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Seminario PINNs

A Physics-informed Deep Neural Network for Harmonization of CT Images

- Mojtaba Zarei, Saman Sotoudeh Paima, Cindy McCabe, Ehsan Abadi,and Ehsan Samei -

Francisco de Izaguirre
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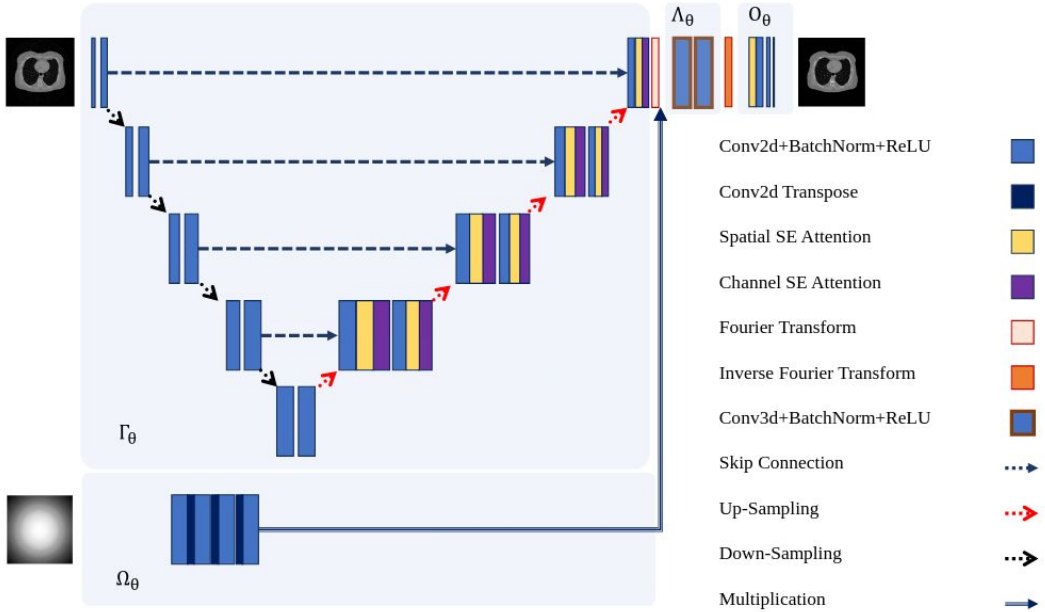
FACULTAD DE INGENIERÍA
175 AÑOS
UNIVERSIDAD DE LA REPÚBLICA URUGUAY

Índice

Disparador

Objective: **Computed Tomography (CT) quantification is affected by the variability in image acquisition and rendition.** This paper aimed to r**educe this variability by harmonizing the images utilizing physics-based deep neural networks (DNNs)**. Methods**: An adversarial generative network** was trained on virtual CT images acquired under various imaging conditions using a virtual imaging platform with 40 computational patient models. These models featured anthropomorphic lungs with different levels of pulmonary diseases, including nodules and emphysema. Imaging was conducted using a validated CT simulator at two dose levels and varying reconstruction kernels. The trained model was tested on an independent virtual test dataset and two clinical datasets.



Presentación del dominio de aplicación

Procesamiento de tomografías computadas.

Problema:

Cambios en el dominio producidos por:

1. Adquisición de la imagen
    a. Tomógrafo
    b. Dosis de contraste
2. Reconstrucción de la imagen
3. Biología del paciente
4. Ruido asociado por el paciente

Presentación del dominio de aplicación

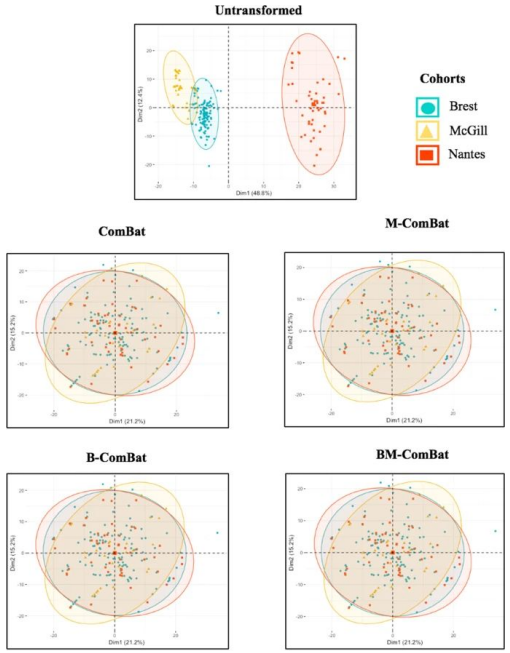
Armonización de imágenes

Definición: Encontrar invarianza en los dominios

Métodos clásicos:

