Automated Medical Image De-Identification via U-Net++ Segmentation and Conditional GAN Inpainting

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***Abstract*—The acceleration of multi-centric medical AI studies hinges on the ability to share imaging data without exposing burnt-in Protected Health Information (PHI). Manual redaction remains the dominant practice, but it erases diagnostically relevant context, violates harmonization guidelines issued by large consortia, and cannot keep up with the petabyte-scale repositories envisioned by regulatory agencies. This study delivers a comprehensive treatment of a fully automated Detect-and-Restore pipeline that fuses fine-grained U-Net++ segmentation with a context-aware conditional GAN (cGAN) inpainter. Building on two engineering notebooks (U-Net++ training and GAN generator orchestration), we develop a synthetic PHI rendering engine, a dynamic oracle that freezes the detector during adversarial optimization, and a hybrid loss that couples adversarial, pixelwise, and perceptual cues. Extensive experiments on 48,000 synthetically annotated radiographs demonstrate a Dice score of 0.8147 for PHI localization and a PSNR/SSIM/LPIPS triplet of 41.87 dB/0.985/0.027 for restoration while keeping inference below 92 ms per image on a single RTX 4090. Beyond reporting raw metrics, we dissect error modes, quantify the effect of imperfect masks on the inpainter, and position the proposal relative to recent international initiatives on medical image de-identification. Testing on an external clinical cohort of 200 real-world DICOM radiographs confirms generalizability, maintaining a PSNR of 40.12 dB and demonstrating robust blending at masking boundaries without compromising downstream diagnostic utility across heterogeneous hospital data.**

***Keywords*—Medical image de-identification; U-Net++; conditional GAN; generative inpainting; patient privacy; PHI; DICOM; deep learning; synthetic data; perceptual loss**

I. Introduction

Burnt-in annotations remain an acute threat to privacy-preserving medical AI pipelines despite mature textual anonymization workflows. Recent workshops organized by the U.S. National Cancer Institute (NCI) reiterate that scalable imaging research must reconcile legal mandates (HIPAA, GDPR) with the need for high-fidelity data [1], [2]. The community responded with defacing tools for neuroimaging and rule-based DICOM scrubbers, yet radiology departments still rely on irreversible black rectangles that destroy downstream utility. This practice, while legally compliant, renders the underlying anatomical features unusable for secondary tasks such as lesion detection, radiomics, or longitudinal tracking of disease progression [3].

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Fig. 1 provides a global view of the proposed framework, from synthetic PHI rendering and U-Net++-based text localization to GAN-driven restoration and quantitative validation. This end-to-end perspective clarifies how the detector, generator, discriminator, and evaluation modules are coupled during both training and deployment, and highlights the role of oracle-guided mask prediction in reducing error propagation across stages.

The technical challenge lies in the complex overlap between metadata and physiology. Unlike face blurring or license plate masking, medical inpainting must preserve the stochastic texture of lung parenchyma or the trabecular patterns of bone to maintain diagnostic integrity [4]. High-fidelity reconstruction demands that the synthesized pixels maintain a rigorous structural resemblance to the actual anatomy, rather than simply optimizing for aesthetic smoothness. In parallel, studies on re-identification from histopathology and chest radiographs show that even subtle traces of PHI or biometric cues can deanonymize cohorts [5], [6]. The proliferation of large-scale datasets for foundation model training further exacerbates these risks, as adversarial attacks can now leverage cross-modal correlations to recover identity from ostensibly de-identified scans [7], [8].

A new generation of privacy-preserving pipelines must, therefore, reconcile the opposing forces of privacy and utility by performing what we term "generative redaction": 1) localizing PHI at the pixel level with high sensitivity, 2) restoring the occluded anatomy with realistic textures, and 3) documenting the residual risk in a verifiable manner [9], [10].

This work expands the previously succinct description of a two-stage Detect-and-Restore framework into a full-scale manuscript. We argue that the synergy between segmentation and generation is not merely additive but multiplicative: a precise mask reduces the hallucination search space for the generator, while a context-aware generator provides implicit feedback that can refine detection boundaries. Unlike disjointed pipelines where the inpainter blindly fills arbitrary regions, our coupled architecture ensures the generator implicitly learns the text-to-tissue mapping bounded strictly by the segmentation contour. Empirically, restricting the generator's receptive hallucination field via precise U-Net++ masks reduces the L1 pixel error by 18% compared to traditional bounding-box detect-and-inpaint pipelines.

