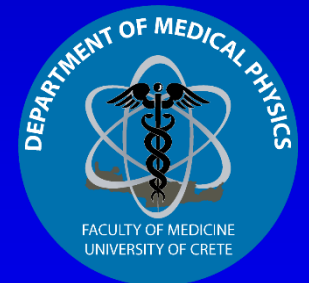


*Challenges of RP in Research and Society Referring to Medical Field*  
*Milan, October 3, 2024*

*ICRP C3 WP on AI in Imaging and Radiotherapy*



**J. Damilakis, MSc, PhD, FIOMP, FIUPESM**  
**Professor and Chairman**  
**School of Medicine**  
**University of Crete**  
**Greece**



# ICRP Working Party on AI

## Working Party

on radiation protection and AI in  
medical imaging and radiotherapy



# ICRP Working Party on AI



Draft Terms of Reference

## Artificial Intelligence (AI)

A Task Group  
Approved by the Main Commission

### Background

The integration of artificial intelligence (AI) in non-medical settings, has grown significantly in various radiological applications. However, concerns regarding safety, ethical considerations, and quality assurance in radiological protection. The impact of AI on the global application of AI in medicine, especially in treatment planning, and decision support systems, innovations are properly integrated within the context of radiological protection.

The rationale for the creation of a dedicated Task Group is to ensure that the adoption of AI aligns with the principles of radiological protection. AI introduces new complexities and potential biases in clinical decision-making. Furthermore, medical applications of AI, particularly in diagnosis and treatment delivery, present both opportunities and challenges to protect patients, staff, and the public.

ICRP has long been at the forefront of providing guidance on the establishment of a Task Group focused on addressing the advancements and the unique challenges that AI introduces in radiological practices, but with a focus on ensuring that AI does not introduce risks to patient safety, radiation protection, and the public. This document includes an explanation of the uncertainties

The key areas of focus will include:

- 1. Quality assurance and validation of AI systems.** It is essential to develop rigorous quality assurance protocols for AI-powered tools before their implementation in clinical practice. This includes establishing criteria for validating the accuracy, reliability, and safety of AI algorithms used in medical imaging, radiation therapy, and other medical radiological applications.
- 2. Radiation dose estimation and optimization.** AI technologies should support dose optimization strategies that minimize patient and operator exposure while maintaining diagnostic quality. The Task Group will provide guidance on how AI can be leveraged to improve radiation protection practices in medical and other settings.
- 3. Ethical and legal considerations.** AI systems must adhere to ethical standards, particularly in terms of patient consent, data privacy, and transparency. The Task Group will assess how AI technologies can be aligned with existing ethical frameworks for radiological protection.
- 4. AI in non-medical radiological protection.** In non-medical sectors, AI is increasingly being utilized in areas such as environmental monitoring, and nuclear safety. The Task Group will provide recommendations on the use of AI for ensuring the safe handling of radioactive materials and for improving radiation monitoring and emergency response systems.
- 5. Training and education for radiological protection personnel.** As AI systems are introduced into radiological protection workflows, there is a need for targeted training programs to ensure that personnel are proficient in the use of these technologies. The Task Group will recommend strategies for integrating AI education into radiological protection training curricula. There is a critical need for communication amongst colleagues and the public in using AI as a tool that will not replace expert workers but will enhance them.

# Key areas of focus: QA of AI tools

**nature**

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[nature](#) > [news feature](#) > article

NEWS FEATURE | 21 August 2024

## The testing of AI in medicine is a mess. Here's how it should be done

Hundreds of medical algorithms have been approved on basis of limited clinical data. Scientists are debating who should test these tools and how best to do it.

QA and validation of AI systems

in imaging and radiotherapy

is needed to ensure

Accuracy

Reliability

Safety

# Data quality

This screenshot shows the Kaggle dataset page for 'Chest X-Ray Images (Pneumonia)' by Paul Mooney. The dataset is updated 6 years ago and contains 5,863 images across 2 categories. The page includes a search bar, navigation links (Home, Competitions, Datasets, Models, Code, Discussions, Learn, More), and a sidebar with a 'Create' button. The main content area features a 'Data Card' tab, a 'Code (2161)' tab, and a 'Discussion (59)' tab. Below the tabs is an 'About Dataset' section with a 'Context' link to a URL: [http://www.cell.com/cell/fulltext/S0092-8674\(18\)30154-](http://www.cell.com/cell/fulltext/S0092-8674(18)30154-). Two chest X-ray images are shown side-by-side, labeled 'Normal' and 'Bacterial Pneumonia'.

