Aplicaciones en radioterapia

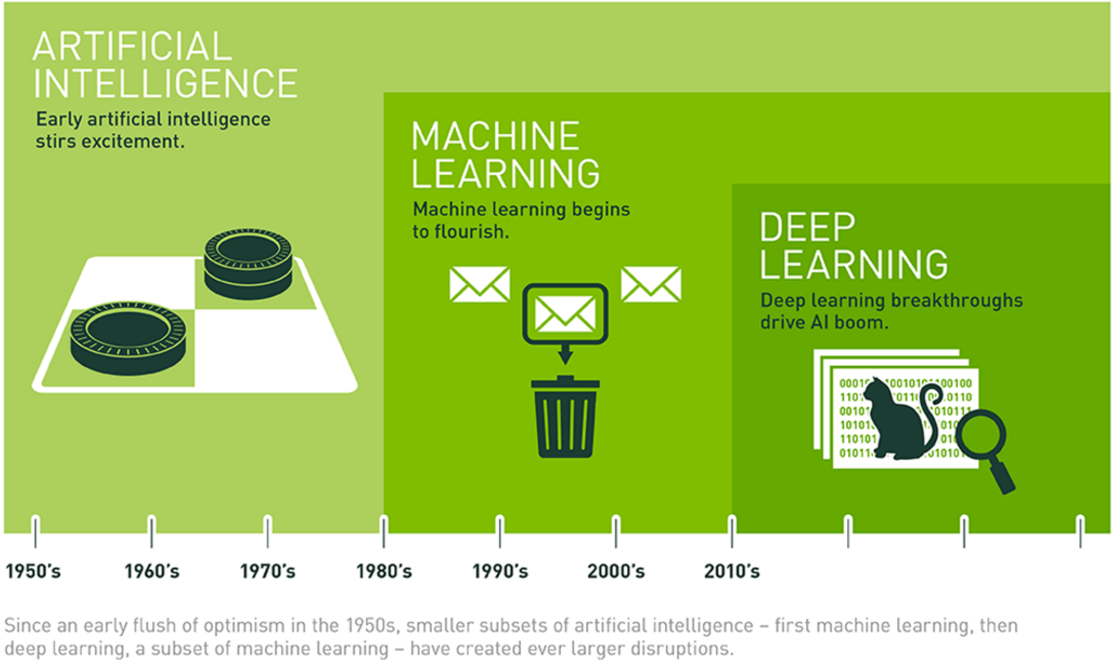
Eva Ambroa Rey
Consorci Sanitari de Terrassa

INTELIGENCIA ARTIFICIAL

ÍNDICE

1. INTRODUCCIÓN

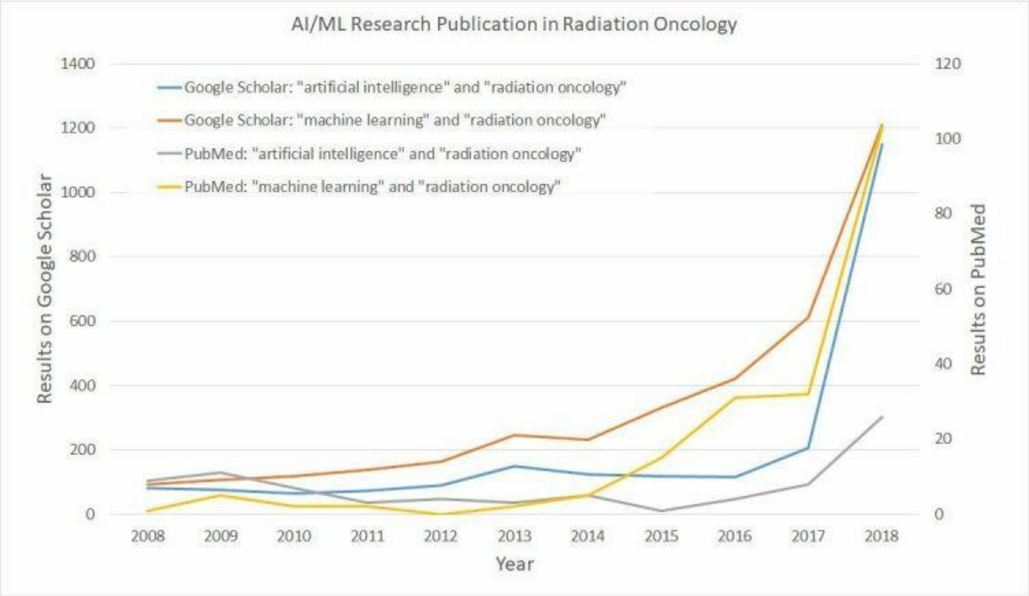
Evolución histórica



Fuente: Michael Copeland What's The Difference Between AI, Machine Learning And Deep Learning, NVIDIA Blogs

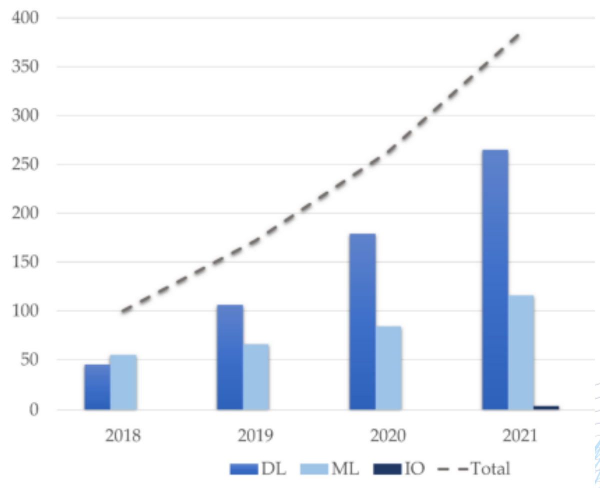
¿Cuál es la situación en RT?

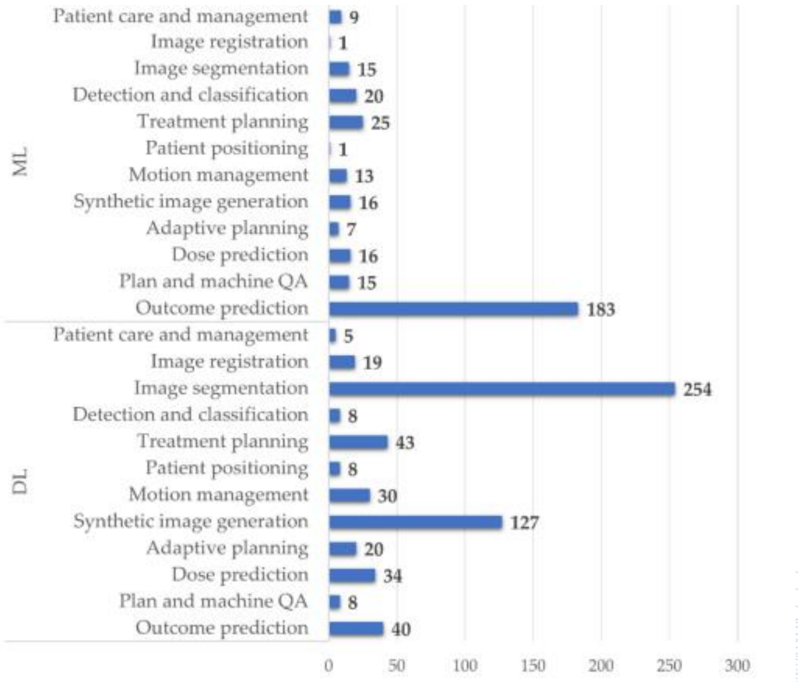
- clasificación de tumores
- segmentación de imágenes
- predicción de dosis
- evaluación del plan
- predicción de resultados
- ...