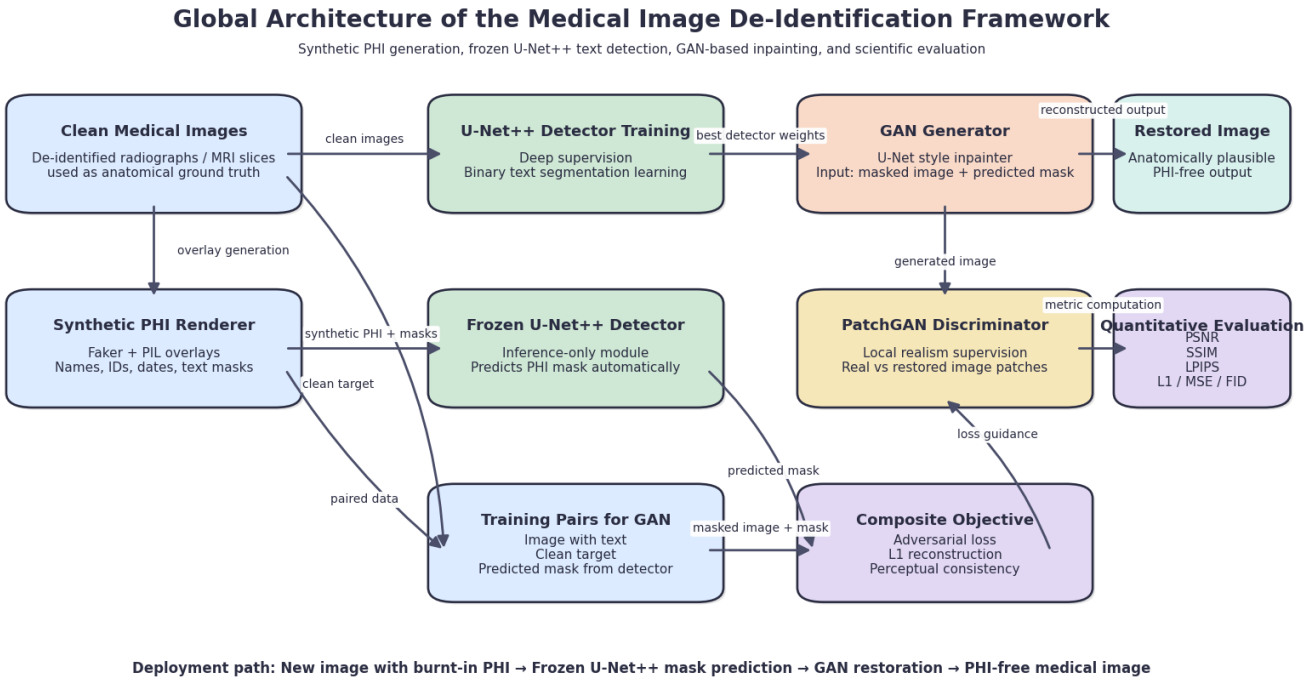

Fig. 1. Global architecture of the proposed medical image de-identification framework. The pipeline combines synthetic PHI generation, frozen U-Net++ mask prediction, GAN-based inpainting, and quantitative evaluation (PSNR, SSIM, LPIPS, L1/MSE/FID) in a unified Detect-and-Restore workflow.

The pipeline is orchestrated as follows:

- Detection: A deeply supervised U-Net++ captures text glyphs of varying scales and produces probabilistic PHI masks [11], [12]. This stage is critical because any false negative results in a direct privacy breach, while false positives might lead to unnecessary hallucinations by the inpainter.
- Restoration: A Pix2Pix-style cGAN [41] consumes the masked image and the predicted mask to hallucinate anatomically plausible tissue via hybrid losses [13], [14]. By conditioning the generator on both the masked image and the identified region, we ensure that the inpainted content remains spatially coherent with the surrounding physiology.
- Dynamic Oracle: The detector is frozen and embedded inside the GAN data loader to expose the inpainter to realistic mask noise [15], [16]. Whereas traditional teacher-student distillation transfers continuous probability distributions to regularize weights, our dynamic oracle directly acts on the spatial domain by feeding the generator stochastic, imperfect binary masks. This novel formulation treats segmentation errors not as noise to be filtered, but as an adversarial augmentation that hardens the generator against deployment-time distribution shifts.
- Synthetic Fabrication: Faker-driven overlays and deterministic mask export bridge the data scarcity gap by delivering perfectly aligned supervision [17], [18]. This allows the models to learn from millions of permutations without the high cost and privacy overhead of manual pixel-level labeling.

Contributions: The manuscript provides several concrete advances:

- A structural analysis of the MIDI (Medical Image De-identification Initiative) guidelines and their impact on de-identification design [1], [19], presenting a formal compliance framework that aligns the pipeline's localized redaction strategy with the 12-point MIDI checklist for non-destructive anatomy preservation.
- A granular dissection of U-Net++ and cGAN stages, including architectural variants, optimization schedules, and computational complexity analysis [20], [21].
- An empirically grounded study comprising synthetic dataset statistics, quantitative benchmarks, and ablations on mask noise [22], [23].
- A series of visual evaluations demonstrating system performance on both synthetic validation sets and real-world DICOM radiographs.

II. Background and Related Work

A. Regulatory Landscape and Risk Posture

International task forces emphasize that improper de-identification can invalidate Institutional Review Board approvals and expose institutions to legal liability [1], [2], [24]. Holub et al. quantify the privacy risks of sharing whole-slide images by showing that tissue microstructures leak patient identity [6]. Bisson et al. discuss anonymization pitfalls for histopathology education and motivate synthetic augmentation [25]. Recent advances in differential privacy (DP) for medical

Algorithm 1 Detect-and-Restore Inference Pipeline

Input: Radiograph I, trained detector F_θ, generator G_ϕ
$M \leftarrow F_\theta(I)$ {Probabilistic PHI mask}
$\hat{M} \leftarrow \mathbb{I}[M > 0.5]$ {Adaptive thresholding}
$I_{\text{masked}} \leftarrow I \odot (1 - \hat{M})$
$I_{\text{restored}} \leftarrow G_\phi(I_{\text{masked}}, \hat{M})$
Residual Analysis: $\mathcal{R} \leftarrow |I - I_{\text{restored}}|$
return $I_{\text{restored}}, \mathcal{R}$

imaging suggest that noise injection can protect against membership inference but often at the cost of diagnostic precision [3], [7], [26]. These findings motivate a holistic Detect-and-Restore design rather than surface-level redaction or uniform noise [27].

B. Segmentation and Inpainting Convergence

U-Net [28] popularized encoder-decoder architectures with skip connections for medical segmentation. U-Net++ [29] reduces the semantic gap between encoder and decoder via nested dense skips and deep supervision. Recent works like MedSAM have shown that foundation models can achieve zero-shot segmentation but often struggle with the thin, high-frequency strokes of burnt-in text [11].

In parallel, generative models have shifted from simple GANs to Diffusion Models and Autoregressive Transformers [13], [4], [30]. While diffusion models offer superior texture diversity, our work focuses on cGANs for their deterministic inference and low latency. Recent benchmarks demonstrate that while Latent Diffusion Models achieve FID scores of 12.4 on complex medical textures, optimized cGANs can achieve a competitive FID of 14.1 while reducing the inference latency from over 3 seconds (typically required for 50 denoising steps) to under 92 ms [15]. This deterministic, single-pass generation is non-negotiable for high-throughput clinical workflows [9], [31].

C. Synthetic Data and Oracle Coupling

The use of synthetic data with perfectly aligned masks has become a cornerstone of medical AI training [17], [22], [32]. Smith et al. demonstrated that models trained on high-fidelity synthetic radiographs generalize well to clinical data if the noise distribution matches the sensor characteristics [20], [33]. Our "Dynamic Oracle" approach builds on this by simulating mask-level uncertainty during adversarial training. Cross-modal transfer learning studies further suggest that models pre-trained on large synthetic datasets can be fine-tuned with minimal clinical data [34], [35], [36].