This screenshot shows the Kaggle dataset page for 'Chest X-ray (Covid-19 & Pneumonia)' by Prashant Patel. The dataset is updated 3 years ago and contains 158 images. The page includes a search bar, navigation links, and a sidebar. The main content area features a 'Data Card' tab, a 'Code (96)' tab, and a 'Discussion (2)' tab. Below the tabs is an 'About Dataset' section with a 'Context' link. The context text states: 'COVID-19 (coronavirus disease 2019) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a strain of coronavirus. The first cases were seen in Wuhan, China, in late December 2019 before spreading globally. The current outbreak was officially recognized as a pandemic by the World Health Organization (WHO) on 11 March 2020. Currently Reverse transcription polymerase chain reaction (RT-PCR) is used for diagnosis of the COVID-19. X-ray machines are widely available and provide images for diagnosis quickly so chest X-ray images can be very useful in early diagnosis of COVID-19.' The 'Content' section states: 'Dataset is organized into 2 folders (train, test) and both train and test contain 3 subfolders (COVID19, PNEUMONIA, NORMAL). DataSet contains total 6432 x-ray images and test data have 20% of total images.' The 'Acknowledgements' section states: 'Images are collected from various publicly available resources. If you use the data for research please give credit to authors:'. On the right side, there is a 'Usability' section with a score of 5.00, a 'License' section with 'Unknown', an 'Expected update frequency' section with 'Not specified', and a 'Tags' section with 'Computer Science', 'Health', 'Deep Learning', 'Coronavirus', and 'CNN'.

# Checklist for AI in medical imaging (CLAIM)

Radiology: Artificial Intelligence

Checklist for Artificial Intelligence in Medical Imaging (CLAIM): 2024 Update

Checklist for Artificial Intelligence in Medical Imaging (CLAIM): 2024 Update		
Section/Topic	No.	Item
TITLE/ABSTRACT	1	Identification as a study of AI methodology, specifying the category of technology used (eg, deep learning)
ABSTRACT	2	Summary of study design, methods, results, and conclusions
INTRODUCTION	3	Scientific and/or clinical background, including the intended use and role of the AI approach
	4	Study aims, objectives, and hypotheses
METHODS	5	Prospective or retrospective study

**CLAIM 2024 Update Panel:** Sunhy Abbara, Saif Afat, Udunna C. Anazodo, Anna Androshchenko, Folkert W. Asselbergs, Aldo Badano, Bettina Baessler, Bayarbaatar el B. Brismar, Giovanni E. Cacciamani, John A. Carrino, . Chiang, Tessa S. Cook, Renato Cuocolo, John Dami-Carlo N. De Cecco, Hesham Elhalawani, Guillermo edorov, Benjamin Fine, Adam E. Flanders, Judy Wawira er, Safwan S. Halabi, Sven Haller, William Hsu, Krishna -Cramer, Apostolos H. Karantanas, Felipe C. Kitamura, oh, Elmar Kotter, Elizabeth A. Krupinski, Curtis P. Lantio Maas, Anant Madabhushi, Lena Maier-Hein, Kostas tí, Jaishree Naidoo, Emanuele Neri, Robert Ochs, Nikos Papathomas, Katja Pinker-Domenig, Daniel Pinto dos Iros Protonotarios, Mauricio Reyes, Veronica Rotemberg, iel Salinas-Miranda, Francesco Sardanelli, Mark E. Schenza, Ronnie Sebros, Prateek Sharma, An Tang, Antonios er Laak, Peter M. A. van Ooijen, Vasantha K. Venugopal, Wood, Carol C. Wu, Greg Zaharchuk, Marc Zins

<i>Data</i>	7	Data sources
	8	Inclusion and exclusion criteria
	9	Data preprocessing
	10	Selection of data subsets
	11	De-identification methods
	12	How missing data were handled
	13	Image acquisition protocol
<i>Reference Standard</i>	14	Definition of method(s) used to obtain reference standard
	15	Rationale for choosing the reference standard
	16	Source of reference standard annotations
	17	Annotation of test set
	18	Measures of inter- and intrarater variability of features described by the annotators