Jarrett D, Stride E, Vallis K, Gooding MJ. Applications and limitations of machine learning in radiation oncology. The British Journal of Radiology. 2019 Aug;92(1100):20190001. DOI: 10.1259/bjr.20190001.

Tipos de publicaciones en RT (PubMed y Scopus)





Fuente: Santoro M, Strolin S, Paolani G, et al. (2022). Recent Applications of Artificial Intelligence in Radiotherapy: Where We Are and Beyond. Applied Sciences. 12. 3223. 10.3390/app12073223. .

Strategies for effective physics plan and chart review in radiation therapy: Report of AAPM Task Group 275

- Contorneo erróneo o inexacto
- Márgenes PTV erróneos
- Errores en los contornos dosimétricos

- ¿Pueden las herramientas basadas en ML/DL reducir los fallos a través de controles automatizados?

Ventajas del IA

- Reducir tiempo en tareas laboriosas y repetitivas.
- Mejorar la eficiencia.
- Mejorar la estandarización: reducir diferencias entre observadores.
- Mejorar la precisión.
- …

¿Inconvenientes de la IA?

- Muchas aplicaciones, pero no listas para el uso clínico.
- ¿Cómo poder ... tividad y la seguridad del ...
- ¿Cuándo se a... ntas basadas en IA en la clín...
- ¿Se reducirá la necesidad de personal clínico?
- ¿Cómo se desarrollarán y regularán estos dispositivos y herramientas?

Intelligent Machines

The Dark Secret at the Heart of AI

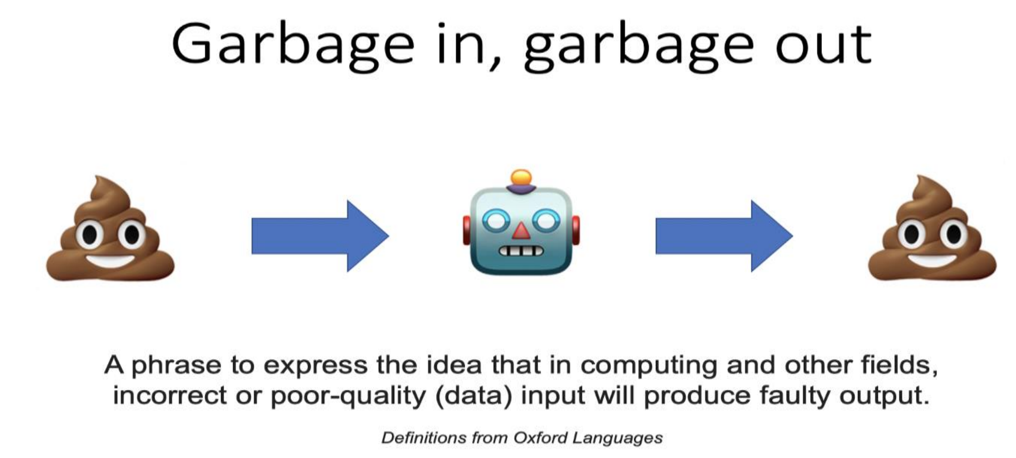
No one really knows how the most advanced algorithms do what they do. That could be a problem.

by Will Knight April 11, 2017

2. CONSIDERACIONES GENERALES

Consideraciones generales

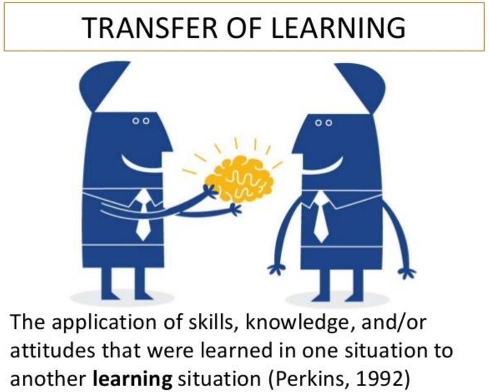
- Calidad de los datos:
  - Incompletos
  - Imprecisos
  - Sesgos
  - Ground truth
  - …



Consideraciones generales

- Cantidad de datos:
  - Tamaño del dataset

Recopilar más datos



VGGNet, ResNET, Inception, Xcaption

- Modelo:
  - ¿Para qué lo voy a utilizar?
  - ¿Es robusto?

3. SIMULACIÓN Y CONTORNEO

Simulación y contorneo

- Contorneo automático.
- Generación de imágenes sintéticas.
- CNNs →OARs tórax, H&N, próstata,…
- Mejorar la variabilidad inter-observador.
- Ganancia de tiempo:
  - 61% CNN vs manual
  - 22% CNN vs Atlas-based

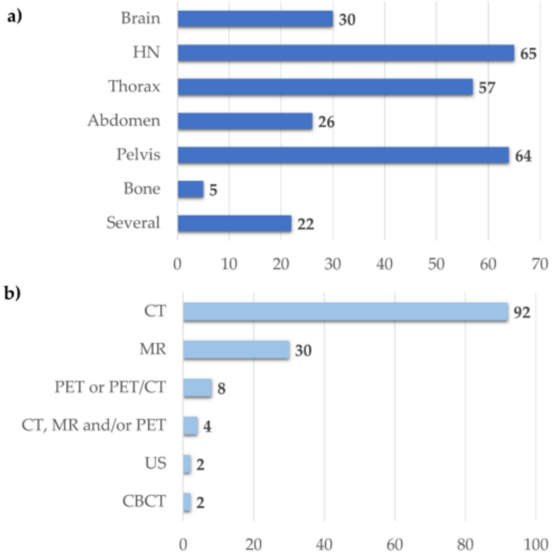


Figure 5. Numbers of identified papers in image segmentation according to **(a)** the contoured district using ML or DL methods, and **(b)** the imaging modality used for segmentation by adopting the convolutional neural network (CNN) approach.

Fuente: Santoro M, Strolin S, Paolani G, et al. (2022). Recent Applications of Artificial Intelligence in Radiotherapy: Where We Are and Beyond. Applied Sciences. 12. 3223. 10.3390/app12073223. .

Contorneo automático

> Radiother Oncol. 2020 Mar;144:152-158. doi: 10.1016/j.radonc.2019.10.019. Epub 2019 Dec 5.

Comparing deep learning-based auto-segmentation of organs at risk and clinical target volumes to expert inter-observer variability in radiotherapy planning

Jordan Wong [1], Allan Fong [2], Nevin McVicar [3], Sally Smith [4], Joshua Giambattista [5], Derek Wells [6], Carter Kolbeck [7], Jonathan Giambattista [8], Lovedeep Gondara [9], Abraham Alexander [10]

Affiliations + expand

PMID: 31812930 DOI: 10.1016/j.radonc.2019.10.019

- U-Net
- SNC, próstata y ORL
- DICE

Conclusions: The accuracy of DCs trained by a single RO is comparable to expert inter-observer variability for the RT planning contours in this study. Use of deep learning-based auto-segmentation in clinical practice will likely lead to significant benefits to RT planning workflow and resources.