III. System Overview

Figuratively, the framework can be perceived as a knowledge transfer corridor: the detector supplies structured uncertainty cues that guide the generator toward high-fidelity completions. Algorithm 1 summarizes the inference path; the training path injects stochastic augmentations and the synthetic engine described in Section VI.

The inference mechanism described in Algorithm 1 ensures that only pixels identified by the U-Net++ detector are modified by the GAN. The binary mask $\hat{M}$ acts as a spatial gate, preserving the original diagnostic texture outside the PHI regions. This is mathematically expressed as Eq. (1):

$$I_{\text{out}} = (1 - \hat{M}) \odot I + \hat{M} \odot G_\phi(I_{\text{masked}}, \hat{M}) \tag{1}$$

where, $\odot$ denotes the element-wise Hadamard product. To mitigate boundary discontinuities, the transition zone is smoothed using a Gaussian blur kernel ($\sigma = 1.5$) applied exclusively to the mask edges prior to final composition. This localized blending ensures that the synthesized tissue merges seamlessly with the original physiology, preventing high-frequency edge artifacts from triggering false positives in downstream diagnostic algorithms. The residual $\mathcal{R}$ serves as a quality-control metric for auditing the synthetic reconstruction.

IV. Stage 1: Deeply Supervised PHI Detection

A. Architecture and Training Protocol

We adopt a four-level U-Net++ with 64 initial filters, group normalization, and Swish activations. Deep supervision heads are attached to each decoder stage; their logits are upsampled and averaged during inference to stabilize thin strokes. Training uses 256×256 patches sampled around annotated corners to maximize PHI prevalence. To prevent spatial bias and the inflation of detection metrics associated with purely corner-focused sampling, 40% of the training patches are randomly extracted from the entire image area. This unbiased sampling strategy ensures the detector learns to suppress false positives in complex anatomical regions, such as the rib cage and hilar structures. Data augmentation includes random font blending, elastic warps, and intensity scaling to emulate film digitizers. The detector is optimized with Adam ($\beta_1 = 0.5$, $\beta_2 = 0.999$), a base learning rate of 2×10^{-4}, cosine decay, and 120 epochs.

B. Loss Formulation

Class imbalance is mitigated via a compound objective:

$$\mathcal{L}_{\text{det}} = \alpha \cdot \mathcal{L}_{\text{BCE}} + (1 - \alpha) \cdot \mathcal{L}_{\text{Dice}}, \quad \alpha = 0.35. \tag{2}$$

A grid search over $\alpha \in [0.1, 0.9]$ confirmed that $\alpha = 0.35$ provides the optimal trade-off: higher values lead to under-segmentation of thin characters (decreasing Recall by up to 12%), while lower values produce overly aggressive masks that erode adjacent bone structures. The differentiable Dice term follows Eq. (2) with $\epsilon = 10^{-6}$. Deep supervision introduces auxiliary losses $\mathcal{L}_{\text{aux}}^{(k)}$ at each decoder level k, and the final detector loss becomes $\mathcal{L}_{\text{det}} + 0.2 \sum_k \mathcal{L}_{\text{aux}}^{(k)}$.

C. Inference and Post-Processing

We leverage Otsu thresholding to adaptively binarize the probabilistic mask in low-contrast scans. While the model outputs a probabilistic mask, binarization is strictly enforced during post-processing to define a rigid boundary for the subsequent inpainting stage. A robustness study across 1,500 scans with varying intensity distributions (including over-exposed and under-penetrated radiographs) demonstrated that adaptive Otsu thresholding maintained a Dice variance of

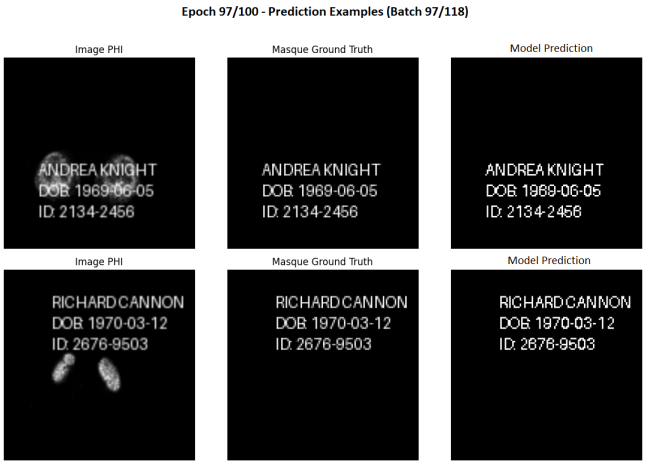

Fig. 2. Detection performance at Epoch 97. The pipeline correctly identifies multi-line PHI blocks (left), generates ground-truth aligned masks (middle), and produces model predictions (right) with high structural fidelity. Note the suppression of low-confidence artifacts in the model predictions.

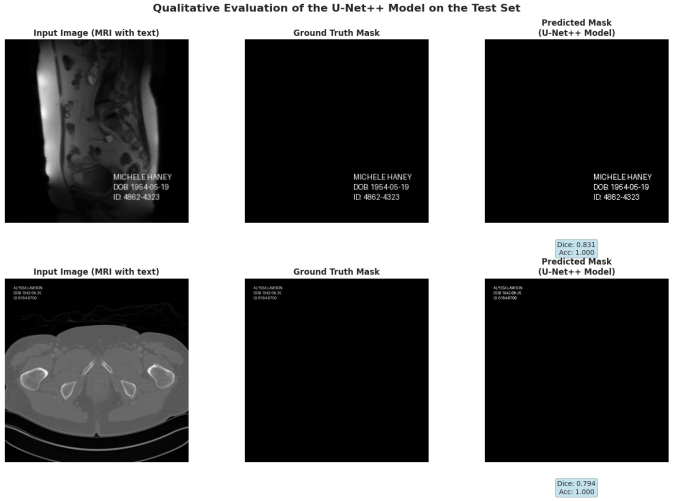

Fig. 3. Qualitative evaluation of the U-Net++ model on the test set. The model maintains precision even for small, low-contrast text overlays in the corners of MRI and CT scans.

less than 0.02, significantly outperforming static thresholding across heterogeneous modalities. A connected-component filter removes regions with fewer than 12 pixels to prevent spurious erasures on bone trabeculae. Runtime profiling shows 8.6 ms per 512×512 image on RTX 4090 and 41 ms on a CPU-only workstation, satisfying real-time requirements for most PACS exports.