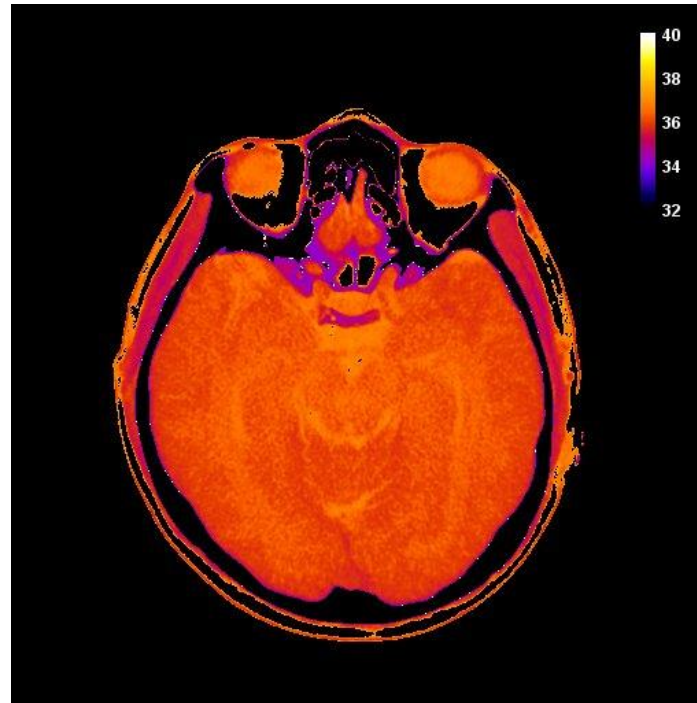
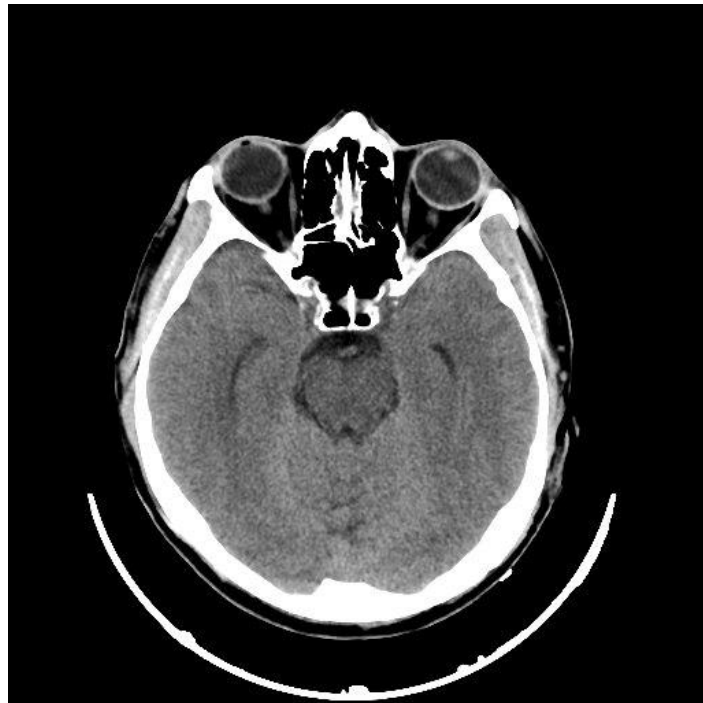
	38	Estimates of diagnostic performance and their precision
	39	Failure analysis of incorrectly classified cases
DISCUSSION	40	Study limitations
	41	Implications for practice, including intended use and/or clinical role
OTHER INFORMATION	42	Provide a reference to the full study protocol or to additional technical details
	43	Statement about the availability of software, trained model, and/or data
	44	Sources of funding and other support; role of funders

Indicate page and/or line number for each checklist item that is present.

