

Aplicaciones en diagnóstico

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Consorci Sanitari de Terrassa

INTELIGENCIA ARTIFICIAL

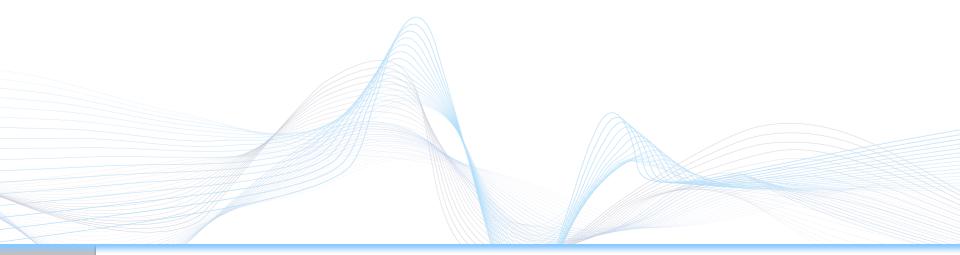


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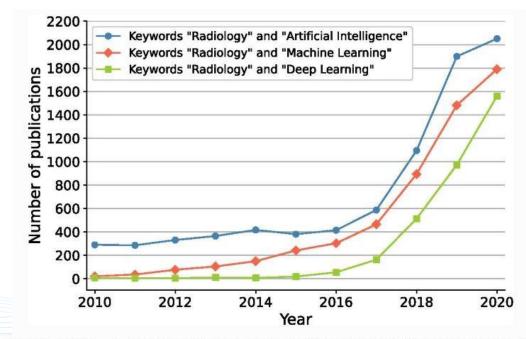


1. INTRODUCCIÓN





IA en diagnóstico



Growth of AI in radiology reflected by the number of publications on PubMed when searching on the terms "radiology" with "artificial intelligence," "machine learning" or "deep learning"



IA en diagnóstico

- 1. Reducir carga de trabajo, aumentar calidad de imagen, velocidad de adquisición...
- 2. Detección de anomalías, segmentación de imagen, CAD.
- 3. Encontrar tendencias: artefactos en la imagen, parámetros inconsistentes de un protocolo, etc.
- 4. Estandarizar la práctica.



IA en Medicina Nuclear y Radiodiagnóstico

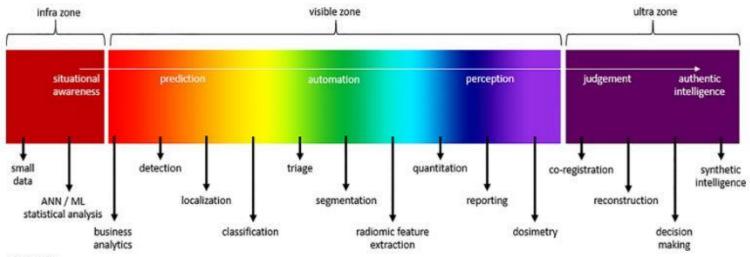


Figure 1

Spectrum of Al applications in nuclear medicine based on complexity, expertise, data and funding.

Fuente: Geoffrey Currie, Eric Rohren, Intelligent Imaging in Nuclear Medicine: the Principles of Artificial Intelligence, Machine Learning and Deep Learning, Seminars in Nuclear Medicine, Volume 51, Issue 2,2021, Pages 102-111



IA en diagnóstico





Bases de datos en diagnóstico



https://www.cancerimagingarchive.net/



https://www.image-net.org/

- NIH Database of 100,000 Chest X-Rays
 - Images, associated clinical data, annotations, and diagnoses
- The Cancer Imaging Archive (TCIA)
 - Formerly the National Biomedical Imaging Archive (NBIA):
 - Lung Image Database Consortium (LIDC)
 - Reference Image Database to Evaluate Response (RIDER)
 - Breast MRI
 - Lung PET/CT
 - Neuro MRI
 - CT Colonography
 - Virtual Colonoscopy
 - Osteoarthritis Initiative (MIA)
 - PET/CT phantom scan collection
- RSNA's Quantitative Imaging Data Warehouse (QIDW)
 - Contains COVID CT
 - Data from phantoms, simulated data
 - Misc. clinical data
 - Includes links to data de-identification tools
 - Related RSNA efforts
- NCI's <u>Imaging Data Commons</u> and <u>Genomic Data Commons</u>
 - DICOM formatted clinical data and annotations for AI/Cloud