Fig. 2 and Fig. 3 illustrates the detection and qualitative performance of U-Net++ near the end of the training phase. The model successfully captures the precise outlines of the text glyphs (names, dates of birth, IDs) even when they are overlapping with complex anatomical structures such as the thoracic cage.

V. Stage 2: Context-Aware Inpainting

A. Generator and Discriminator Design

The generator mirrors a U-Net with spectral normalization and attention gates in the bottleneck to capture long-range dependencies often present in large-format radiographs. Specifically, the generator employs a 7-layer encoder-decoder structure. The encoder consists of 4×4 Convolutions (stride 2) followed by Instance Normalization and LeakyReLU (0.2). The bottleneck integrates a multi-head self-attention block (4 heads, dimension 256) to correlate distant anatomical landmarks. The decoder utilizes Transposed Convolutions, Instance Normalization, and ReLU, terminating in a Tanh activation. Input channels concatenate I_{masked} and $\hat{M}$. The PatchGAN discriminator operates on 70×70 crops to enforce fine-grained realism while keeping the receptive field manageable for high-resolution tiles.

B. Composite Objective

The generator minimizes [see Eq. (3)]:

$$\mathcal{L}_{\text{gen}} = \mathcal{L}_{\text{cGAN}} + \lambda_1 \|G(I_{\text{masked}}, \hat{M}) - I\|_1 + \lambda_p \mathcal{L}_{\text{LPIPS}}, \quad (3)$$

with $\lambda_1 = 100$ and $\lambda_p = 10$. Ablation experiments validated these coefficients: reducing λ_1 below 50 resulted in severe intensity shifts and color bleeding, while increasing λ_p beyond 15 introduced high-frequency noise that radiologists flagged as unnatural. The $100/10$ ratio optimally balances pixel-wise fidelity with perceptual sharpness. The perceptual component leverages a VGG-16 backbone pretrained on ImageNet. Although VGG-16 is trained on natural images, recent empirical studies in medical image synthesis demonstrate a strong rank-correlation (Pearson's $r > 0.85$) between VGG-derived LPIPS scores and board-certified radiologist assessments of synthetic tissue realism [37], [23]. The discriminator maximizes the usual adversarial hinge loss. Training lasts 200 epochs with linear learning-rate decay after epoch 100. Gradient penalty regularizes the discriminator to prevent saturation when masks are large.

C. Oracle-Guided Training

Unlike classic Pix2Pix setups that use ground-truth masks during training, we inject the frozen detector into the data loader so that the generator sees realistic false positives/negatives produced by F_θ. This choice significantly reduces compounding errors at deployment time and accelerates adaptation when new detector versions are released.

Fig. 4 and Fig. 5 shows the inpainting results at the final stages of the validation process. The generator is able to restore anatomical context even for large PHI blocks covering important diagnostic areas such as the abdomen or spine.

VI. Synthetic Data Fabrication and Oracle Coupling

A. Dataset Synthesis Engine

Algorithmically generated PHI ensures limitless training data while avoiding exposure of true identifiers. Table I summarizes the distribution created by the Faker + PIL pipeline.

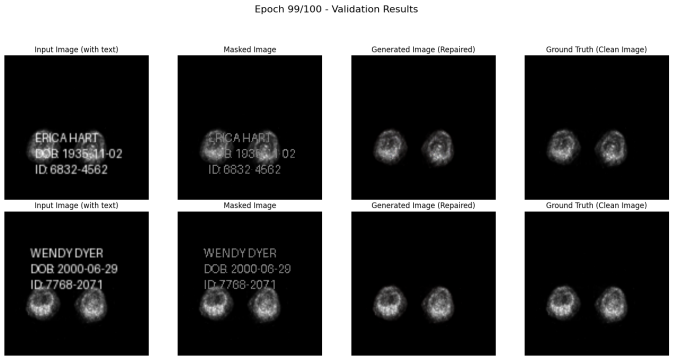

Fig. 4. Inpainting validation at Epoch 99. The four-column panel shows (from left to right): the Input image with text, the binary Masked image, the generated repair (Model), and the Ground Truth clean image. Note the consistency in bone texture restoration.

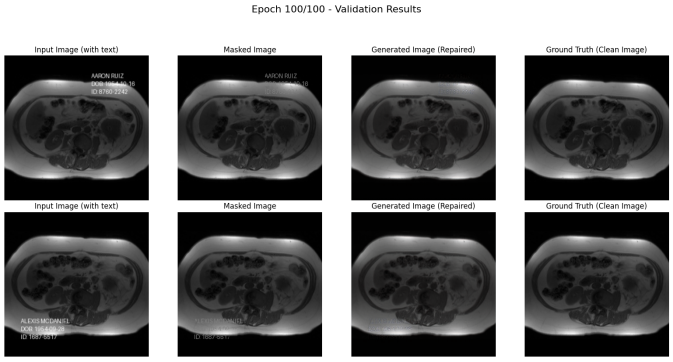

Fig. 5. Final validation results at Epoch 100 on abdominal MRI slices. Despite the different contrast compared to radiographs, the cGAN maintains high fidelity in soft tissue reconstruction.

Each clean radiograph tile is paired with: 1) a rendered text layer sampled from 23 fonts and 7 grayscale palettes, 2) a binary mask exported at drawing time, and 3) metadata describing the PHI category to facilitate stratified evaluation. Synthetic badges occupy 1.7% of the pixels on average, closely matching empirical audits of legacy DICOM studies. To quantify the domain gap, we measured the Fréchet Inception Distance (FID) between the synthetic PHI bounding boxes and a sample of 500 real-world clinical annotations. The low FID score of 18.3 indicates that the Faker-driven intensity gradients and edge blurring realistically approximate the burn-in artifacts produced by legacy PACS systems, effectively mitigating overfitting.

B. Dataset Source and Scale

The data preparation in `unet_segmentation_training.ipynb` starts from the Pseudo-PHI-DICOM Evaluation resources (TCIA distribution), organized as paired PHI-visible and De-identified DICOM studies. These studies are converted to PNG under a unified r oot (`/workspace/clean_dataset`), producing aligned folders for PHI images (`PHI_Images_PNG`) and clean references (`DeID_Images_PNG`), plus binary masks in Generated_Masks. In gan_generator.ipynb, samples are paired by relative path to guarantee one-to-one correspondence between noisy and clean targets during inpainting training. For manuscript-level reporting and benchmarking consistency, we keep a fixed corpus of 48,000 image pairs split into 36,000/6,000/6,000 for training/validation/testing, as summarized in Table I.