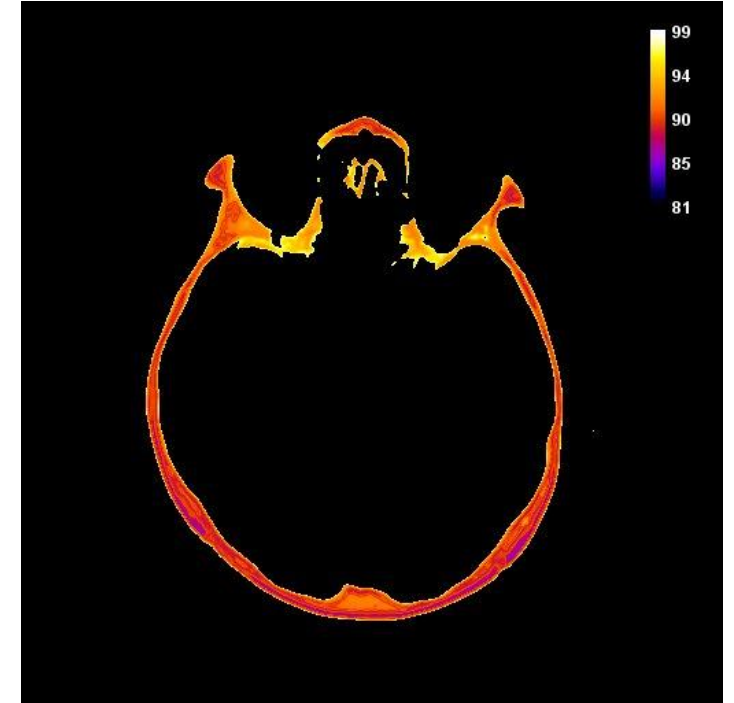


# Key areas of focus: Radiation dose estimation & optimization

AI dose image



AI dose image

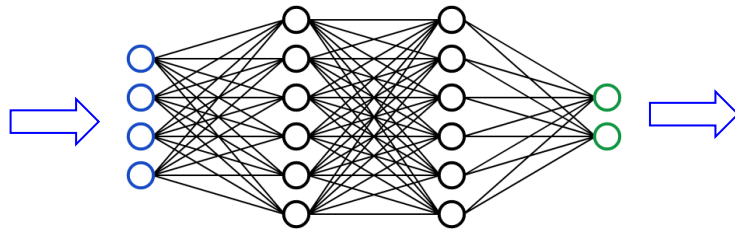


# Deep learning CT reconstruction

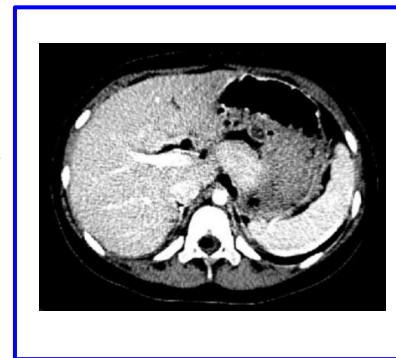
Input image



DNN



Output image



Ground truth



DNN learns by adjusting various parameters via back-propagation:

- high contrast resolution
- low contrast resolution
- image noise
- image texture
- CT number accuracy
- .....



# Image quality improvement

## PLOS ONE

RESEARCH ARTICLE

### Denoising of pediatric low dose abdominal CT using deep learning based algorithm

Hyung Suk Park<sup>1</sup>, Kiwan Jeon<sup>1</sup>, JeongEun Lee<sup>2,3</sup>, Sun Kyoung You<sup>2,3\*</sup>

**1** National Institute for Mathematical Sciences, Daejeon, Republic of Korea, **2** Department of Radiology, Chungnam National University College of Medicine, Daejeon, Republic of Korea, **3** Department of Radiology, Chungnam National University Hospital, Daejeon, Republic of Korea

\* [sunkyou@cnuh.co.kr](mailto:sunkyou@cnuh.co.kr)

Received: 8 July 2021 | Revised: 28 October 2021 | Accepted: 2 November 2021

DOI: 10.1002/mp.15354

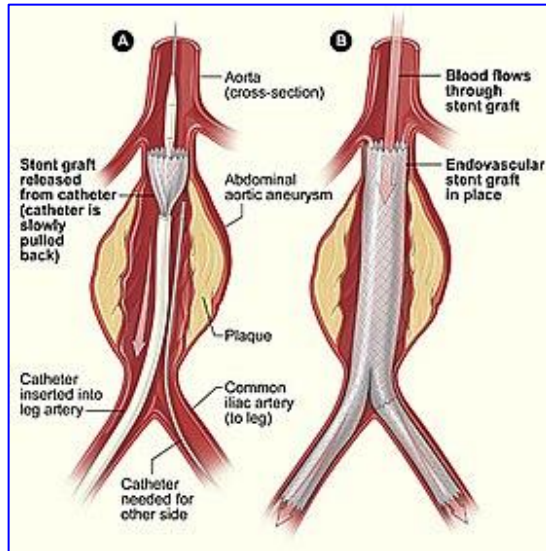
RESEARCH ARTICLE

MEDICAL PHYSICS

### A deep learning method for eliminating head motion artifacts in computed tomography

Bin Su<sup>1,†</sup> | Yuting Wen<sup>2,†</sup> | Yanyan Liu<sup>1,†</sup> | Shu Liao<sup>3</sup> | Jianwei Fu<sup>1</sup> |  
Guotao Quan<sup>1</sup> | Zhenlin Li<sup>2</sup>