https://www.aylward.org/notes/open-access-medical-image-repositories

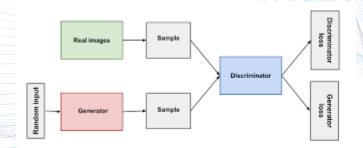


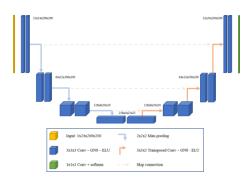
Arquitecturas claves en diagnóstico

1. Res-Net: tareas de clasificación de imágenes.

2. U-Net: segmentación imágenes.

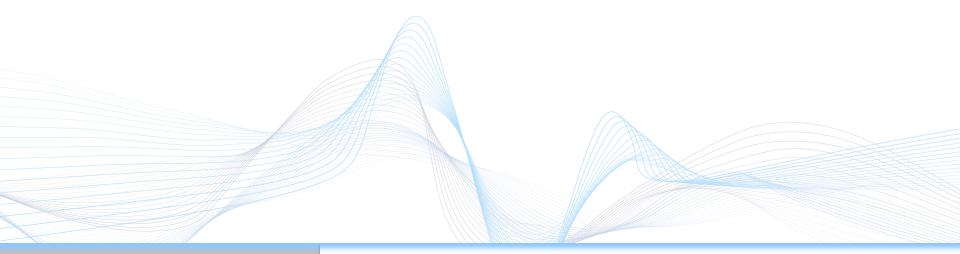
3. GAN: conversión de imágenes (MR→CT)







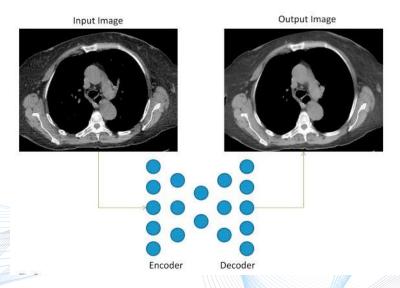
2. ADQUISICIÓN DE IMÁGENES Y PROCESADO





Mejorar calidad de imagen y reducción dosis en CT

- CT de baja dosis → mayor ruido y peor calidad de imagen.
- DL tiene el potencial para reducir aun más las dosis en CT.





Mejorar calidad de imagen y reducción dosis en CT

- Más de 60 radiólogos.
- CT de bajas dosis reconstruidas por CNN vs CT dosis estándar.
- Más del 90% consideraban que las imágenes de la CNN tenían una mayor o igual calidad diagnóstica.

SIIM 2017 Scientific Session Posters & Demonstrations

Diagnostic Quality of Machine Learning Algorithm for Optimization of Low-Dose Computed Tomography Data

Nathan M. Cross, MD, MS, CIIP, University of Pennsylvania; Jason DeBerry, MD; Daniel Ortiz, MD; Justine Kemp, MD; José Morey, MD



Optimización de dosis en CT

Potential of a machine-learning model for dose optimization in CT quality assurance

Axel Meineke¹ · Christian Rubbert² · Lino M. Sawicki² · Christoph Thomas² · Yan Klosterkemper² · Elisabeth Appel² · Julian Caspers^{2,3} · Oliver T. Bethge² · Patric Kröpil² · Gerald Antoch² · Johannes Boos²

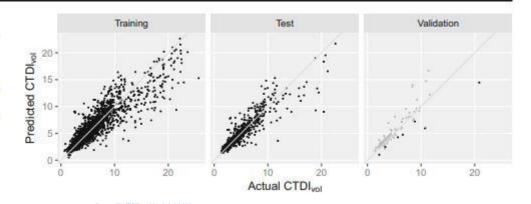
Received: 30 November 2018 / Accepted: 17 January 2019 © European Society of Radiology 2019

- Detectar CT de tórax con potencial de optimización de dosis.
- 3190 CT tórax
- CTDIvol (CT, protocolo, edad, sexo,...)



Optimización de dosis en CT

Fig. 2 Predicted versus actual CTDI_{vol} in the training (RMSE = 1.71), test (RMSE = 1.45), and validation (RMSE = 1.52) dataset. In the graph for the validation dataset, examinations flagged for potential for dose optimization are shown in black, the others in gray



7% de los estudios optimización de dosis potencial



Reducción de ruido en CT

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 36, NO. 12, DECEMBER 2017



Generative Adversarial Networks for Noise Reduction in Low-Dose CT

Jelmer M. Wolterink, Tim Leiner, Max A. Viergever, and Ivana Išgum

- Maniquí antropomórfico
- 28 pacientes con CT cardíaco
- CT con 20% y 100% de la dosis

