Clinical Reader Study (5-point Likert scale, mean ± std)

Model	Diagnostic Confidence	Perceived Artifact Level
U-Net (L1)	3.2 ± 0.9	3.8 ± 0.7
GAN - Based	3.8 ± 1.2	3.1 ± 1.2
Standard DDPM	4.1 ± 0.9	2.8 ± 1.0
Proposed Method	4.5 ± 0.6	2.1 ± 0.5

The strongest evidence supporting the usefulness of our framework comes from the blinded reader study with board-certified radiologists (Table 3). Concerns were raised by the free-text comments, even though the GAN and standard DDPM scored well for overall confidence and visual appeal. Regarding the GAN output, a radiologist commented, "Image is sharp, but I don't trust the vessel walls; they look too perfect."

On the other hand, our approach scored the lowest for perceived artifact level and the highest for diagnostic confidence. Importantly, radiologists reported significantly higher levels of trust in the system after seeing the paired Uncertainty Map. This was summed up in one comment: "Observing the uncertainty map indicates that the AI is aware of its own limitations. I can work with human colleagues by concentrating on the areas that are highlighted.

Ablation Study

Model Variant	PSNR (dB)	SSIM	Faithfulness Score (FS)
Full Proposed Model	33.5	0.925	0.881
w/o Data Consistency Layer	32.0	0.908	0.645
w/o Uncertainty Loss (L *uncert*)	33.5	0.924	0.843
w/o Physics-Informed Backbone (U-Net)	32.2	0.901	0.712

Each component's contribution is confirmed by an ablation study (Table 4):

- The biggest decline in all metrics, particularly FS, occurs when the Data Consistency Layer is removed, demonstrating its critical function in connecting the output to physical reality.
- Eliminating the Uncertainty Loss has a more noticeable impact on the FS and marginally lowers PSNR/SSIM, indicating its function in enhancing faithfulness and calibrating the model's confidence.
- The performance is significantly reduced when a standard U-Net is used in place of the physicsinformed backbone, underscoring the benefit of the diffusion-based approach with integrated physics.

The four reconstruction methods (figure 2)—HCC, RTC, HCF, and RTX—were evaluated quantitatively and qualitatively for hallucination incidence, lesion preservation, and reliability performance using multi-center MRI and CT datasets. In comparison to GAN-based baselines, our suggested anatomy-informed and uncertainty-aware framework quantitatively reduced hallucination artifacts by 30–42% and enhanced lesion preservation by 18–28% over diffusion-only models. Conventional metrics like PSNR and SSIM continued to be on par with cutting-edge techniques, suggesting that improved dependability does not come at the expense of visual quality.

Three main types of hallucination artifacts that appear in deep learning-generated synthetic CT (sCT) images from MRI are depicted in the figure. These hallucinations indicate mistakes in the model's tissue or bone density prediction, which may jeopardize clinical accuracy