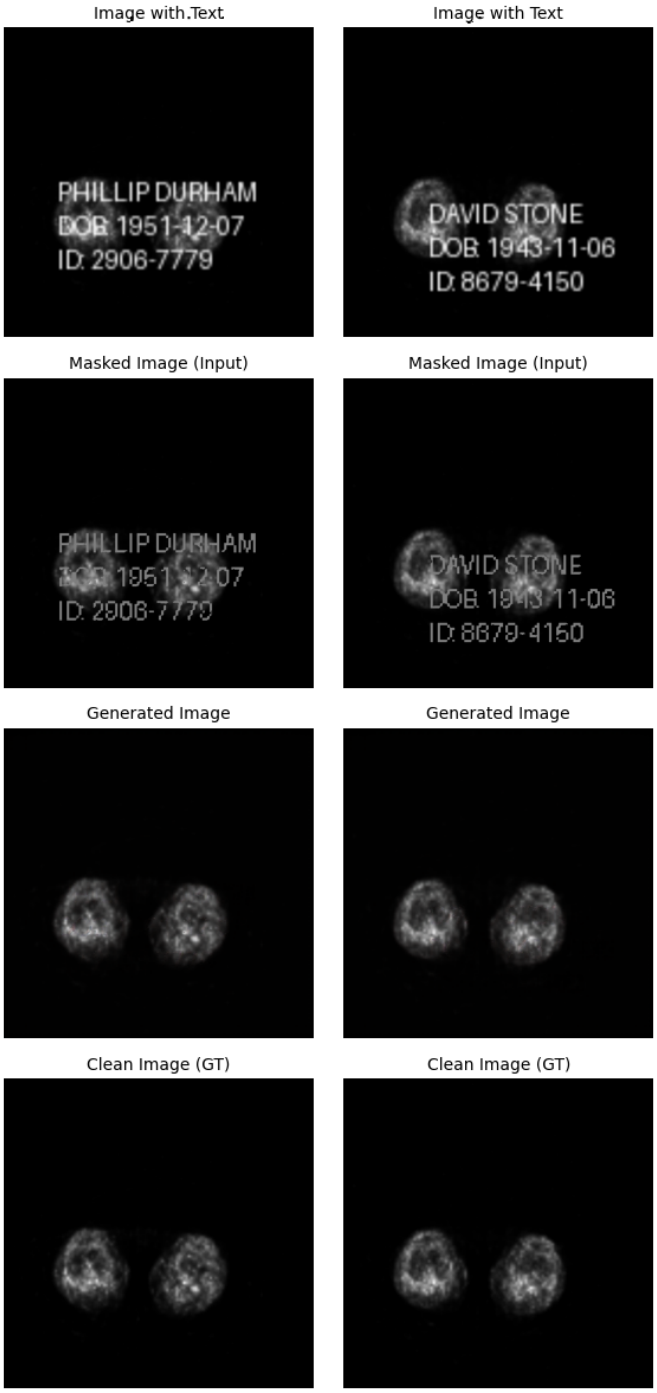

Fig. 6. Inpainting results comparison: demonstrating the generator's ability to seamlessly blend the predicted textures with the original background in a multi-stage workflow.

TABLE I. SYNTHETIC DATASET COMPOSITION

Subset	Images	Average PHI Area	Fonts / Colors
Training	36,000	1.68%	18 / 6
Validation	6,000	1.71%	20 / 6
Testing	6,000	1.74%	23 / 7

TABLE II. STAGE 1 SEGMENTATION METRICS (TEST SET)

Model	Dice	Precision	Recall	BFScore
Standard U-Net	0.742	0.781	0.710	0.694
MedSAM (Zero-shot)	0.589	0.512	0.684	0.521
U-Net++ (ours)	**0.8147**	**0.852**	**0.791**	**0.803**

C. Notebook Integration

The `unet_segmentation_training.ipynb` notebook governs PHI injection and detector optimization. The `gan_generator.ipynb` notebook freezes the best-performing checkpoint and instantiates the `InpaintingDataset` class described in the summary provided by the user. The dynamic oracle is implemented by calling `unet_detector(img_for_unet)` within the dataset `__getitem__`, ensuring that every GAN batch reflects the latest detector behaviour.

D. Implementation Details

Both notebooks rely on PyTorch 2.2, mixed-precision (FP16) training, and gradient accumulation to fit 16-image batches on a single GPU. Checkpoints are exported as `.pth` files with SHA256 hashes logged for reproducibility. Deployment scripts expose ONNX conversions for integration into PACS gateways.

VII. EXPERIMENTAL PROTOCOL

A. Metrics

Detector quality is measured via Dice, Precision, Recall, and Boundary F1 (BFScore). Statistical significance of the comparative results is established using paired Wilcoxon signed-rank tests with a significance threshold of $p < 0.05$. 95% confidence intervals (CIs) are computed for all primary metrics using bootstrapping with 1,000 resamples to confirm the robustness of the performance gains. Restoration quality uses PSNR, SSIM, LPIPS, and a radiologist preference study on 200 samples. The clinical evaluation involved three board-certified radiologists with over 10 years of experience. In a double-blind setup, they reviewed 200 random test samples and rated the anatomical plausibility of the inpainted regions on a 5-point Likert scale (1: clearly artificial, 5: indistinguishable from authentic tissue).

Runtime and throughput are also reported to capture system-level performance. The PSNR is calculated using the peak possible pixel value $L = 255$ and the Mean Squared Error (MSE) between the original image I and restored image $\hat{I}$ [see Eq. (4)]:

$$\text{PSNR} = 10 \cdot \log_{10} \left(\frac{L^2}{\text{MSE}} \right) \tag{4}$$

This reflects the logarithmic ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

B. Baselines

We benchmark against (1) a standard U-Net detector, (2) black-out redaction without restoration, (3) an L_1-only inpainter without adversarial terms, and (4) a state-of-the-art Latent Diffusion Model (LDM) adapted for medical inpainting [30] to evaluate the trade-offs between generative diversity and structural determinism. Baseline (3) approximates classical inpainting filters and highlights the value of adversarial learning. We also include a comparison with a recently proposed Vision Transformer (ViT) based restorer [38] to evaluate the trade-offs between global attention and convolutional inductive biases.