# Establishment of DRLs using AI



## Endovascular Aneurysm Repair

Physica Medica 114 (2023) 103140

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

**Physica Medica**

journal homepage: [www.elsevier.com/locate/ejmp](http://www.elsevier.com/locate/ejmp)

ELSEVIER

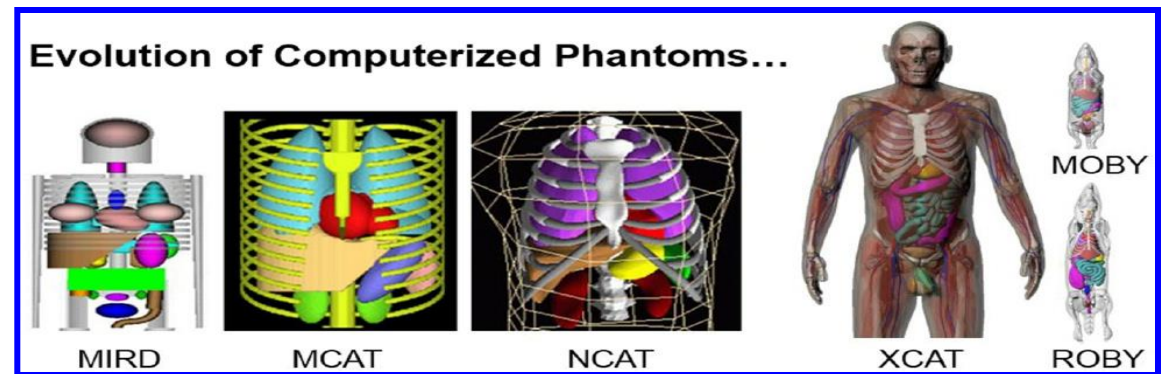
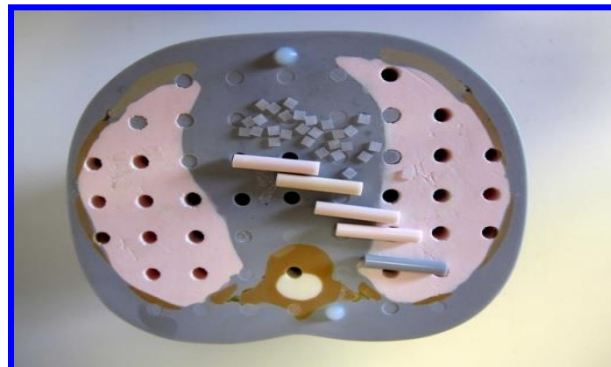
Physica Medica  
European Journal  
of Medical Physics

A neural network-enhanced methodology for the rapid establishment of local DRLs in interventional radiology: EVAR as a case example