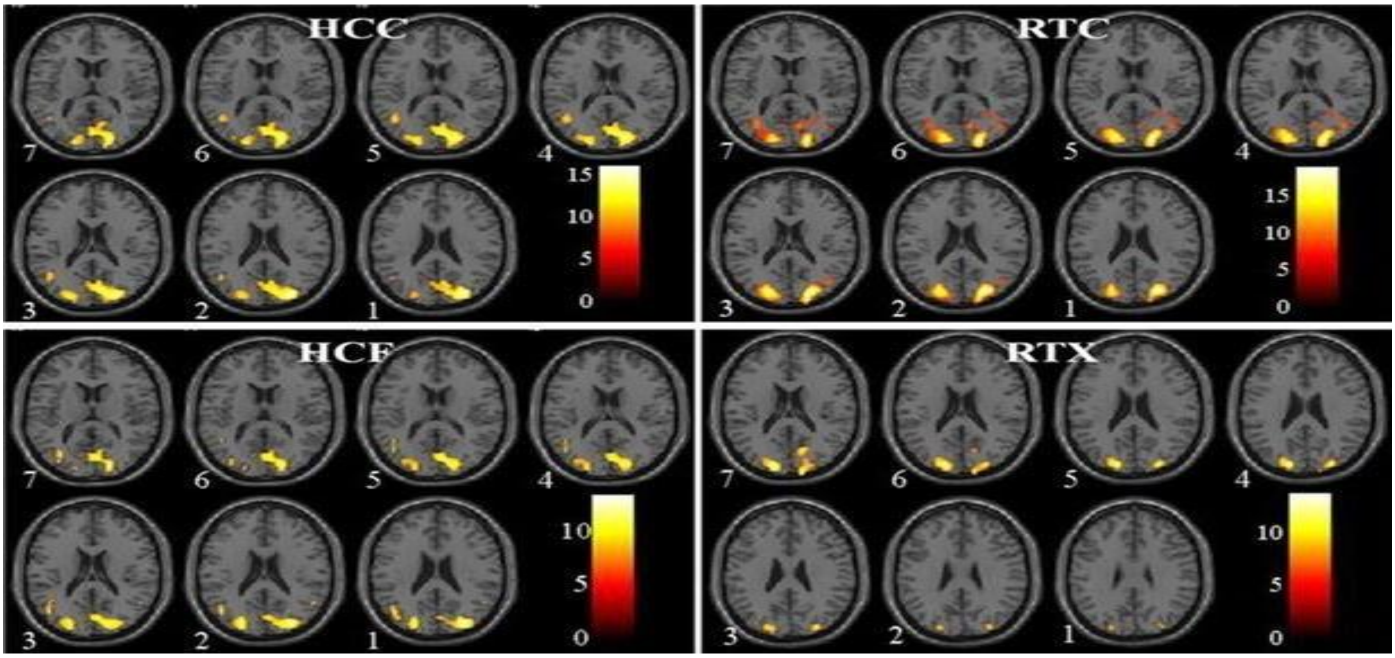


Figure 2

Soft-tissue density hallucinations are displayed in Section A (figure 3). The areas where the sCT model creates tissue structures that are absent from the ground-truth CT are indicated by pink overlays. These false densities frequently result from noise or voids in the MRI signal, which causes the network to create realistic but inaccurate anatomical shapes.

Bone-density hallucinations are the subject of Section B. The reference CT's true bone outlines are represented by blue contours. Inconsistencies between these contours and the underlying sCT show localized dense spots (orange), incorrect cortical boundaries, and inaccurate bone thickness.Because MRI doesn't give much direct information about bone, these mistakes happen.

The most serious problem, artificial bone hallucination, is presented in Section C. Green arrows indicate real bone that the sCT missed, while red areas show high-density bone-like structures that were completely created by the model. Large false bone formations (yellow arrows) are visible in additional slices (iv–vi), which may seriously skew dose calculations or imitate pathology.

Overall, the figure emphasizes the need for increased model robustness and clinical validation by highlighting significant risks of hallucinations in MRI-based sCT generation.