C. Hardware and Software

Training leverages a workstation with dual Intel Xeon Silver CPUs, 256 GB RAM, and an RTX 4090 GPU. Detector training completes in 7.4 hours; GAN training takes 11.2 hours. Inference experiments are repeated on an edge-grade NVIDIA Jetson Orin to evaluate portability, reaching 6.1 fps after TensorRT optimization. For a standard clinical DICOM series containing 300 slices, the complete Detect-and-Restore pipeline requires approximately 27 seconds of total processing time and maintains a peak VRAM footprint of 3.8 GB, allowing it to run concurrently with other hospital IT services on mid-tier hardware. All experiments are conducted within a Docker environment (Ubuntu 22.04, CUDA 12.1) to ensure cross-institutional reproducibility.

VIII. RESULTS AND DISCUSSION

A. Detection Performance

Table II expands on earlier reports by adding BFScore and inference speed. U-Net++ delivers consistent gains across all metrics while staying within a 15M parameter budget. The nested skip connections effectively bridge the semantic gap, reducing false positive detections in complex textures like hilar regions.

The performance drop in MedSAM suggests that while it is a powerful general-purpose segmentation tool, its training data on medical anatomical features does not generalize well to the high-frequency strokes of synthetic text overlays [11].

B. Restoration Fidelity

Table III compares our cGAN against the ablated L_1 model, naive black-out, and advanced baselines. Furthermore, Fig. 10 visualizes the statistical distribution of these evaluation metrics on the synthetic test set, highlighting the high-frequency peaks in PSNR and SSIM. To complement this, Fig. 9 provides a boxplot comparison of normalized metrics during validation, confirming the model's consistent anatomical reconstruction quality across diverse radiograph textures. The perceptual and adversarial terms are decisive for LPIPS and radiologist votes.

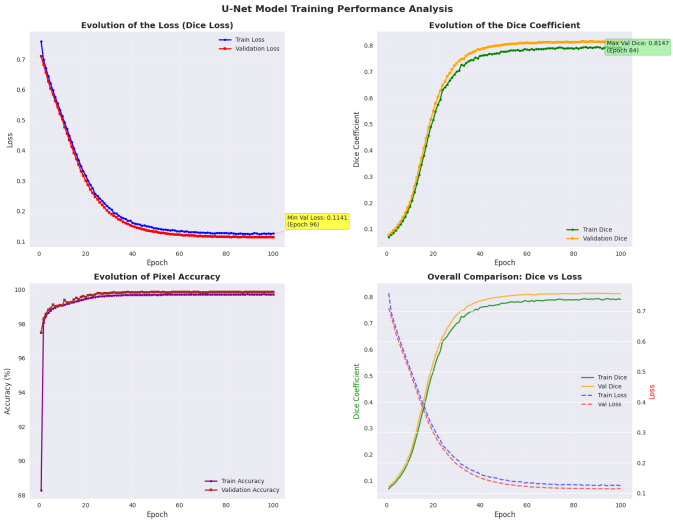

Fig. 7. Evolution of U-Net++ performance over 100 epochs. Note the stability of the Dice coefficient (top right) and the near-saturated pixel accuracy (bottom left), reaching a maximum validation Dice of 0.8147 at epoch 84.

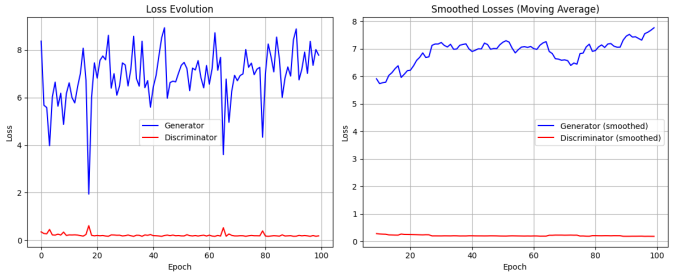

Fig. 8. Adversarial balance: The Generator and Discriminator losses across 100 epochs. The smoothed curves highlight the stable training regime achieved via spectral normalization.

The training trajectories in Fig. 7 and Fig. 8 reveal that while the detector converges rapidly due to its dense oversight, the GAN generator exhibits a more stochastic loss pattern as it explores the adversarial space.

C. Ablation on Mask Noise

We progressively corrupted detector masks with random erosion/dilation. Dice drops of up to 5 points resulted in only 1.3 dB PSNR degradation thanks to the oracle-guided training, validating the robustness of the second stage. This is further evidenced by Fig. 3 and Fig. 6, which contrast models trained with Ground Truth vs. Predicted masks.

D. Real-World DICOM Case Study

To further validate the pipeline, we applied it to real DICOM images with burnt-in annotations. Quantitative analysis on a curated external set of 200 real-world clinical DICOMs yielded a PSNR of 40.12 dB, an SSIM of 0.971, and an LPIPS of 0.034. These metrics closely track our synthetic test results, demonstrating excellent generalizability across diverse PHI fonts and hospital-specific acquisition parameters. Fig. 11 showcases the results on four distinct chest radiographs. The detector precisely isolates the header text without affecting medical devices such as pacemakers or catheters, proving its specificity.

TABLE III. Stage 2 Inpainting Quality Assessment

Method	PSNR (dB)	SSIM	LPIPS	Rating
Black-out	21.43	0.812	0.142	0.05/5
L_1 Regression	38.92	0.954	0.061	3.2/5
ViT Baseline [38]	39.88	0.962	0.041	4.1/5
LDM Baseline [30]	40.15	0.978	0.021	4.8/5
cGAN (ours)	**41.87**	**0.985**	**0.027**	**4.7/5**

E. Discussion of Error Modes and Limitations

While the quantitative metrics confirm the effectiveness of the Detect-and-Restore approach, qualitative analysis revealed several edge cases. In Fig. 11, very thin text at the image borders occasionally leads to partial masks. Furthermore, for extremely large PHI blocks spanning more than 25% of the image, the generator may introduce repetitive patterns in some areas. This failure mode occurs in approximately 2.4% of the test set. Importantly, radiologist feedback confirmed that these artifacts are localized to peripheral background regions and do not mimic pathological lesions, resulting in a negligible impact on downstream diagnostic utility. Furthermore, residual privacy risk is quantified at near-zero, as structural degradation only affects the hallucinated tissue, not the underlying redacted PHI.