1. Combat
2. Métodos basados en Bayes

“While these approaches are promising, they are influenced by their sensitivity to assumptions about the data distribution and linearity, batch size, data scaling, parameter initialization, and potential removal of true biological variability “



https://www.nature.com/articles/s41598-020-66110-w

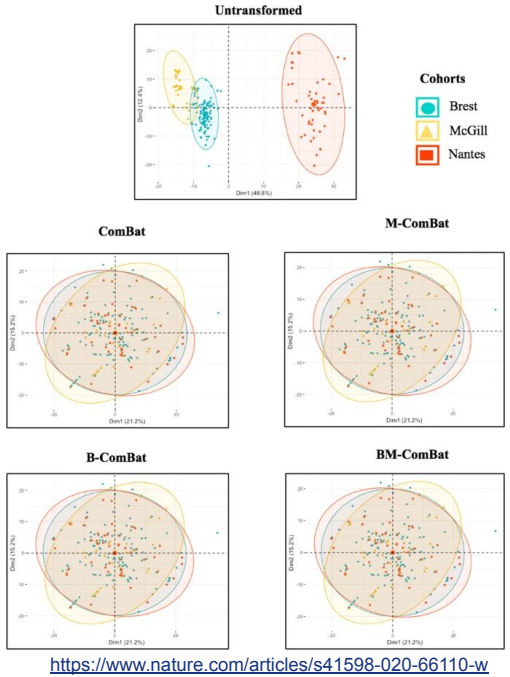
Presentación del dominio de aplicación

Armonización de imágenes

Definición: “Harmonization refers to minimizing the variance of image quantifications across datasets acquired using a variety of imaging protocols and scanner model”

Métodos clásicos:

1. Combat
2. Métodos basados en Bayes



https://www.nature.com/articles/s41598-020-66110-w

Presentación de elementos

Generative Adversarial Network (GAN)

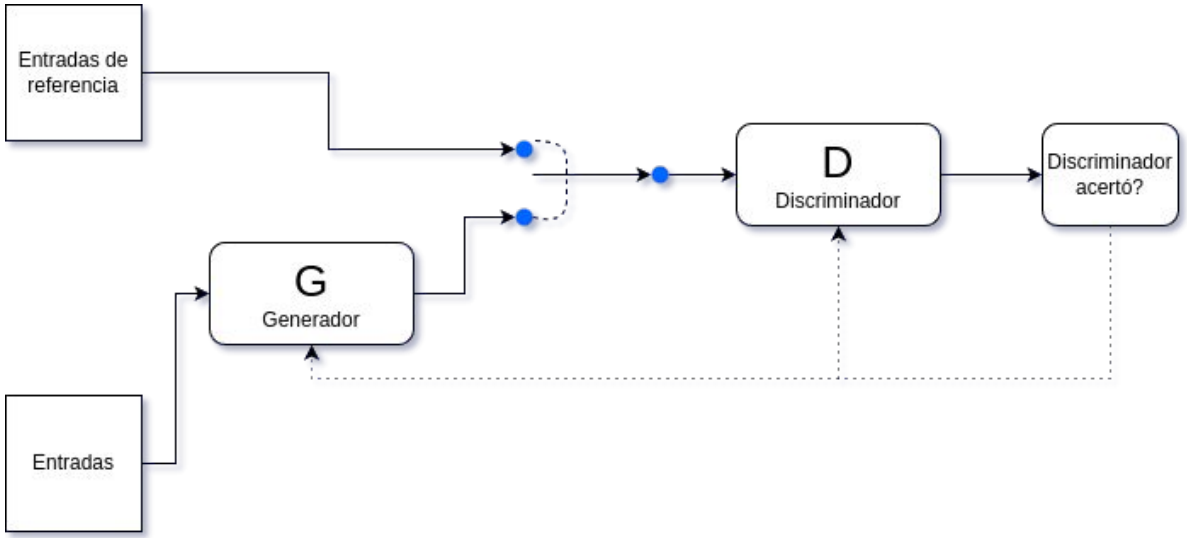
Porqué?

“..offer a methodology to align distributions and learn invariant features, and thus an opportunity for harmonizing medical images..”

“…in improving the reproducibility and performance of radiomic features in CT scans…”

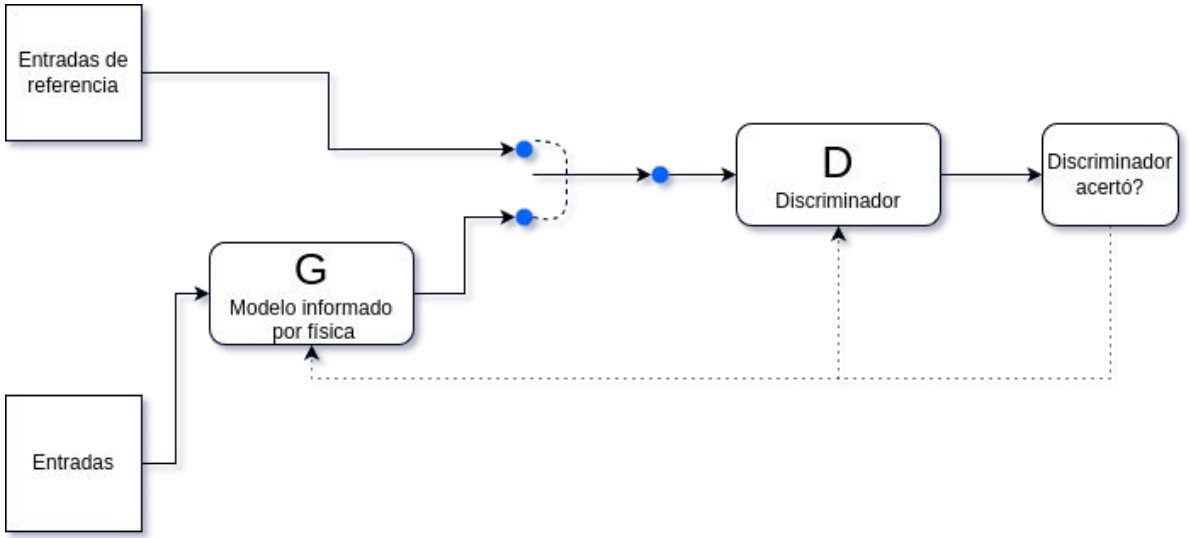
Presentación de elementos

Generative Adversarial Network (GAN)