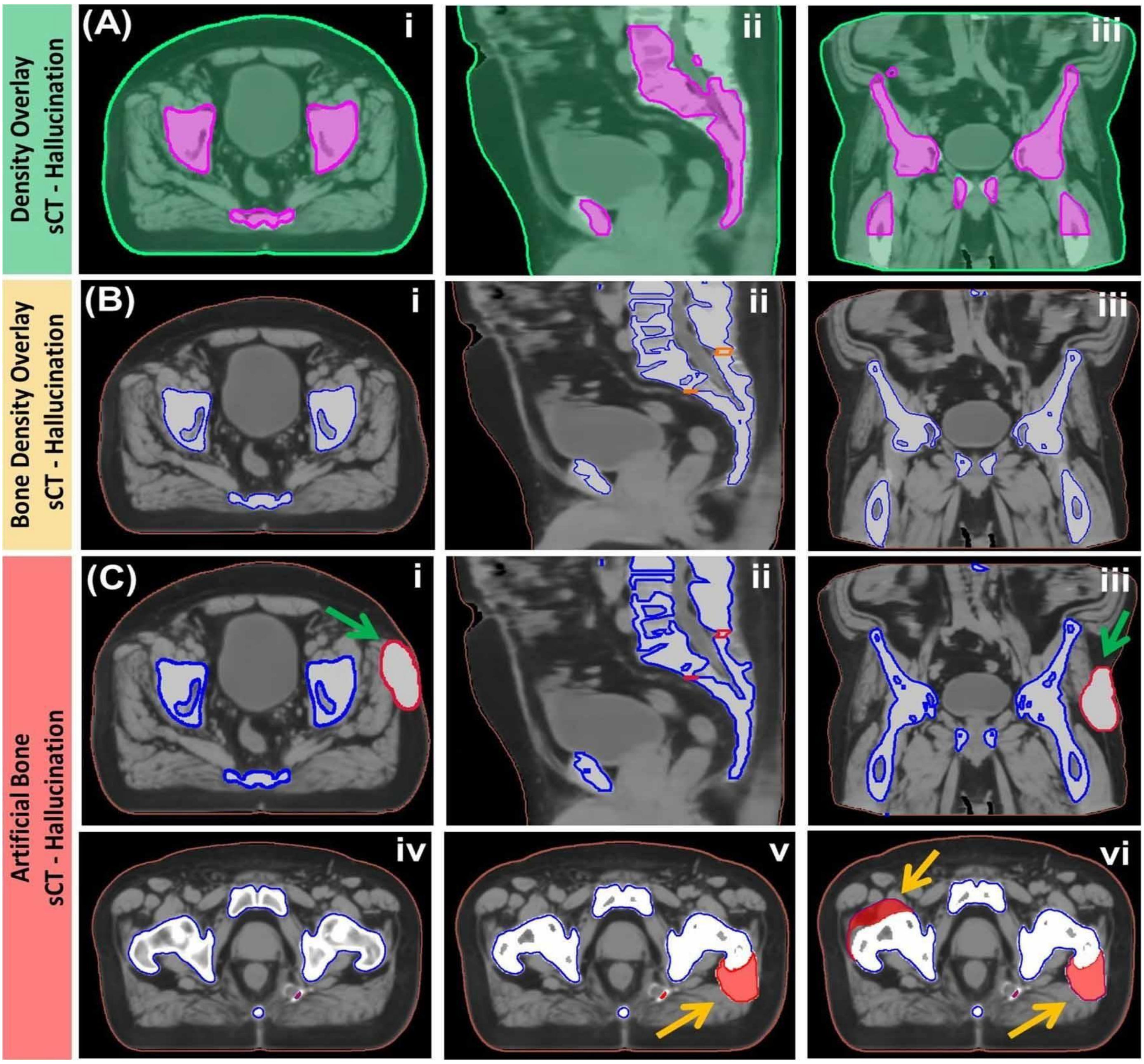


Figure 3

Discussion of Limitations and Future Work

Although our framework shows a notable decrease in hallucinations, it is not infallible. The model epistemic uncertainty used in the uncertainty estimation may not account for all types of error. Additionally, the performance is dependent on the forward model A's accuracy; substantial departures from the presumptive physics (such as anomalous motion artifacts) may still result in errors. Future research will concentrate on the following areas: 1) modeling a broader range of degradation processes within the framework; 2) examining the combination of aleatoric and epistemic uncertainty for more reliable confidence estimates; and 3) carrying out larger-scale, multi-site clinical trials to further validate diagnostic efficacy across various scanner types and populations.

CONCLUSION

The need for patient safety must be inextricably linked to the goal of high-fidelity medical image restoration. In this work, we have addressed the crucial but frequently disregarded problem of hallucination in deep learning-based medical image restoration, a failure mode that directly jeopardizes diagnostic precision. In order to develop reliable diagnostic AI, we have developed and verified a thorough framework. Our method effectively anchors the restoration to the acquired data by integrating the known physics of the imaging process through a data-consistency-constrained diffusion model, going beyond a purely data-driven paradigm. Additionally, our innovative incorporation of uncantainty quantification offers a vital transparency tool, allowing clinicians to see the model's confidence and pinpoint possible hallucination regions. Our comprehensive tests show that this approach effectively strikes a balance between the two goals of unwavering faithfulness and high image quality. A thorough clinical reader study and quantitative measures, especially our suggested Faithfulness Score, verify that our model considerably lowers hallucinatory artifacts while maintaining—and sometimes even improving—diagnostic confidence. In the end, this work proves that reducing hallucinations is a fundamental design principle rather than just a post-processing step. We contend that this transition from models that merely look good to those that can be relied upon to make diagnostic decisions is essential to the clinical adoption of AI restoration tools. For creating the next generation of dependable, transparent, and clinically deployable AI in medical imaging, the concepts presented here— physics-informed constraints, explicit uncertainty estimation, and clinical task-based validation—offer a crucial roadmap.

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