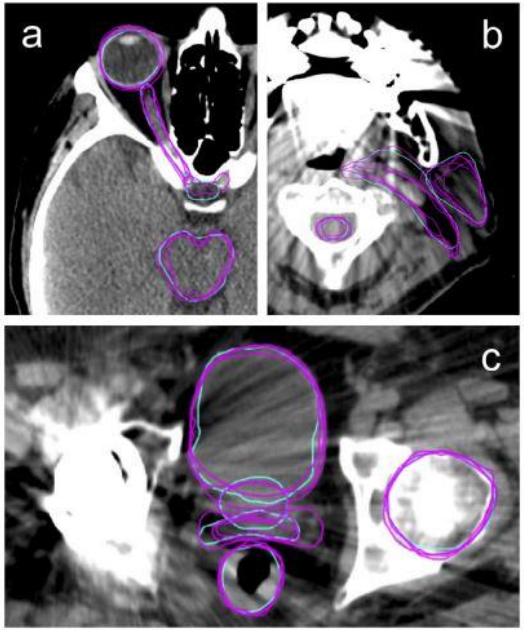


Fig. 1. Example of expert Radiation Oncologist contour (EC) inter-observer variability and deep learning-based auto-segmented contours (DC) for central nervous system (CNS) (a), head and neck (H&N); (b), and prostate; (c) radiotherapy planning structures. See Supplementary files for additional examples. Purple = ECs, blue = DC.

Diferencia entre los tiempos de contorneo DC (CNN) y EC (OR):

- CNS: 7.3 min (95%)
- ORL: 26 min (98%)
- Próstata: 20.8 min (98%)

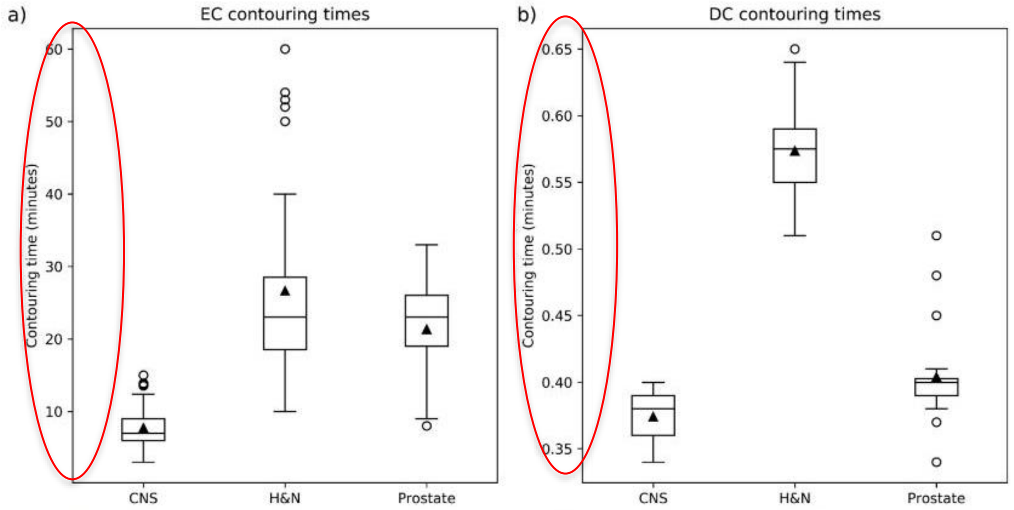


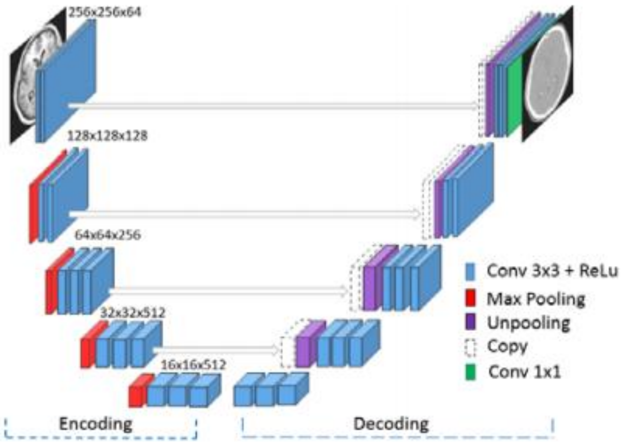
Fig. 2. Central nervous system (CNS), head and neck (H&N), and prostate radiotherapy planning contouring time data for (a) expert Radiation Oncologist contours (EC) inter-observer variability and (b) deep learning-based auto-segmented contours (DC).

CT sintético

Med Phys. 2017 Apr;44(4):1408-1419. doi: 10.1002/mp.12155. Epub 2017 Mar 21.

MR-based synthetic CT generation using a deep convolutional neural network method

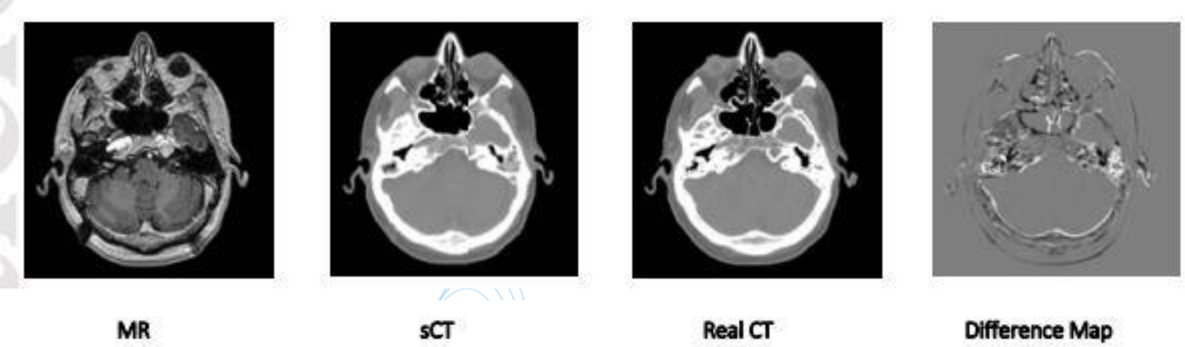
Xiao Han [1]



- 18 pacientes radiocirugía
- Pares de imágenes CT/MR
- U-Net modificada

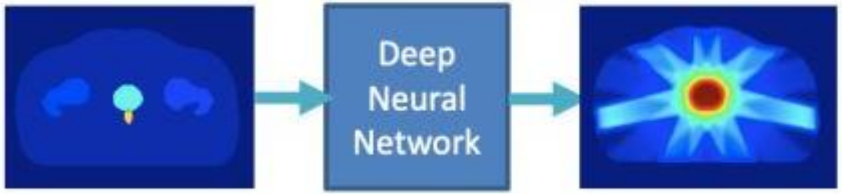
+ transfer learning (VGG16)

CT sintético



- DCNN simular a los modelos generados por atlas
- Segundos en generar el CT sintético

4. PLANIFICACIÓN DEL TRATAMIENTO



Posibles aplicaciones

- Guía/orientación en la planificación de ttos.
- Planificación automática.
- Predicción de toxicidades.
- Comparación de modalidades (IMRT/VMAT/3D…).
- Cálculo de dosis.
- Selección de ángulos.
- …