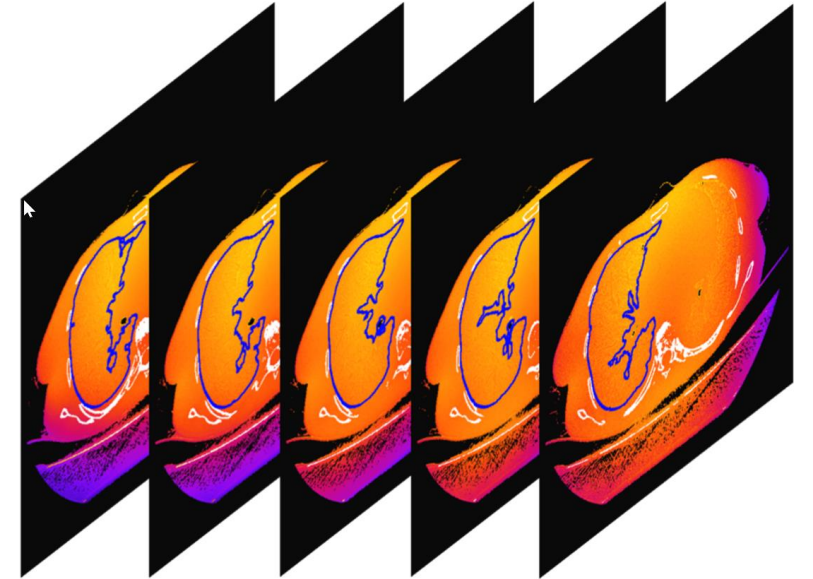
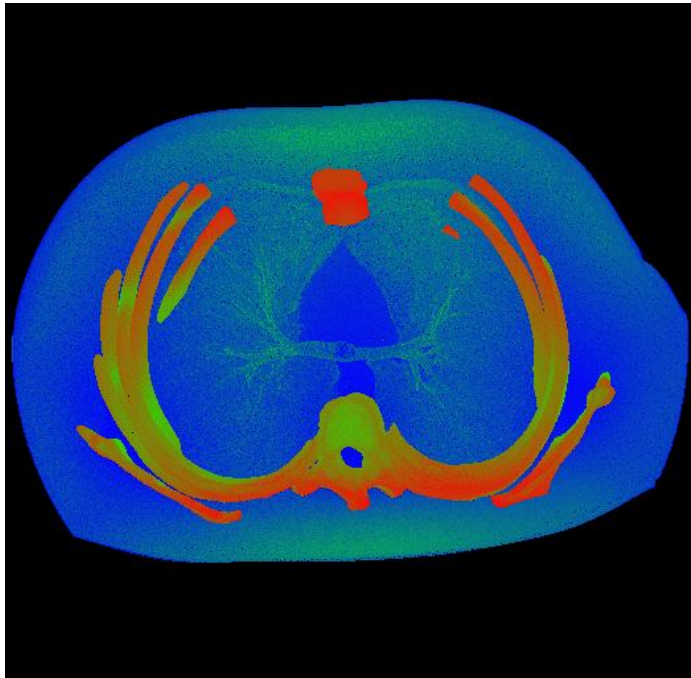
Eleftherios Tzanis, John Damilakis\*

*Department of Medical Physics, School of Medicine, University of Crete, P.O. Box 2208, 71003 Heraklion, Crete, Greece*

# Patient dosimetry: How do we estimate patient doses?



# Patient-specific and equipment specific dosimetry



# Real time personalized patient dosimetry

## We need

- **Equipment-specific dosimetry**
- **True patient-specific dosimetry**
- **Protocol-specific dosimetry**
- **Real-time dosimetry**

**for organ and tissue dose estimation**

# Real time personalized dosimetry

**Organ dose information will be automatically incorporated into the structured reporting templates so referring physicians will have complete information about patient doses and risks**



# AI-powered patient radiation dose prediction

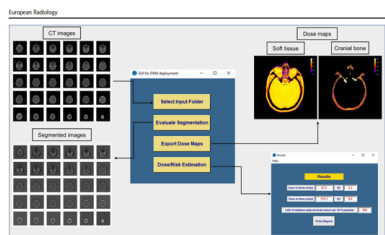
## AI-assisted organ dose estimation

European Radiology  
<https://doi.org/10.1007/s00381-022-04876-w>  
**COMPUTED TOMOGRAPHY**

**A novel methodology to train and deploy a machine learning model for personalized dose assessment in head CT**

Eleftherios Tzanis<sup>1</sup> · John Damilakis<sup>1</sup>

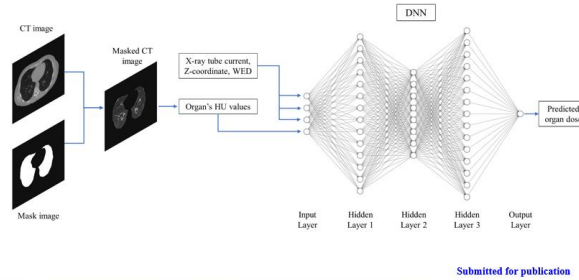
Received: 8 December 2021 / Revised: 28 February 2022 / Accepted: 19 March 2022  
 © The Author(s), under exclusive license to European Society of Radiology 2022



**Fig. 3** The graphical user interface. Using the DNN model, the software produces dose maps for each imported CT image. By selecting the "DoseRisk Estimator" button, the dose to the brain and cranial bones as well as the LAR of radiation-induced cancer risk is automatically calculated.