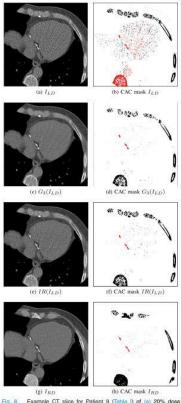


Fig. 8. Example CT slice for Patient 9 (Table I) of (a) 20% dose EBP reconstruction I_D and (b) corresponding arrey caldification (CAC) scoring mask, (c) 20% dose generator G_3 reconstruction $G_3(I_D)$ and (d) corresponding CAC scoring mask, (e) 20% dose generator IR reconstruction IR_{I_D} and (I) corresponding CAC scoring mask, and (g) routine-dose FBP reconstruction I_{RD} and (h) corresponding CAC scoring mask, All images have window levelwidth 90750 HU. CAC scoring masks show all voxels \geq 130 HU in black, and voxels selected by CAC scoring with connected component labeling in red.



Resonancia magnética

- Necesidad de protocolos de adquisición rápidos.
- DL puede reconstruir RM usando datos sin procesar → reducción en más del 50% del tiempo de escaneo.

Magn Reson Med. 2018 Jun; 79(6): 3055-3071.

PMID: 29115689

Published online 2017 Nov 8. doi: 10.1002/mrm.26977

Learning a Variational Network for Reconstruction of Accelerated MRI Data

Kerstin Hammernik, ^{1,*} Teresa Klatzer, ¹ Erich Kobler, ¹ Michael P Recht, ^{2,3} Daniel K Sodickson, ^{2,3} Thomas Pock, ^{1,4} and Florian Knoll^{2,3}

> IEEE Trans Med Imaging. 2016 May;35(5):1344-1351. doi: 10.1109/TMI.2016.2551324. Epub 2016 Apr 6.

q-Space Deep Learning: Twelve-Fold Shorter and Model-Free Diffusion MRI Scans

Vladimir Golkov, Alexey Dosovitskiy, Jonathan I Sperl, Marion I Menzel, Michael Czisch, Philipp Samann, Thomas Brox, Daniel Cremers



Resonancia magnética

- Largos tiempo de adquisición.
- CNN para maximizar el número de estudios que de pueden adquirir en un turno de trabajo.
- Parámetros de entradas: protocolo, edad, contraste, media de secuencias requeridas según protocolo.
- Reducir costes.
- Optimizar tiempo.

Conference Paper

MRI Schedule Optimization through Discrete Event Simulation and Neural Networks as a means of Increasing Scanner Productivity

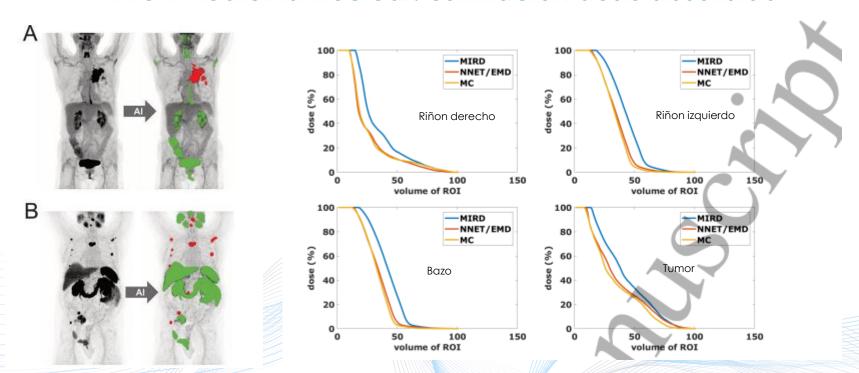
November 2016

Conference: Radiological Society of North America Annual Meeting 2016 · At: Chicago, IL

. ..



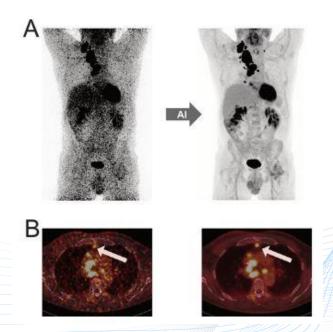
IA en Medicina Nuclear: estimación dosis absorbida



Fuente: R Seifert, M Weber, et al. Artificial Intelligence and Machine Learning in Nuclear Medicine: Future Perspectives, Seminars in Nuclear. Medicine, Volume 51, Issue 2,2021,