Presentación de elementos

Generative Adversarial Network (GAN)



Presentación de elementos

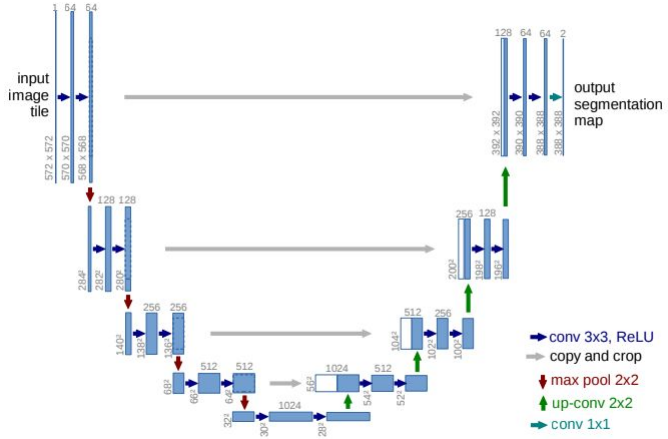
U-NET

Originalmente propuesta para segmentación de imágenes médicas

Es completamente convolucional.

El decoder logra mantener las estructuras y contexto que se observan en el encoder

“The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization”



https://arxiv.org/pdf/1505.04597

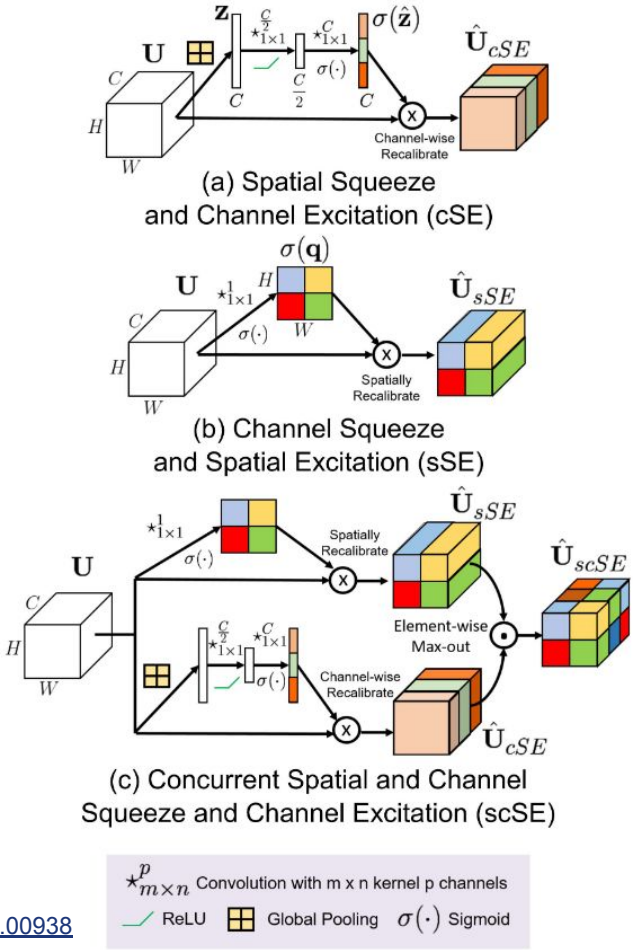
Presentación de elementos

“Squeeze and Excitation” Blocks

cSE - Priorizar canales importantes

sSE - Ayuda a una segmentación más fina

Mecanismos de atención



https://arxiv.org/abs/1705.00938

Presentación de elementos

Elementos ópticos

Point Spread Function (PSF) - Respuesta al impulso 2D

Module Transfer Function (MTF)

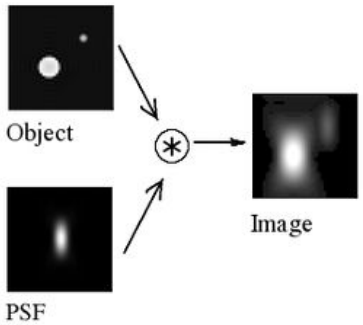
Optical Transfer Function (OTF)

Edge Spread Function (ESF) - Respuesta a un borde

Lineal Spread Function (LSF) - Respuesta de un borde infinitesimal

Resolution Index (RI)

Isocentro - Punto del espacio sobre el que gira la unidad



https://aapm.onlinelibrary.wiley.com/doi/10.1118/1.4961984
https://en.wikipedia.org/wiki/Point_spread_function