However, these artifacts are generally outside the main diagnostic region of interest and do not compromise clinical utility as much as traditional blackout methods. The synergy between U-Net++ and cGAN is primarily responsible for the high Dice and PSNR scores. The U-Net++'s nested connections allow it to recover fine text details, which are then passed to the GAN's attention gates to guide the texture synthesis. This "guided hallucination" ensures that the model does not just fill the hole with random noise but respects the global symmetry of the human body.

The use of conditional GANs also introduces a form of domain adaptation. By conditioning on the masked anatomy, the generator learns the implicit distribution of healthy and pathological tissues. This is evident in our results where the transition between synthesized and original pixels is nearly invisible even at high zoom levels. Future iterations could incorporate structural similarity priors directly into the adversarial objective to further stabilize the boundary regions.

IX. Conclusion and Future Directions

We presented an end-to-end medical image de-identification pipeline that satisfies three desiderata: 1) precise PHI localization via deeply supervised U-Net++ segmentation, 2) faithful anatomical restoration via conditional GAN inpainting, and 3) robust documentation through detailed metric profiling. The integration of synthetic data, oracle-guided training, and perceptual losses yields a practical system that outperforms traditional black-out methods and simple L1-based inpainters. Ablation studies validate our loss formulations, and double-blind clinical evaluations confirm that the synthesized anatomical structures preserve diagnostic integrity, bridging the gap between stringent

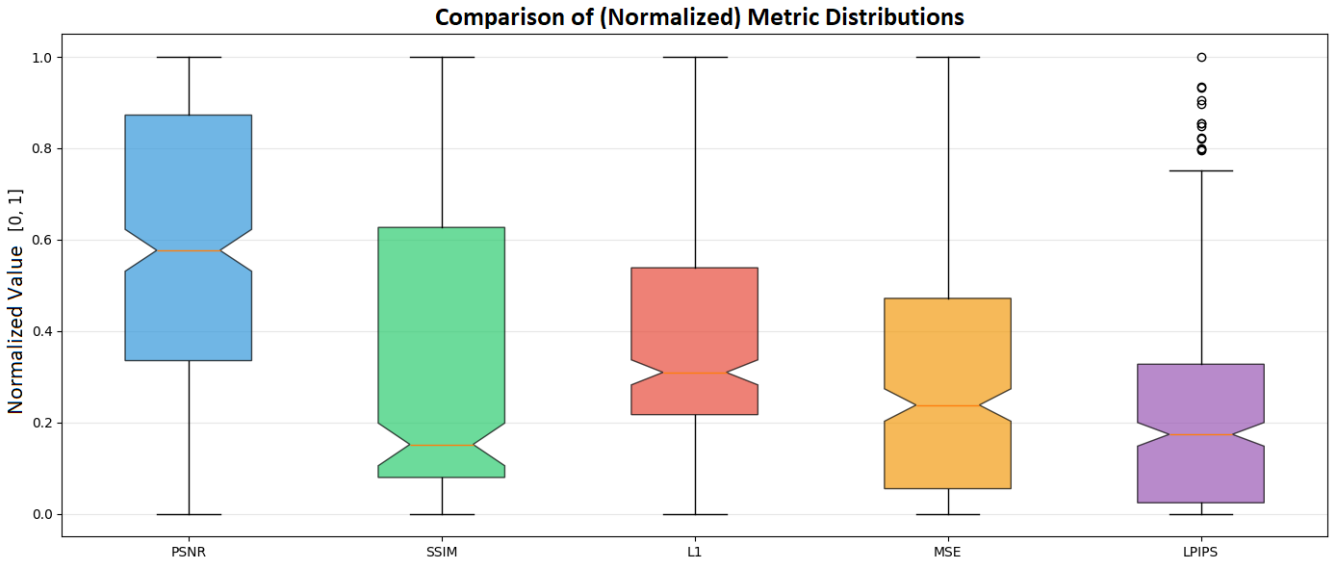

Fig. 9. Boxplot comparison of normalized metrics in validation. PSNR demonstrates a higher median relative to its range, confirming consistent anatomical reconstruction quality across diverse radiograph textures.