European Radiology, April 2022

## An automated ML-based methodology for chest and abdomen CT



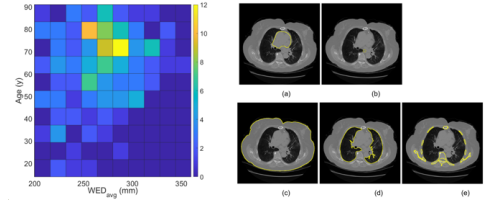
Submitted for publication

## Rapid workflow based on DNN to estimate organ doses from CT

**Features:** mA, scan length, WED

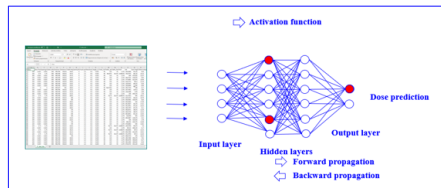
**Ground truth:** Patient-specific doses

- DNN implemented in MATLAB
- 3 hidden layers with ReLU
- Number of nodes: 100, 200, 50



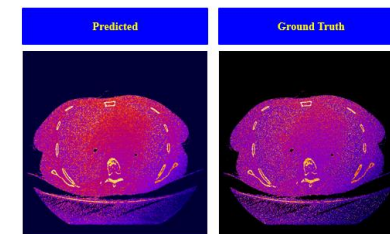
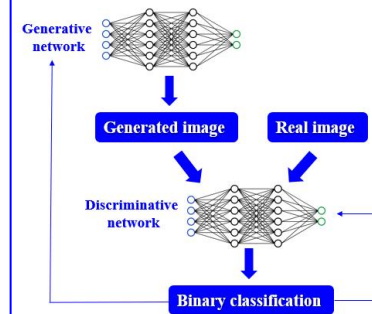
SINFONIA

## AI-based dose estimation for organs exposed to scattered radiation



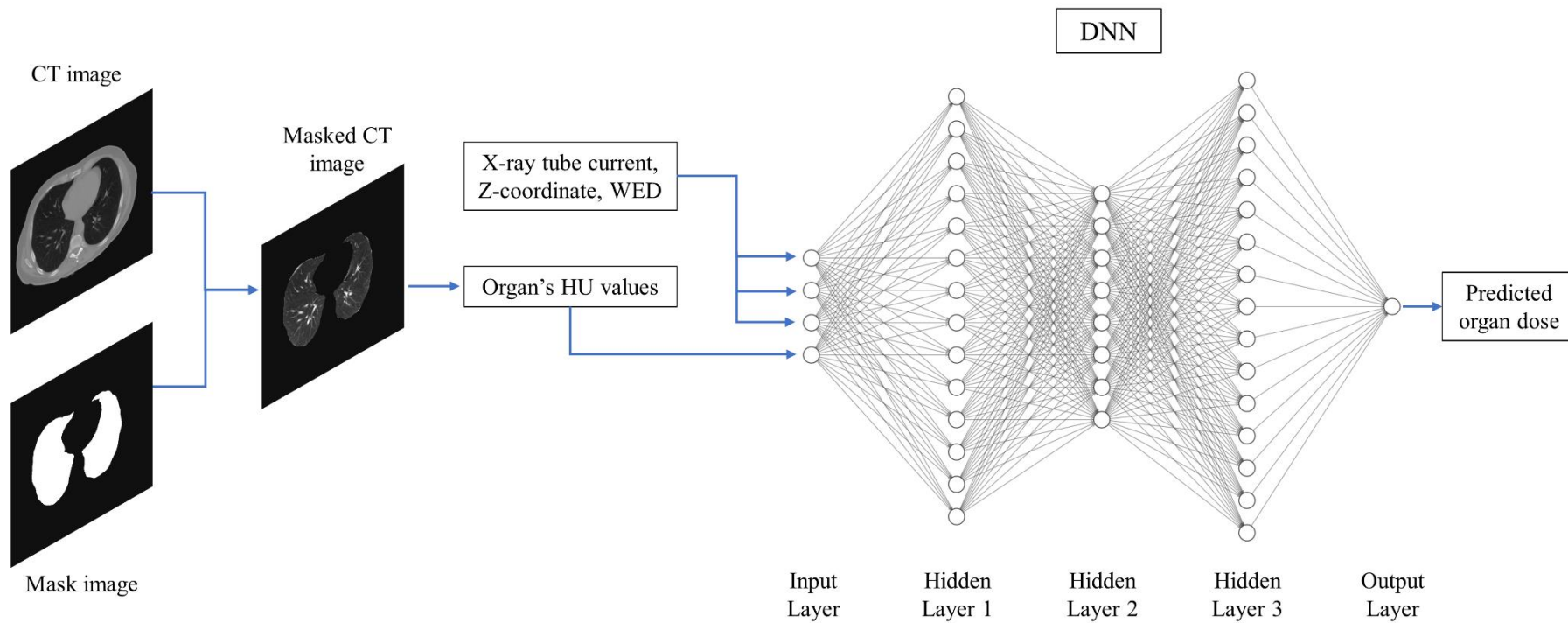
How can we train and evaluate a deep learning model for the prediction of liver dose in adult thorax CT examinations?