IA en Medicina Nuclear: reducción de ruido



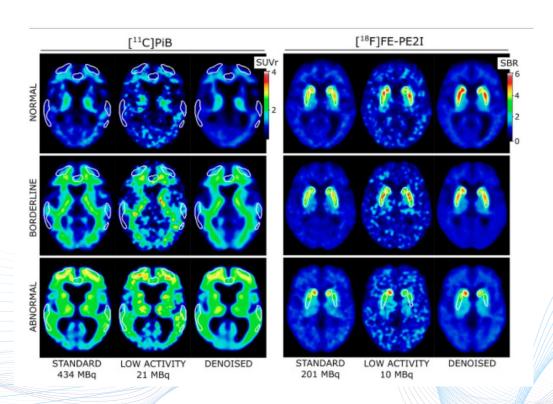
Fuente: R Seifert, M Weber, et al. Artificial Intelligence and Machine Learning in Nuclear Medicine: Future Perspectives, Seminars in Nuclear. Medicine, Volume 51, Issue 2,2021, > Neuroimage. 2022 Oct 1;259:119412. doi: 10.1016/j.neuroimage.2022.119412. Epub 2022 Jun 24.

Deep learning based low-activity PET reconstruction of [11C]PiB and [18F]FE-PE2I in neurodegenerative disorders

Raphaël Sura Daveau ¹, Ian Law ¹, Otto Mølby Henriksen ¹, Steen Gregers Hasselbalch ², Ulrik Bjørn Andersen ¹, Lasse Anderberg ¹, Liselotte Højgaard ¹, Flemming Littrup Andersen ¹, Claes Nøhr Ladefoged ³



IA en Medicina Nuclear: reducción de ruido





IA en Medicina Nuclear: reducción de ruido

> Phys Med Biol. 2021 Feb 25;66(5):054003. doi: 10.1088/1361-6560/abe225.

Low-dose PET image noise reduction using deep learning: application to cardiac viability FDG imaging in patients with ischemic heart disease

Claes Nøhr Ladefoged 1 , Philip Hasbak 1 , Charlotte Hornnes 1 , Liselotte Højgaard 1 , Flemming Littrup Andersen 1

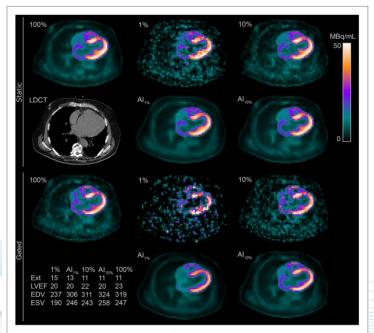


Figure 3. Static (top two rows) and gated (bottom two rows) [18F]FDG-PET images from a representative patient showing the effect of applying de-noising (Al_{1%} and Al_{10%}) to the low-dose images (1% and 10%). Low-dose CT (LDCT) shown for reference in mediastinum CT window. Extent (Ext), LVEF, EDV, and ESV for the single subject are given for each dose-reduced image and the full-dose reference.



DETECTORES PET Y SPECT

Posición

Improving depth-of-interaction resolution in pixellated PET detectors using neural networks

Artem Zatcepin^{1,5}, Marco Pizzichemi², Andrea Polesel^{2,3}, Marco Paganoni³, Etiennette Auffray²,

Sibylle I Ziegler^{1,4} and Negar Omidvari^{1,6}

Published 28 August 2020 • © 2020 Institute of Physics and Engineering in Medicine

Physics in Medicine & Biology, Volume 65, Number 17

Home > Review of Scientific Instruments > Volume 92, Issue 1 > 10.1063/5.0035991

No Access • Submitted: 02 November 2020 • Accepted: 30 December 2020 • Published Online: 29 January 2021

High-performance coded aperture gamma camera based on monolithic GAGG:Ce crystal

Review of Scientific Instruments 92, 013106 (2021); https://doi.org/10.1063/5.0035991

Journals & Magazines > IEEE Transactions on Nuclear ... > Volume: 62 Issue: 1

Scattering

Sensitivity Increase Through a Neural Network Method for LOR Recove ICS Triple Coincidences in High-Resolution Pixelated- Detectors PET Scanners

Publisher: IEEE





Jean-Baptiste Michaud; Marc-André Tétrault; Jean-François Beaudoin; Jules Cadorette; Jean-Daniel Leroux; Charles-Antoine ...



DETECTORES PET Y SPECT

TOF (tiempo de vuelo).

> Phys Med Biol. 2018 Jan 11;63(2):02LT01. doi: 10.1088/1361-6560/aa9dc5.