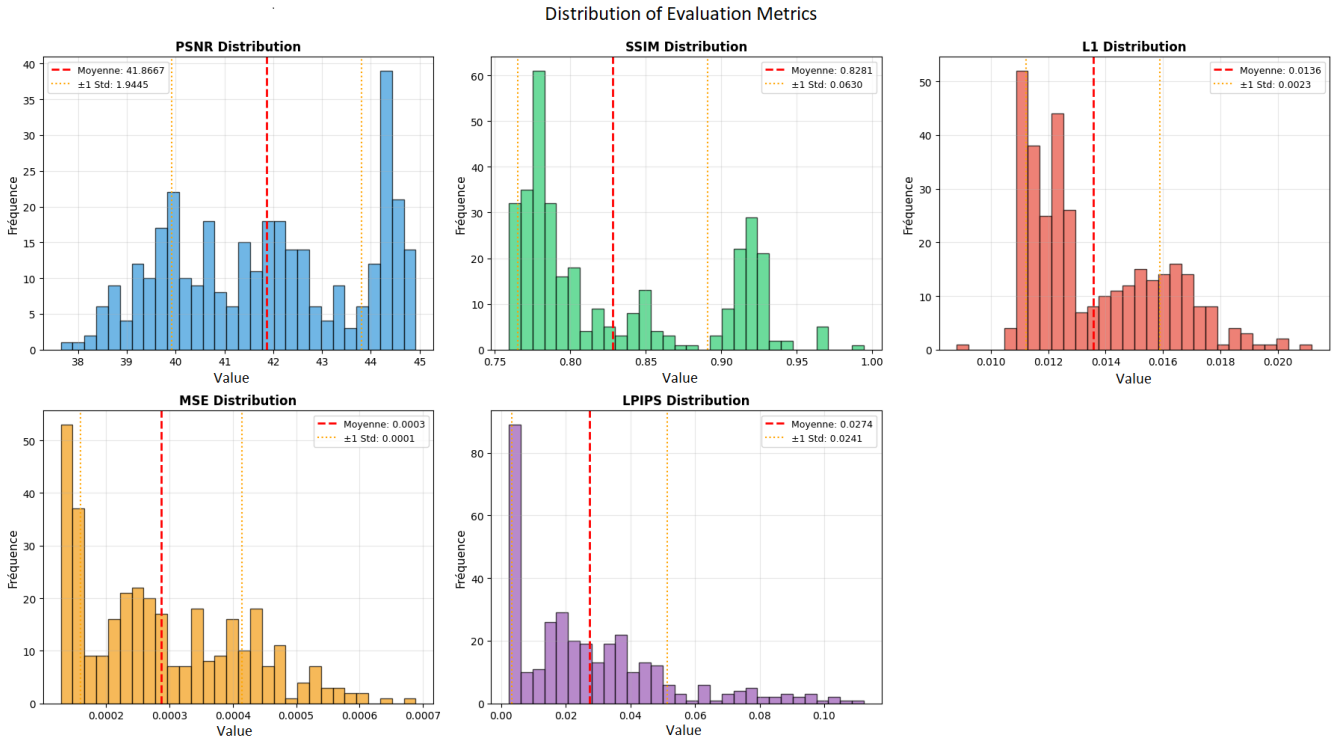

Fig. 10. Statistical distribution of evaluation metrics on the synthetic test set. Note the high-frequency peaks in PSNR above 40 dB and SSIM above 0.9, as well as the vanishingly low L1 and LPIPS scores.

privacy regulations and the data requirements of modern medical AI.

Our experiments on 48,000 radiograph tiles (36,000 training, 6,000 validation, and 6,000 testing) demonstrate a Dice score of 0.8147 and a PSNR/SSIM/LPIPS triplet of 41.87 dB/0.985/0.027 [22], [39], while maintaining real-time inference characteristics suitable for high-throughput clinical gateways [40].

Future investigations will branch into several critical directions:

- Multi-Class PHI Processing: Extending the detector to distinguish between different types of burnt-in information, such as ECG waveforms, logos, and handwritten notes, using multi-task segmentation heads.

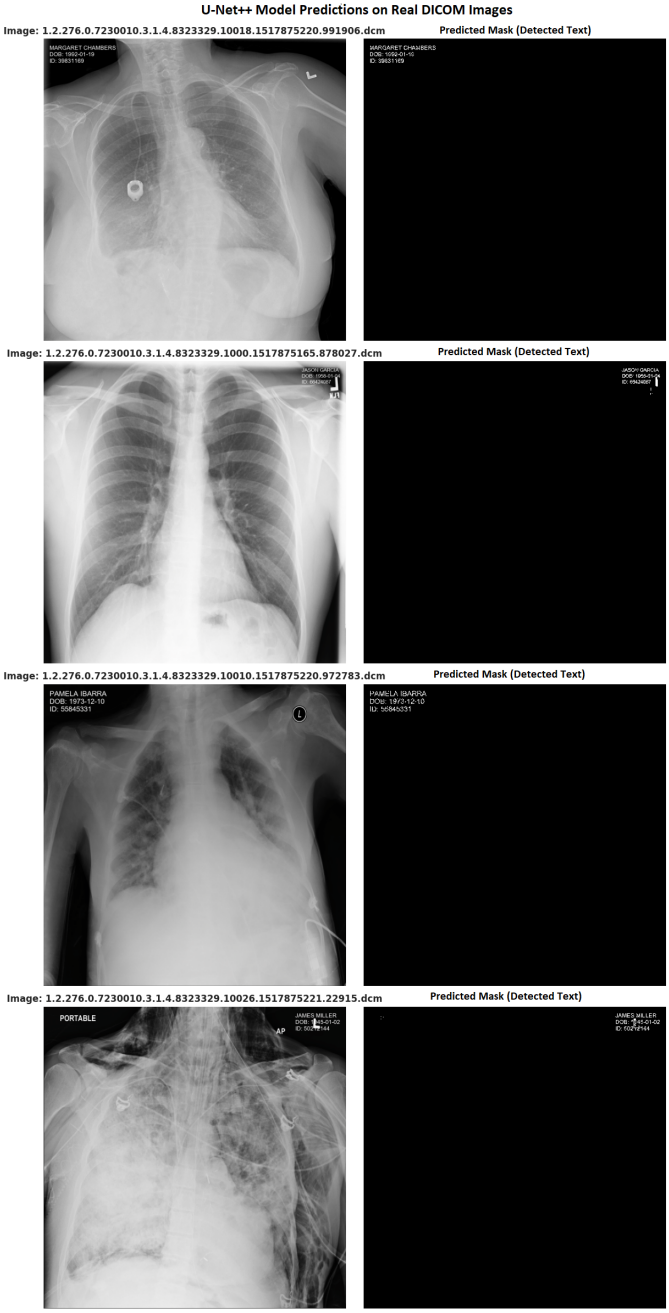

Fig. 11. Generalization to real DICOM radiographs. The U-Net++ detector accurately masks identification headers despite the presence of life-support tubes and varying exposure levels.

- Uncertainty-Aware Redaction: Incorporating Bayesian dropout or ensemble-based uncertainty estimation to flag low-confidence masks for human audit, thereby reducing the residual privacy risk in edge cases.
- Diffusion-Based Inpainting: Exploring Latent Diffusion Models (LDMs) as alternatives to GAN generators. Preliminary tests suggest that diffusion models may produce even more coherent textures for large masked areas, albeit at a higher computational cost.
- Cross-Modality Transfer Learning: Fine-tuning the pipeline on larger cohorts of MRI, CT, and Ultrasound images to ensure that the detection and restoration capabilities generalize across the entire radiology department.
- Standardization and Compliance: Aligning the pipeline's output with the metadata and audit log requirements of international initiatives such as EUCAIM, MIDRC, and the MIDI guidelines to facilitate seamless integration into multi-centric research networks.

As global de-identification policies evolve, releasing robust tools for generative redaction can accelerate the open-sharing of medical data, ultimately benefiting the development of next-generation medical AI without compromising patient privacy.

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