Presentación de elementos

Elementos ópticos

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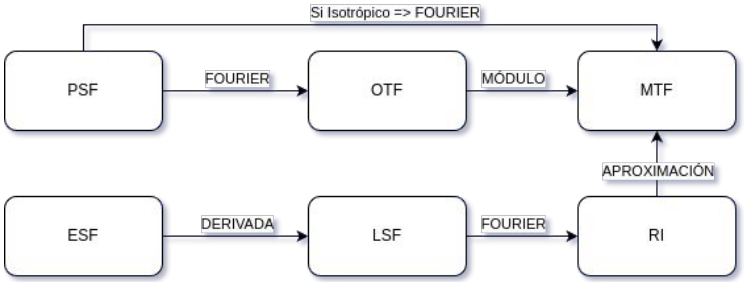
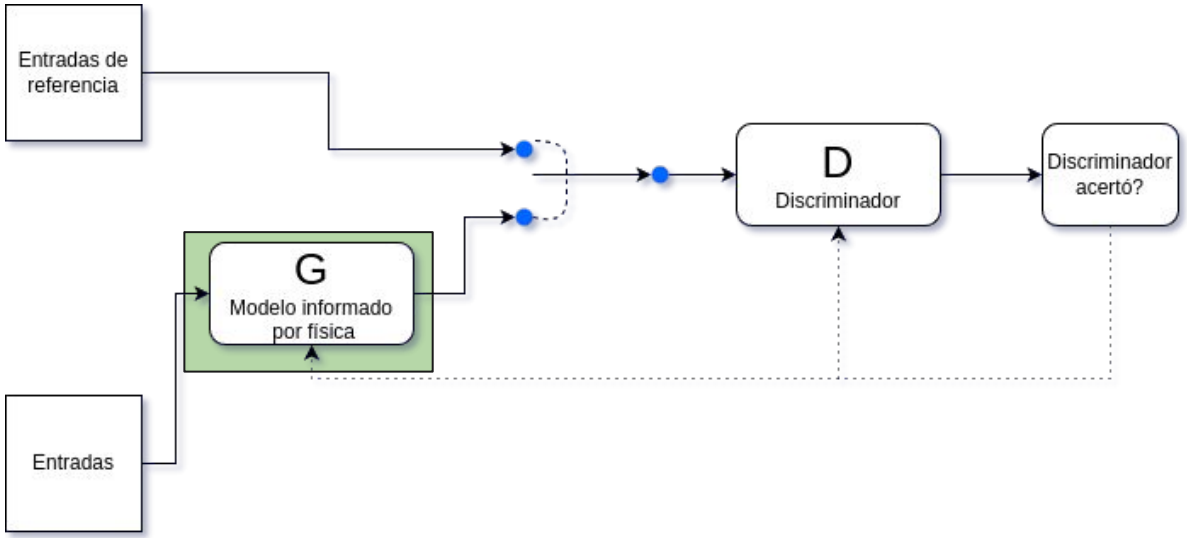


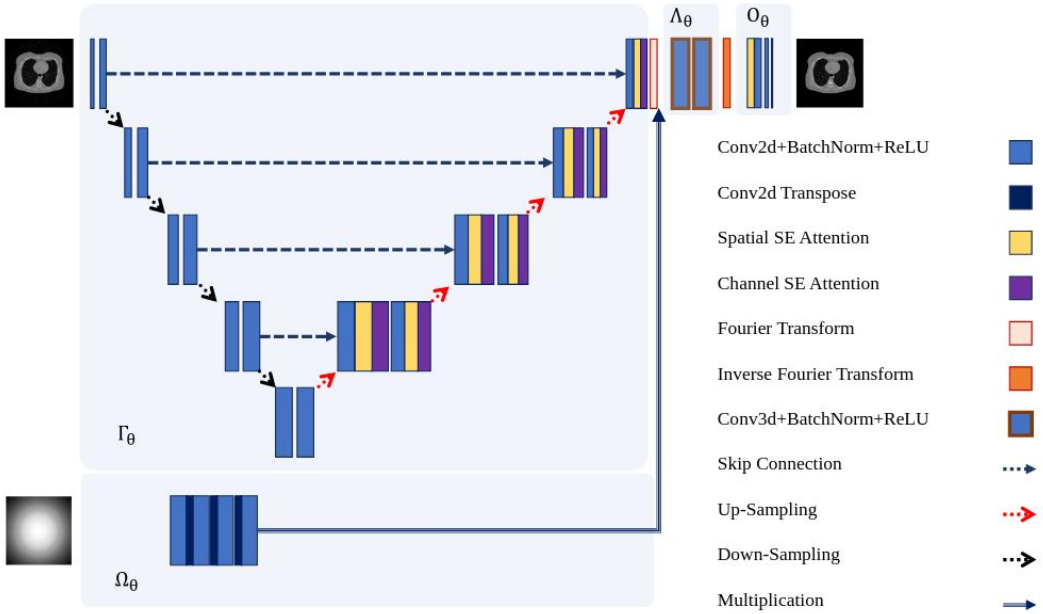
https://en.wikipedia.org/wiki/Optical_transfer_function

Presentación de elementos

Generative Adversarial Network (GAN)



Presentación de la arquitectura



$$I_b(x,y) = \mathcal{F}^{-1}\Big[\mathcal{F}\big[I_a(x,y)\big] \times \frac{\mathcal{F}\big[PSF_b(x,y)\big]}{\mathcal{F}\big[PSF_a(x,y)\big]}\Big], \quad (1)$$

$$I_b(x,y) = \mathcal{F}^{-1}\Big[\mathcal{F}\big[I_a(x,y)\big] \times \mathrm{MTF}_{ratio}(w)\Big]. \quad (2)$$

$$\begin{aligned} I_h(x,y) &= O_\theta\Big(\mathcal{F}^{-1}\Big[\Lambda_\theta\Big(\mathcal{F}\big[\Gamma_\theta(I_{nh}(x,y))\big], \Omega_\theta(\mathrm{MTF}_{2D})\Big)\Big]\Big) \\ &= G_\theta(I_{nh}(x,y), \mathrm{MTF}_{2D}), \end{aligned} \quad (3)$$