Using convolutional neural networks to estimate time-of-flight from PET detector waveforms

Eric Berg ¹, Simon R Cherry



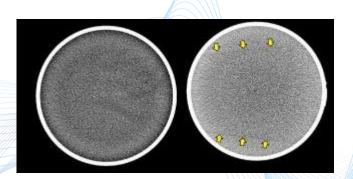
3. CONTROL DE CALIDAD





Aplicaciones de la IA en el CC

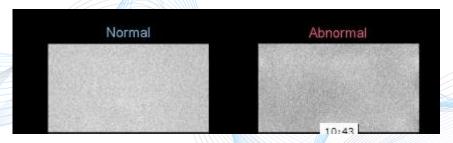
- Evaluación de imágenes: uniformidad, patrones, artefactos, ...
- Limitación: artefactos muy variados.
- DL requiere mayor poder computacional y mayores conjuntos de datos.





CONTROL DE CALIDAD EN RX y MN

- CNN para identificar imágenes normales vs anormales
 - Entrenando un CNN supervisada (etiquetado manual de imágenes): requiere tiempo.
 - Entrenar la CNN para que identifique solamente las anormales y poner una etiqueta para que la RF la revise.





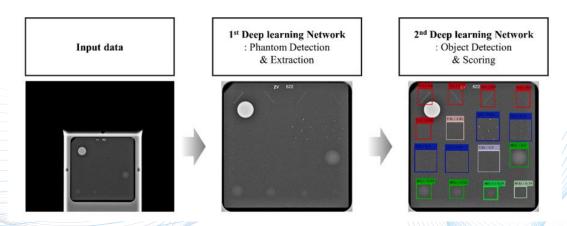
CC mamógrafo

ARTÍCULO

Reliable quality assurance of X-ray mammography scanner by evaluation the standard mammography phantom image using an interpretable deep learning model

Jang-Hoon Oh, Hyug-Gi Kim, Kyung Mi Lee y Chang-Woo Ryu
European Journal of Radiology, 2022-09-01, Volumen 154, Artículo 110369, Copyright © 2022 Elsevier B.V.

- 2208 imágenes de 3 maniquíes, (1808 training/400 test)
- Red YOLO





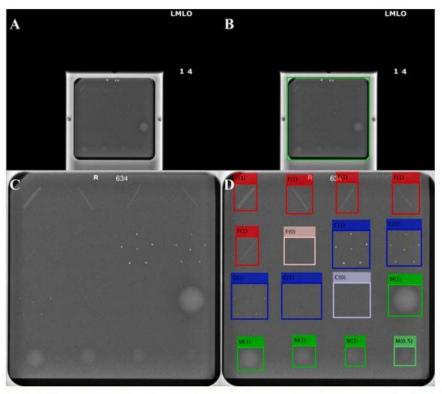


Fig. 2. Data labeling for model training of the mammography phantom. (A) The example of the original input image. (B) The result of mammography phantom detection. The phantom region is outlined by a green rectangle. (C) The phantom region image that is extracted by the mammography phantom detection network. (D) The result of the phantom object detection network. A detection result of '1', '0.5', or '0' points was represented by dark red to bright red for the fiber group, dark blue to bright blue for the specks group, and dark green to bright green for the mass group.

- 6369 de 6400 objetos detectados
- Precisión de 0,995.



CC para RM de difusión

RM de difusión → artefactos varios

Front Neurosci. 2019; 13: 1456.

Published online 2020 Jan 22. doi: 10.3389/fnins.2019.01456

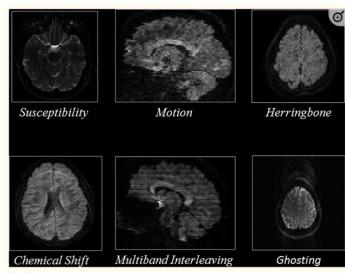
PMCID: PMC6987246

PMID: 32038150

QC-Automator: Deep Learning-Based Automated Quality Control for Diffusion MR Images

Zahra Riahi Samani, * Jacob Antony Alappatt, Drew Parker, Abdol Aziz Ould Ismail, and Ragini Verma

- CNN + transfer learning
- 132000 cortes axiales y 200000 sagitales
- 5 escaner
- 98% de precisión





4. CONCLUSIONES

- 1. Adquisición, procesamiento, mejora de imágenes...
- 2. Aumento de la velocidad y/o precisión.
- 3. Futuro tareas más complejas con mejor rendimiento en diagnóstico.
- 4. Cantidad de conjuntos de datos limitada.
- 5. Mejor compresión de la IA.