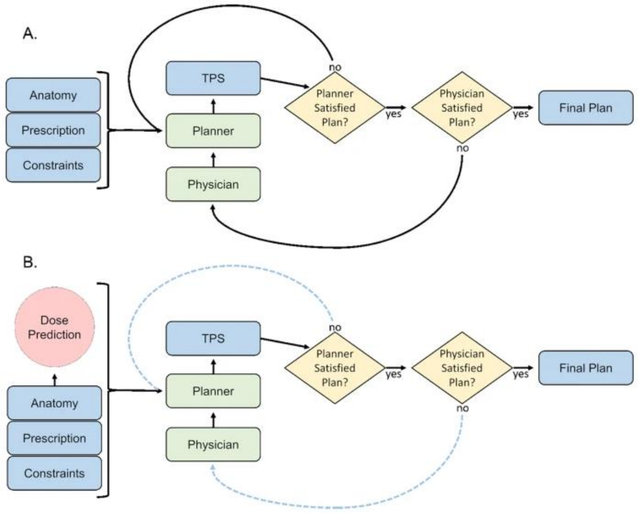
Predicción de distribución de dosis

Article | Open Access | Published: 31 January 2019

A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning

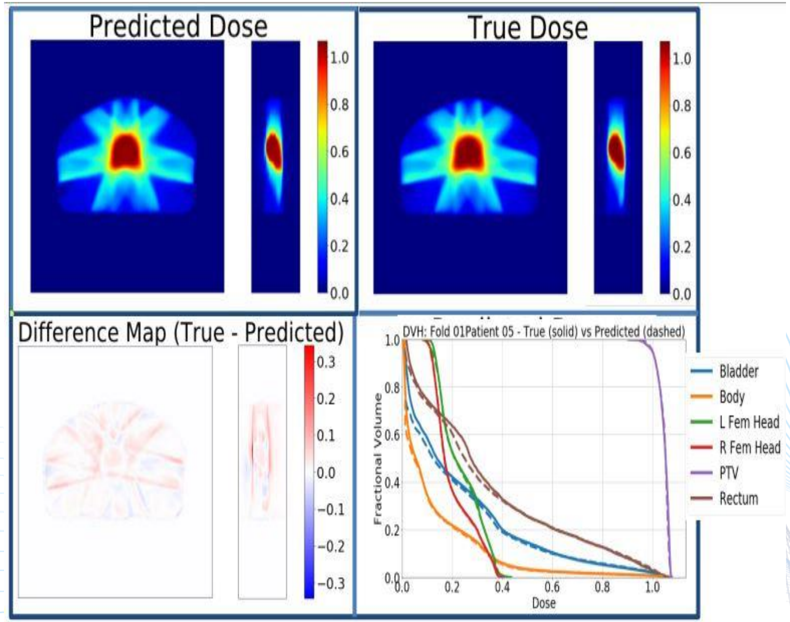
Dan Nguyen, Troy Long, Xun Jia, Weiguo Lu, Xuejun Gu, Zohaib Iqbal & Steve Jiang

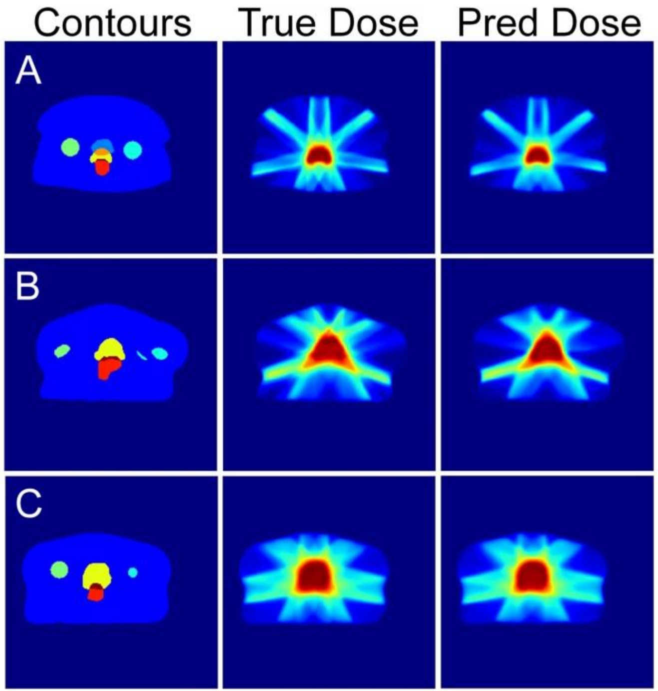
- U-net
- 88 IMRT plans (8 pacientes test)
- Input: cortes individuales
- Output: distribución de dosis para cada corte



(**A**) Current treatment planning workflow. (**B**) Proposed workflow with AI-based dose prediction. Less iterations denoted as dotted-blue lines. TPS = treatment planning system.

Predicción de distribución de dosis





Example dose predictions from the U-net model on several patients with vastly different geometries.

Predicción DVH

Med Dosim. 2021 Apr 22;S0958-3947(21)00025-X. doi: 10.1016/j.meddos.2021.03.005.
Online ahead of print.

Convolutional neural network and transfer learning for dose volume histogram prediction for prostate cancer radiotherapy

Eva M Ambroa [1], Jaime Pérez-Alija [2], Pedro Gallego [3]

Affiliations + expand

PMID: 33896700 DOI: 10.1016/j.meddos.2021.03.005

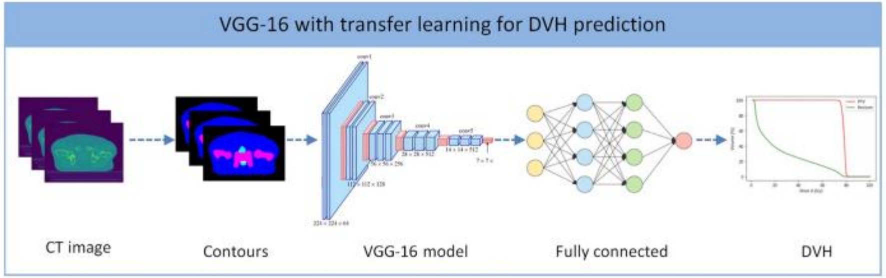


Fig. 1. Network architecture.

- Transfer learning VGG-16+fully connected
- 144 VMAT (SIB)
- Input: estructuras de cada corte
- Output: DVH recto y vejiga para cada corte
- Ground truth

- Precisión:
    - 66.7% (sin ground truth)
    - 100% (con ground truth)