Metodología

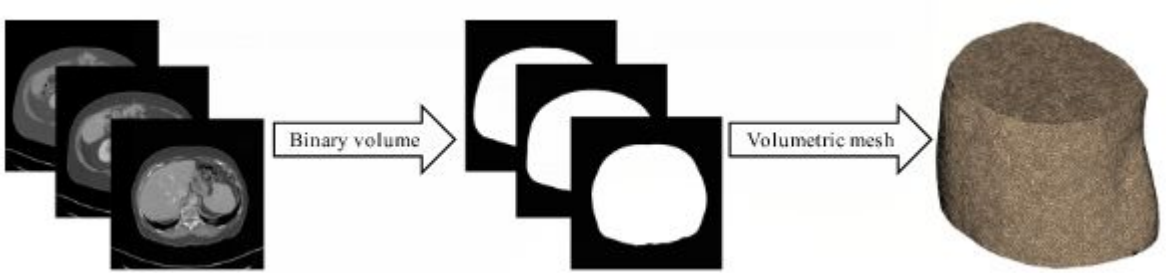
Dataset

40 XCAT simulados.

32 versiones (variación de kernels y de dosis)

Dataset con imágenes reales para testing

Metodología

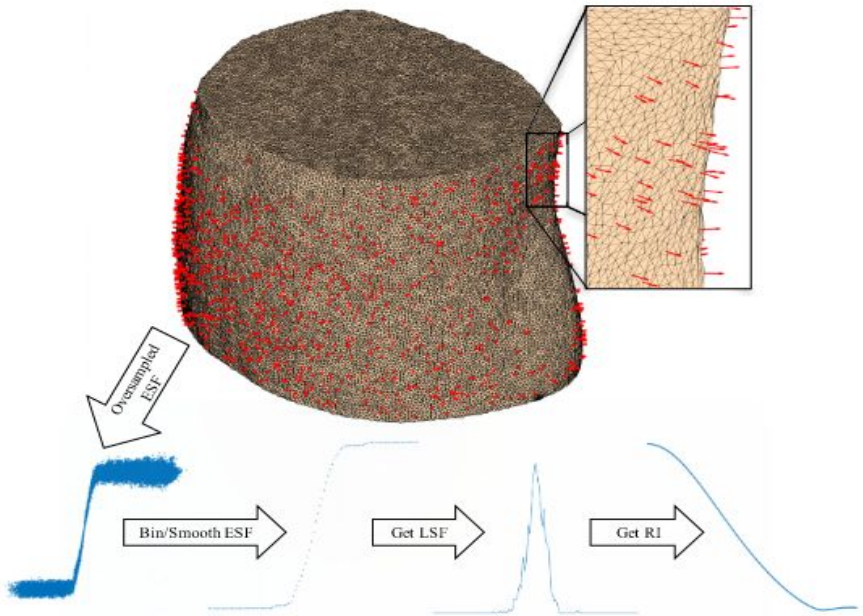


Estimación de MTF

1 - Se segmenta el cuerpo

2 - Se estima la ESF en la interfaz aire-piel

3 - Se estima la MTF



https://aapm.onlinelibrary.wiley.com/doi/10.1118/1.4961984

Metodología

Losses

1 - Hubber (distancia pixeles)

2 - Wasserstein con penalización de gradiente (adversaria)

3 - Perceptual (textura)

$$\mathcal{L}_d(I_h, I_r) = \begin{cases} 0.5 \cdot (I_h - I_r)^2, & \text{if } |I_h - I_r| \leqslant \delta \\ \delta \cdot (|I_h - I_r| - 0.5 \cdot \delta), & \text{if } |I_h - I_r| > \delta \end{cases}, \quad (4)$$

$$\begin{aligned} \text{WGAN}_{\text{GP}} &= D_\theta(I_{r,nh}) - \mathbb{E}[D_\theta(I_{h,nh})] \\ &\quad + \lambda_{GP}\mathbb{E}[(\|\nabla_{\tilde{I}} D_\theta(\tilde{I})\|_2 - 1)^2], \quad (5) \end{aligned}$$