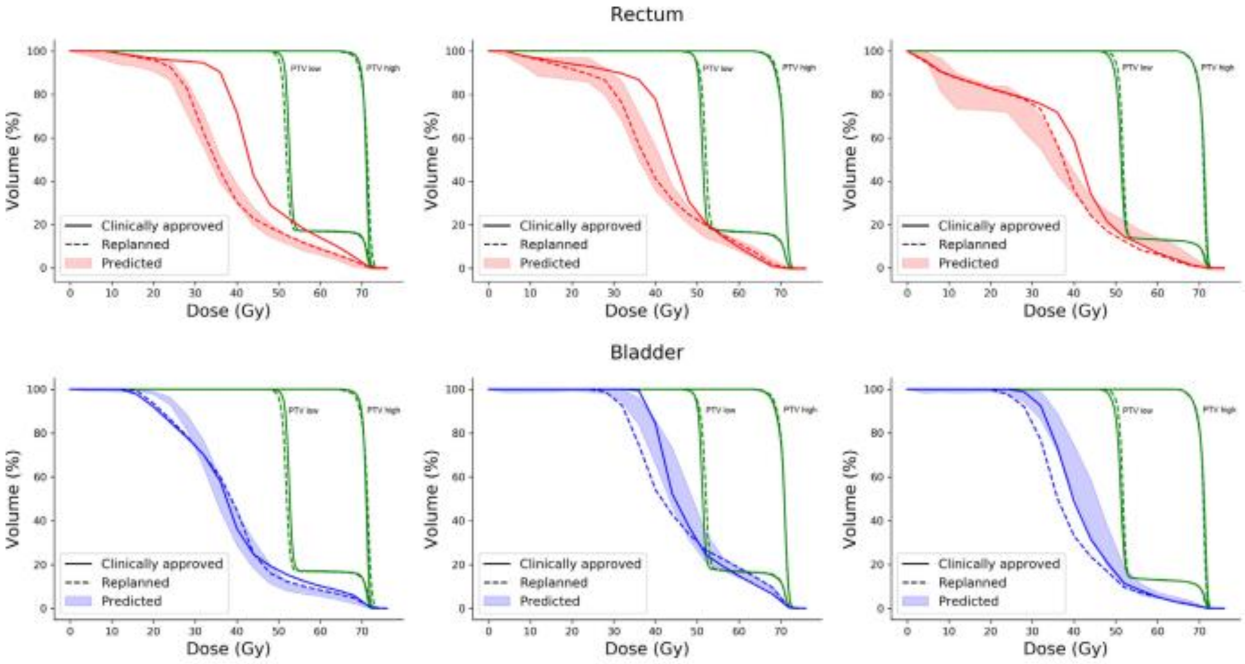


Fig. 5. Clinically approved (solid line), predicted (shaded area) and replanned (dashed line) DVH for patients in the second set (shaded area is a 2 sigma prediction).

Cálculo de dosis

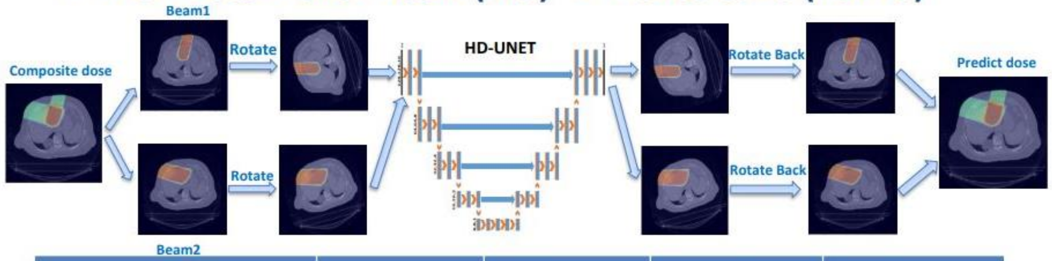
Physics > Medical Physics

[Submitted on 6 Apr 2020]

Improving Proton Dose Calculation Accuracy by Using Deep Learning

Chao Wu, Dan Nguyen, Yixun Xing, Ana Barragan Montero, Jan Schuemann, Haijiao Shang, Yuehu Pu, Steve Jiang

- MGH Data: Pencil Beam (XiO) → Monte Carlo (TOPAS)



	HN	Liver	Prostate	Lung
Number of patients	90	93	75	32
Number of beams	726	218	260	91
Pencil Beam vs MC	(73.3±6.3) %	(79.2±5.1) %	(73.3±2.7) %	(65.4±5.3) %
Predicted vs MC	(92.8±2.9) %	(92.7±2.9) %	(99.6±0.3) %	(89.7±3.8) %

- Input: dosis PB y CT
- 290 pacientes para entrenar, validad y probar el modelo.
- Gamma 1%1mm

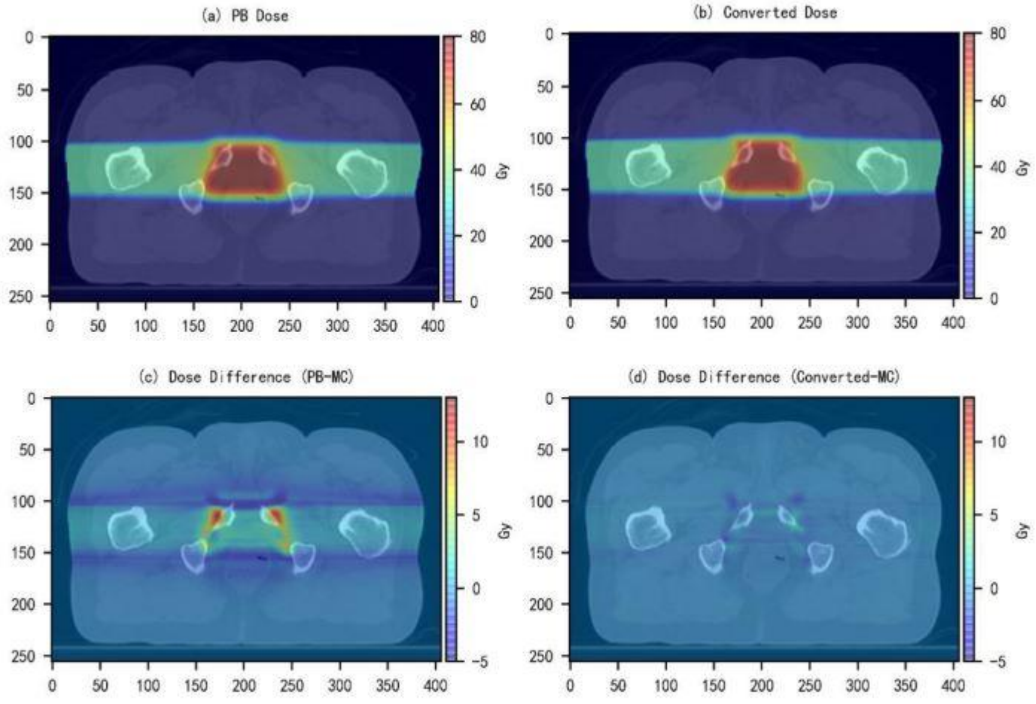


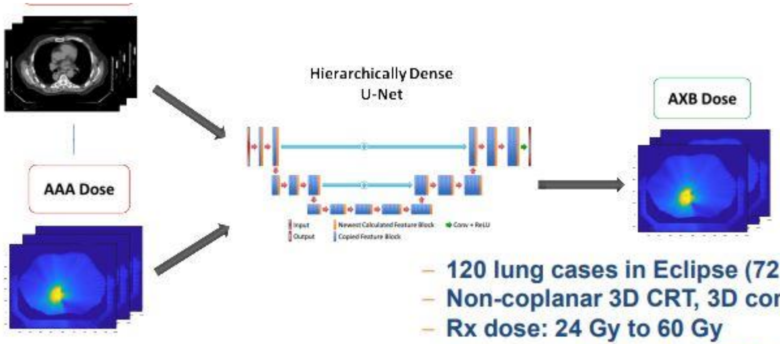
Figure 6. Dose color wash of an axial slice close to the center of the target volume for one example prostate test patient. (a) PB dose distribution; (b) converted dose distribution; (c) absolute dose difference between the PB dose distribution and the MC dose distribution (PB-MC); and (d) absolute dose difference between the Converted dose distribution and the MC dose distribution (Converted-MC).