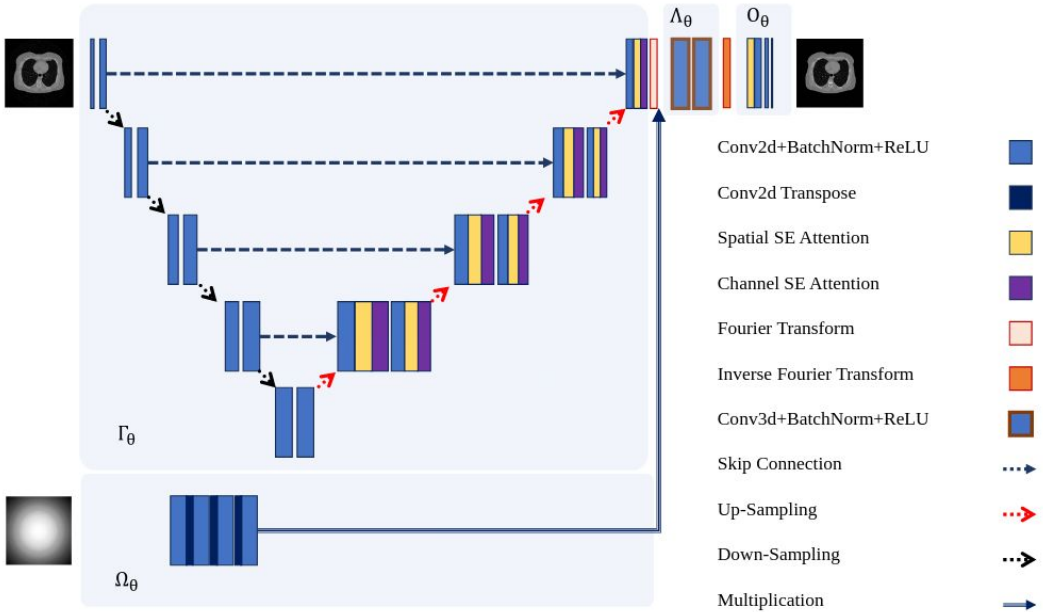
$$\mathcal{L}_a(I_h) = \mathbb{E}[D_\theta(I_{h,nh})]. \quad (6)$$

$$\mathcal{L}_t(I_h, I_r) = \sum_{i=1}^{N} \text{MSE}\left(\frac{Gm(\text{VGG}_i(I_h))}{\|Gm(\text{VGG}_i(I_h))\|}, \frac{Gm(\text{VGG}_i(I_r))}{\|Gm(\text{VGG}_i(I_r))\|}\right), \quad (7)$$

$$\mathcal{L}_H(I_h, I_r) = \lambda_d \mathcal{L}_d(I_h, I_r) + \lambda_a \mathcal{L}_a(I_h) + \lambda_t \mathcal{L}_t(I_h, I_r), \quad (8)$$

$$\lambda_d = 1000, \lambda_t = 50, \text{ and } \lambda_a = 1$$

Repaso de lo propuesto

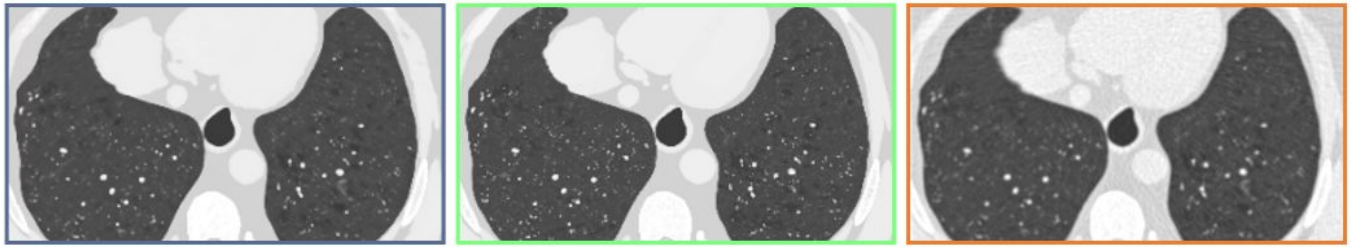


$$I_b(x,y) = \mathcal{F}^{-1}\Big[\mathcal{F}\big[I_a(x,y)\big] \times \frac{\mathcal{F}\big[PSF_b(x,y)\big]}{\mathcal{F}\big[PSF_a(x,y)\big]}\Big], \quad (1)$$

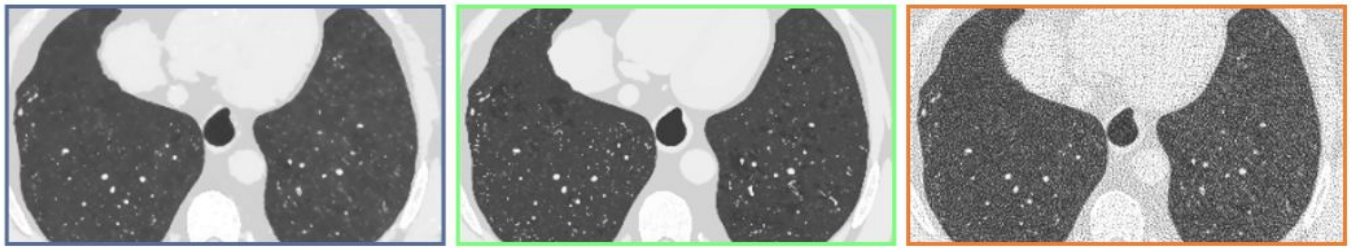
$$I_b(x,y) = \mathcal{F}^{-1}\Big[\mathcal{F}\big[I_a(x,y)\big] \times \mathrm{MTF}_{ratio}(w)\Big]. \quad (2)$$

$$\begin{aligned} I_h(x,y) &= O_\theta\Big(\mathcal{F}^{-1}\Big[\Lambda_\theta\Big(\mathcal{F}\big[\Gamma_\theta(I_{nh}(x,y))\big], \Omega_\theta(\mathrm{MTF}_{2\mathrm{D}})\Big)\Big]\Big) \\ &= G_\theta(I_{nh}(x,y), \mathrm{MTF}_{2\mathrm{D}}), \end{aligned} \quad (3)$$