Cálculo de dosis

[Submitted on 6 May 2020 (v1), last revised 15 May 2020 (this version, v2)]

Boosting radiotherapy dose calculation accuracy with deep learning

Yixun Xing, Ph.D., You Zhang, Ph.D., Dan Nguyen, Ph.D., Mu-Han Lin, Ph.D., Weiguo Lu, Ph.D., Steve Jiang, Ph.D



- 120 lung cases in Eclipse (72 training/18 validation/30 testing)
- Non-coplanar 3D CRT, 3D conformal arc, IMRT, and VMAT plans
- Rx dose: 24 Gy to 60 Gy
- Energy: 6 MV, 10 MV, 6xFFF, and 10xFFF

Dose Maps	Gamma Pass rates		MSE	% of voxels over 3% dose diff of Rx dose
	2mm/2%	1mm/1%		
Original AAA dose	(97.7±2.1)%	(86.0±9.8)%	0.52±0.26	(2.01±1.19)%
Converted AXB dose	(99.9±0.4)%	(98.3±1.7)%	0.16±0.10	(0.46±0.46)%

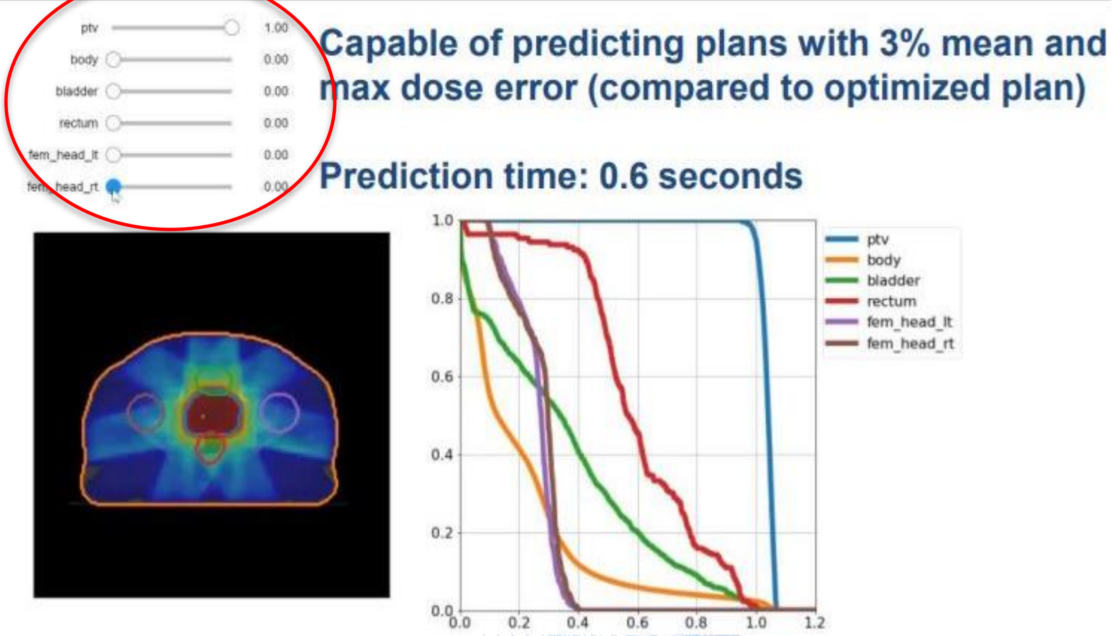
Predicción de dosis en tiempo real con navegación de Pareto

Physics > Medical Physics

[Submitted on 11 Jun 2019 (v1), last revised 31 Jul 2019 (this version, v2)]

Generating Pareto optimal dose distributions for radiation therapy treatment planning

Dan Nguyen, Azar Sadeghnejad Barkousaraie, Chenyang Shen, Xun Jia, Steve Jiang



5. ADMINISTRACIÓN DEL TRATAMIENTO

Aplicaciones de la IA en la administración del tto

- Posicionamiento paciente.
- Monitorización durante el tratamiento (rastreo de tumores, marcadores, etc).
- Patrones de respiración para predecir la posición del tumor.
- Predecir cambios anatómicos en pacientes.
- …

Registro deformable de CBCT a CT

ACCEPTED MANUSCRIPT

An unsupervised convolutional neural network-based algorithm for deformable image registration

To cite this article before publication: Vasant P Kearney *et al* 2018 *Phys. Med. Biol.* in press https://doi.org/1

- Red tipo DC-IGN
- CBCT a CT
- 285 ORL
- Evaluación en 100 casos sintéticos y 12 casos clínicos
- CNN vs IC Demons y LDIR
- 3.5 s en hacer una predicción

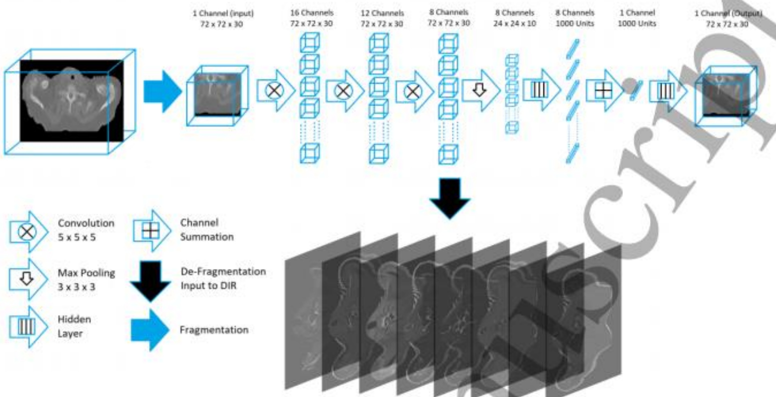


Figure 1. The model architecture is shown for the all steps within the network.