Resultados que obtienen

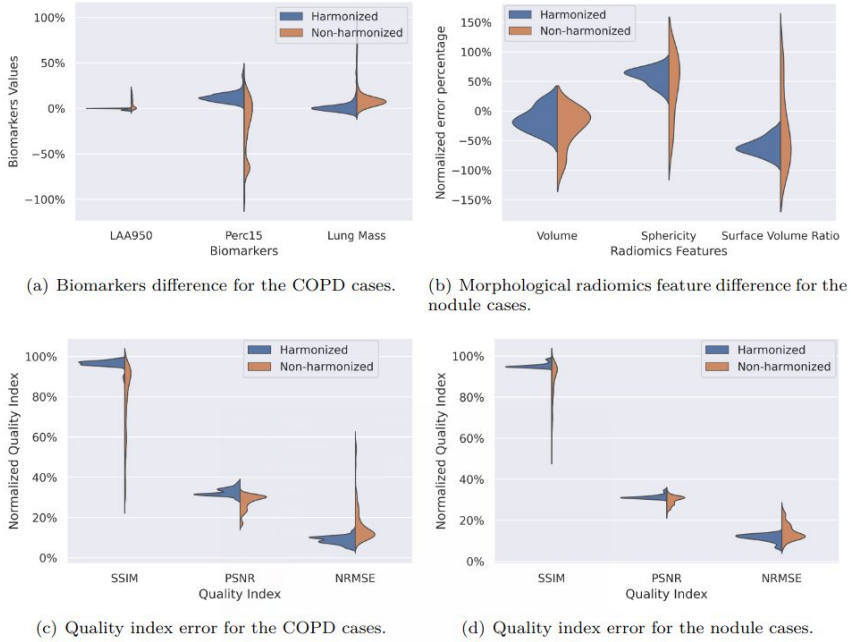


(a) High dose and smooth kernel rendition.



(b) Low dose and sharp kernel rendition.

Resultados que obtienen



(a) Biomarkers difference for the COPD cases.

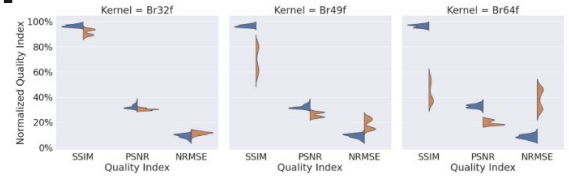
(b) Morphological radiomics feature difference for the nodule cases.

(c) Quality index error for the COPD cases.

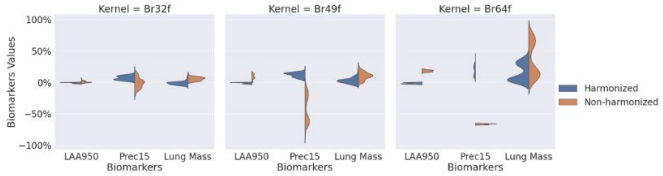
(d) Quality index error for the nodule cases.

Fig. 3. The quantitative outcomes for the nodule cases (right column) and COPD cases (left column). To compare the PSNR values with other measurements, their values in dB were divided by 100.

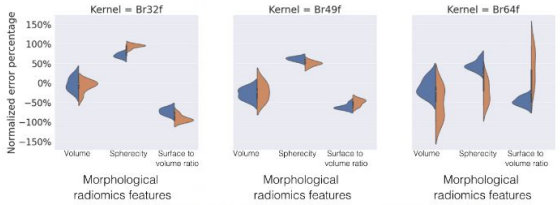
Resultados que obtienen



(a) Quality index variability across kernels.



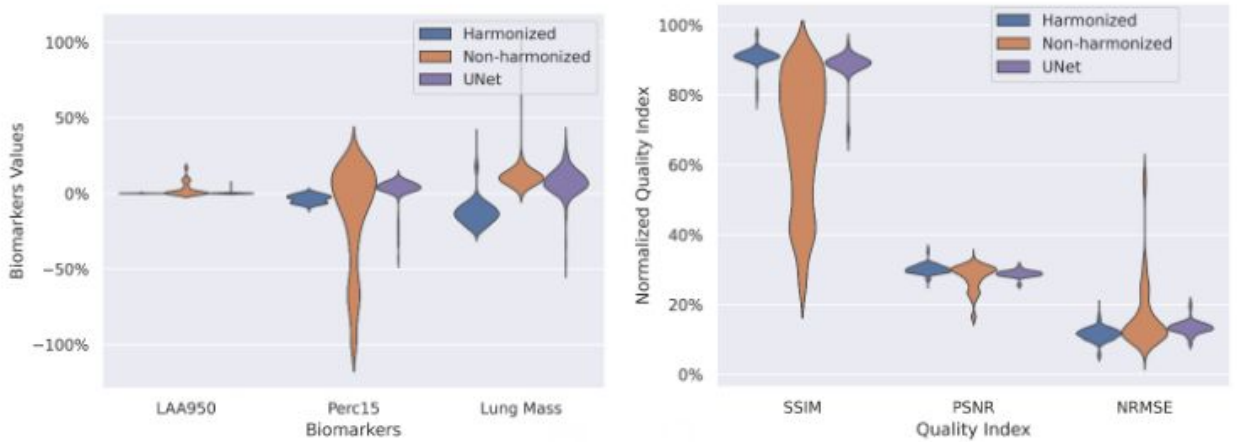
(b) COPD biomarkers variability across kernels.



(c) Morphological radiomics feature variability across kernels.

Fig. 4. Analyzing the differences in bias and variability between harmonized and non-harmonized images according to the deployed smooth, average, and sharp kernels.