Registro deformable de CBCT a CT

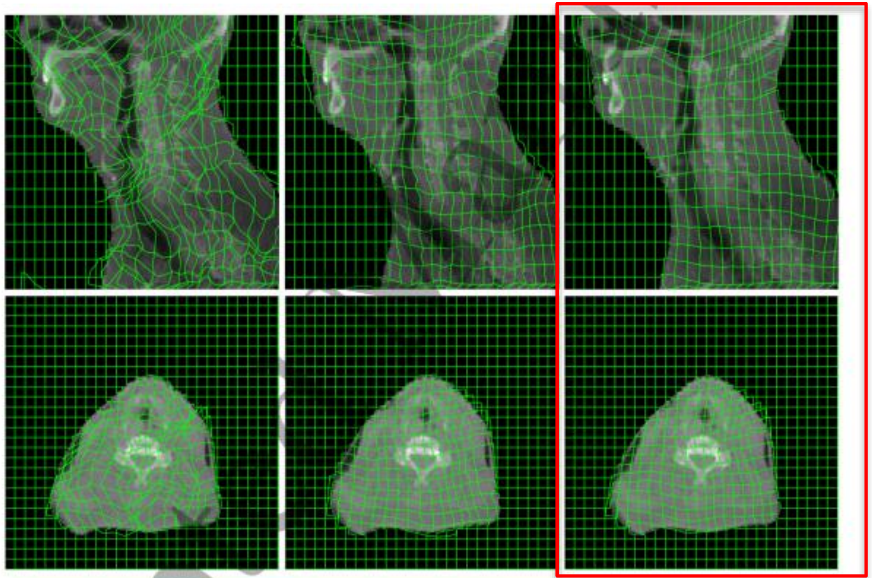


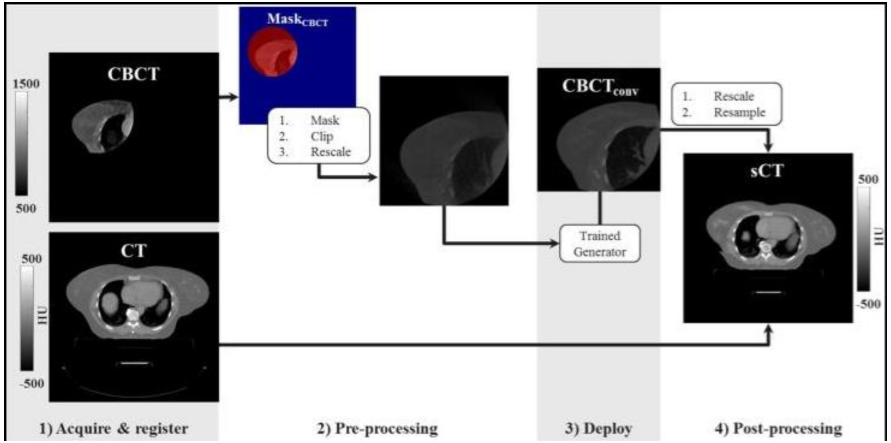
Figure 6. A deformed grid superimposed of the static image is shown for the IC Demons (left), LDIR (center), and DCIGN (right).

RT adaptativa sobre CBCT

› Phys Imaging Radiat Oncol. 2020 May 25;14:24-31. doi: 10.1016/j.phro.2020.04.002.
eCollection 2020 Apr.

A single neural network for cone-beam computed tomography-based radiotherapy of head-and-neck, lung and breast cancer

Matteo Maspero [1 2], Antonetta C Houweling [1], Mark H F Savenije [1 2], Tristan C F van Heijst [1], Joost J C Verhoeff [1], Alexis N T J Kotte [1], Cornelis A T van den Berg [1 2]



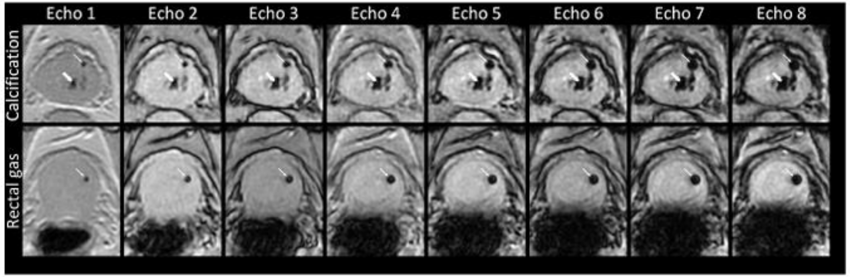
- 99 ORL, pulmón y mama
- Red tipo GANs
- Gamma CT vs sCT
- Reducción de artefactos
- Diferencia de dosis medias<0.5% en zonas de dosis altas
- Tiempo <10s con GPU y 40s en CPU

Identificación de marcadores fiduciales

Phys Med Biol. 2020 Nov 12;65(22):225011. doi: 10.1088/1361-6560/abb0f9.

Development and evaluation of a deep learning based artificial intelligence for automatic identification of gold fiducial markers in an MRI-only prostate radiotherapy workflow

Christian Jamtheim Gustafsson [1, 2], Johan Swärd [3], Stefan Ingi Adalbjörnsson [4], Andreas Jakobsson [3], Lars E Olsson [1, 2]



- 326 próstatas (287 entrenamiento y validación; 39 test)
- Modelo HighRes3DNet
- 36 de 39 pacientes tenían los fiducales bien marcados
- Sensiblidad de detección del 97.4%

6. CONTROL DE CALIDAD

Control calidad Virtual IMRT

A mathematical framework for virtual IMRT QA using machine learning

G. Valdes, R. Scheuermann, C. Y. Hung, A. Olszanski, M. Bellerive, T. D. Solberg

First published: 20 June 2016 | https://doi.org/10.1118/1.4953835 | Citations: 90

- 498 IMRT
- Gamma 3%3mm
- Array 2D

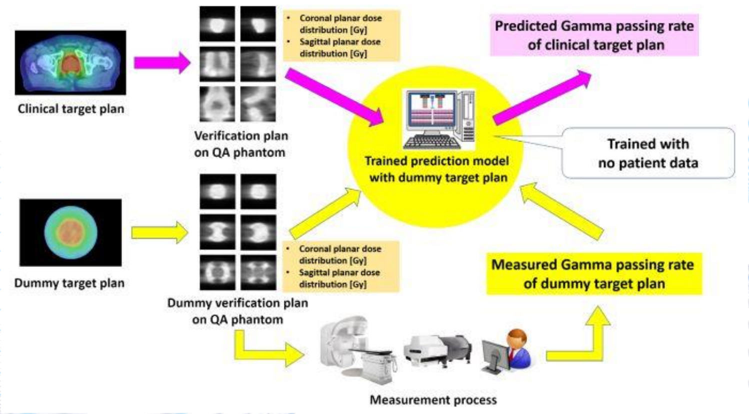
- 78 métricas
- CNN para correlacionar las métricas con el índice gamma
- Índices gamma dentro del 3%

Control calidad Virtual VMAT

Systematic method for a deep learning-based prediction model for gamma evaluation in patient-specific quality assurance of volumetric modulated arc therapy

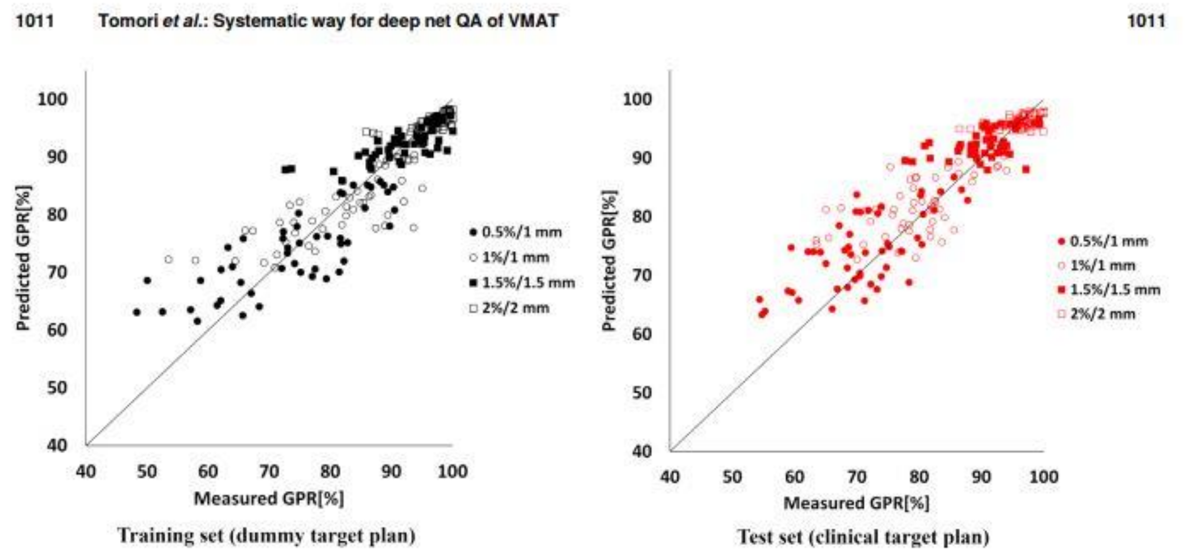
Seiji Tomori, Noriyuki Kadoya, Tomohiro Kajikawa, Yuto Kimura, Kakutarou Narazaki, Takahiro Ochi, Keiichi Jingu