Resultados que obtienen

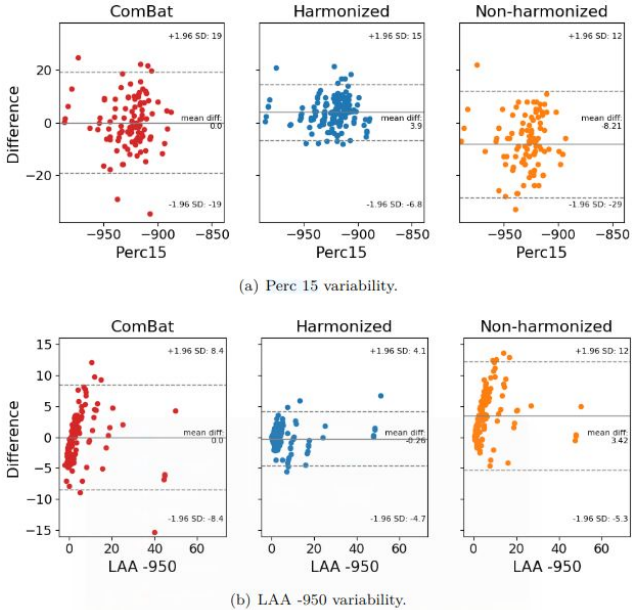


(a) Biomarkers difference for the COPD cases.

(b) Quality index error for the COPD cases.

Fig. 5. The quantitative outcomes for COPD cases in the ablation study. To compare the PSNR values with other measurements, their values in dB were divided by 100. The blue, red, and purple data are measured metrics and biomarkers from the harmonized, non-harmonized, and Unet output images, respectively.

Resultados que obtienen



(a) Perc 15 variability.

(b) LAA -950 variability.

Fig. 6. COPD biomarkers variability and bias with respect to the smooth kernel and high dose renditions in COPDGene dataset. The results, from left to right, were obtained from the ComBat feature harmonization algorithm, proposed harmonizer, and non-harmonized images, respectively.

Resultados que obtienen

TABLE II

QUANTITATIVE RESULTS ON THE TEST SET WITH LUNG NODULE INSERTED. THE FIRST THREE METRICS WERE MEASURED ON A SINGLE 2D SLICE, AND RADIOMICS FEATURES WERE MEASURED ON THE 3D SLICES.

	NRMSE (%)	SSIM (%)	PSNR (dB)
H	**11.5±1.9**	**95.1±1.3**	**31.3±1.1**
NH	14.2±4.0	87.4±9.1	29.6±2.3
	$V_{\text{NRMSE}(\%)}$	$A/V_{\text{NRMSE}(\%)}$	$S_{\text{NRMSE}(\%)}$
H	**2.1±1.3**	**14.2±3.0**	16.5±**3.8**
NH	3.4±2.5	14.8±6.9	**16.3**±8.45

TABLE III

QUANTITATIVE RESULTS ON THE COPD TEST SET FOR THE ABLATION STUDY. ALL METRICS WERE MEASURED ON A SINGLE 2D SLICE.

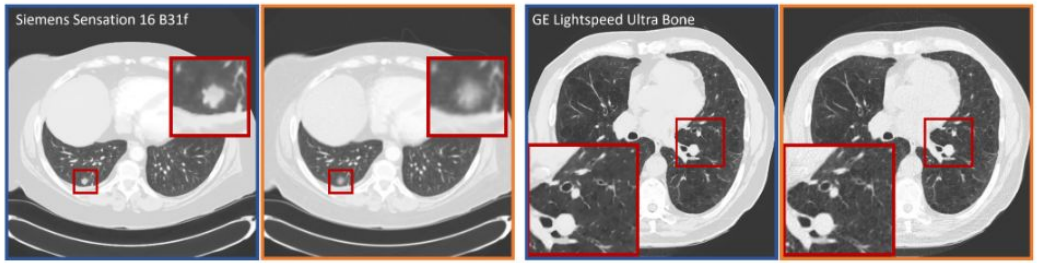
	NRMSE (%)	SSIM (%)	PSNR (dB)
H	**11.5±1.9**	**91.0±2.5**	**30.2**±1.4
UNet	13.4±1.9	88.4±4.2	28.8±**1.0**
	|Δ|LAA -950 (%)	|Δ|Perc 15 (HU)	|Δ|Lung mass (g)
H	**0.17±0.24**	**6.3±4.1**	0.3±0.12
UNet	0.54±1.93	10.7±10.9	**0.1±0.07**

TABLE IV

VARIABILITY ANALYSIS IN QUANTIFICATION OF THE COPD BIOMARKERS FOR HARMONIZED AND NON-HARMONIZED IMAGES.

	Kernel	Dose	LAA -950	Perc 15
H	-	-	**1.11**	**-915**
NH	Smooth	Regular	**1.91**	**-922**
H	-	-	**5.17**	**-932**
NH	Medium	Regular	11.81	-946
H	-	-	**3.87**	**-919**
NH	Smooth	Low	7.86	-931
H	-	-	**1.83**	**-920**
NH	Smooth	Low	6.19	-932
H	-	-	**1.86**	**-915**
NH	Smooth	Low	2.54	**-923**

Resultados que obtienen



(a) Siemens. (b) GE.

(c) Toshiba. (d) Philips.

Fig. 9. Harmonization results across different vendors. Non-harmonized (in orange square) and the corresponding harmonized (in blue square) images.