First published: 26 December 2020 | https://doi.org/10.1002/mp.14682 | Citations: 10



- 147 planes VMAT:
  - Training: 96 dummy plan
  - Test: 51 planes clínicos
- Input: planos coronal y sagital
- Predicción Gamma: 0.5%/0.5mm hasta 3%/3mm

Virtual VMAT QA



Sociedad Española de Física Médica

Control calidad paciente

TABLE 2 | Summary of studies on patient-specific QA using machine learning techniques.

Group	TPS/Delivery	QA Source	Data Source	ML Model	Research Highlight
Valdes et al. (2016)	Eclipse/Varian	MapCHECK2	498 IMRT Plans	Poisson Regression	Founding Paper
Valdes et al. (2017)	Eclipse/Varian	Portal Dosimetry	203 IMRT Beams	Poisson Regression	Multi-sites Validation
Interian et al. (2018)	Eclipse/Varian	MapCHECK2	498 IMRT Plans	Convolutional Neural Network	Fluence Maps as Input
Tomori et al. (2018)	iPlan/Varian	EBT3 film	60 IMRT Plans	Convolutional Neural Network	Planar Dose, Volumes, MU
Lam et al. (2019)	Eclipse/Varian	Portal Dosimetry	1,497 IMRT Beams	AdaBoost, Random Forest, XGBoost	Tree-based High Accuracy
Nyflot et al. (2019)	Pinnacle/Elekta	EPID	186 IMRT Beams	Convolutional Neural Network	Image, Texture Features
Granville et al. (2019)	Monaco/Elekta	Delta4	1,620 VMAT Beams	Support Vector Classifier	1st VMAT & w/ QC Metrics
Ono et al. (2019)	RayStation, Eclipse/Vero, Varian	ArcCHECK	600 VMAT Plans	Regression Tree, Multiple Regression, Neural Network	ML Models Comparison
Li et al. (2019b)	Eclipse/Varian	MatriXX	255 VMAT Beams	Poisson Lasso & Random Forest	Specificity & Sensitivity
Wang et al. (in Press)	Eclipse/Varian	MatriXX	576 VMAT Beams	Hybrid Model ACLR	High Prediction Accuracy
Wall and Fontenot (2020)	Pinnacle/Elekta	MapCHECK2	500 VMAT Plans	Linear Regression, SVM, Tree-based, ANN	ML Models Comparison
Hirashima et al. (2020)	RayStation, Eclipse/ Vero, Varian	ArcCHECK	1,255 VMAT Plans	Hybrid Model XGBoost	Plan Complexity & Dosiomics

Chan, M., Witztum, A., & Valdes, G. (2020). Integration of AI and Machine Learning in Radiotherapy QA. UCSF. Report #: ARTN 577620. ht sefm Sociedad Española de Física Médica

MLC QA

Phys Med Biol. 2016 Mar 21;61(6):2514-31. doi: 10.1088/0031-9155/61/6/2514. Epub 2016 Mar 7.

A machine learning approach to the accurate prediction of multi-leaf collimator positional errors

Joel N K Carlson [1], Jong Min Park, So-Yeon Park, Jong In Park, Yunseok Choi, Sung-Joon Ye

Affiliations + expand

PMID: 26948678 DOI: 10.1088/0031-9155/61/6/2514

- 78 VMAT (ORL y próstata) de 3 instituciones
- Regresión lineal, random forest y un modelo cubista

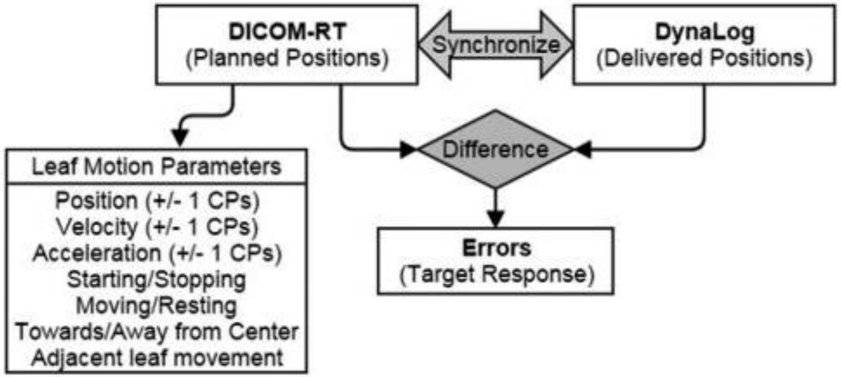


Figure 1. Workflow of the extraction of errors between DICOM-RT and DynaLog files, and the extraction of leaf motion parameters from planned positions.

Control calidad LINAC

TABLE 1 | Summary of studies on machine QA using machine learning techniques in a chronological order.

References	QA Source	Data Source	ML Model	Task
Carlson et al. (2016)	DICOM_RT, Dynalog files	74 VMAT plans	Regression, Random Forest, Cubist	MLC Position Errors Detection
Li and Chan (2017)	Daily QA Device	5-year Daily QA Data	ANN Time-Series, ARIMA Models	Symmetry Prediction
Sun et al. (2018)	Ion Chamber	1,754 Proton Fields	Random Forrest, XGBoost, Cubist	Output for Compact Proton Machine
El Naqa et al. (2019)	EPID	119 Images from 8 Linacs	Support Vector Data Description, Clustering	Gantry Sag, Radiation Field Shift, MLC Offset
Grewal et al. (2020)	Ion Chamber	4,231 Proton Fields	Gaussian Processes, Shallow NN	Output and Patient QA Proton Machine
Osman et al. (2020)	log files	400 machine delivery log files	ANN	MLC Discrepancies during Delivery & Feedback
Chuang et al. (in press)	Trajectory log files	116 IMRT plans, 125 VMAT plans	Boosted Tree Outperformed LR	MLC Discrepancies during Delivery & Feedback
Zhao et al. (in press)	Water Tank Measurement	43 Truebeam PDD, Profiles	Multivariate Regression (Ridge)	Modeling of Beam Data Linac Commissioning

Chan, M., Witztum, A., & Valdes, G. (2020). Integration of AI and Machine Learning in Radiotherapy QA. UCSF. Report #: ARTN 577620. ht

Conclusiones

- Aplicaciones de IA en todo el flujo radioterápico.
- ML para predicción de resultados.
- DL para segmentación y generación imágenes sintéticas.
- Reducir drásticamente tiempo en tareas repetitivas.
- Mejorar la calidad.
- Reducir la variación inter-observador.
- Toma decisiones.
- Armonizar herramientas de IA en la práctica clínica.

¡Muchas gracias por vuestra atención!