## Generative Adversarial Networks (GANs)



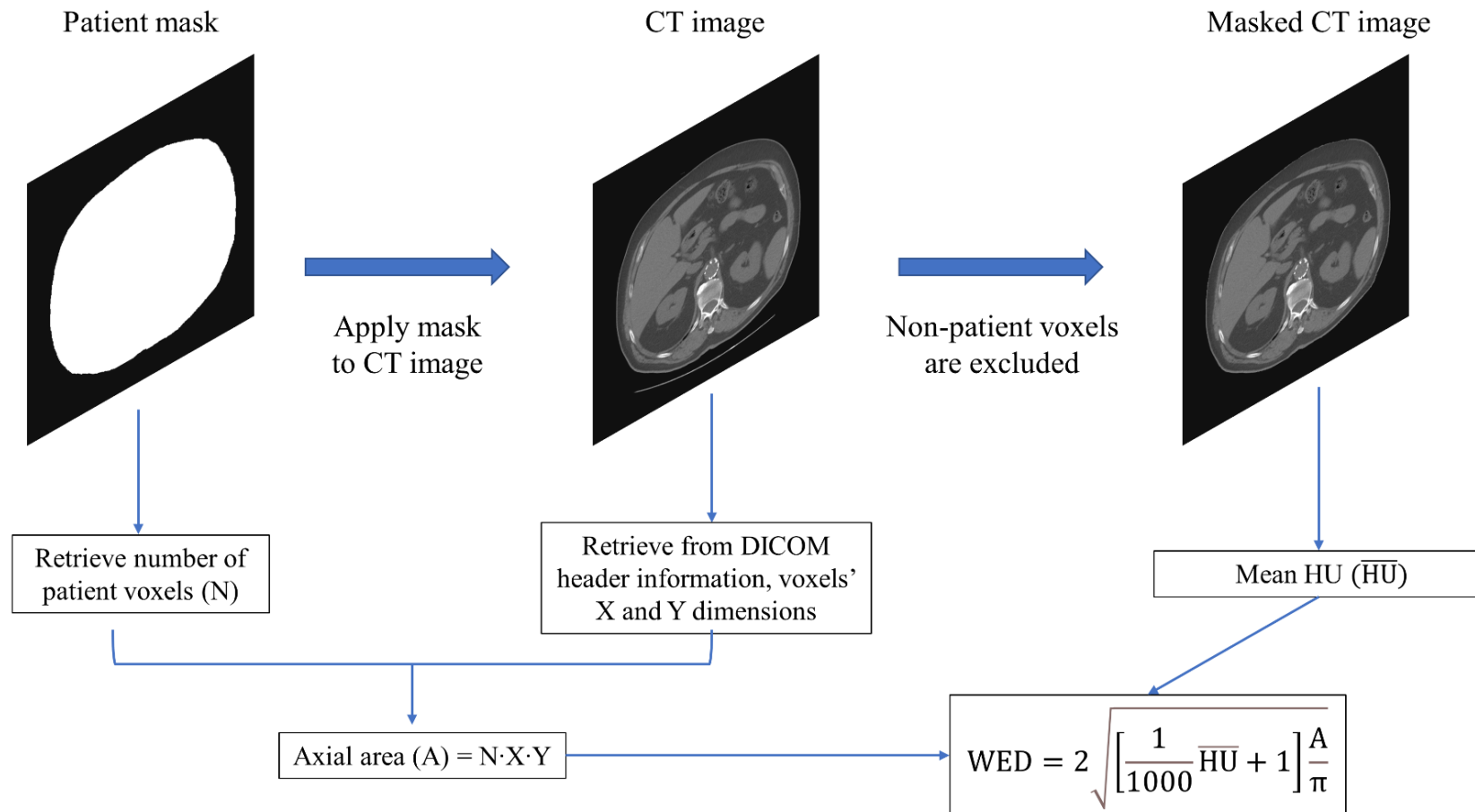
Work in progress

# An automated ML-based methodology for CT



Submitted for publication

# An automated ML-based methodology for CT



# An automated ML-based methodology for CT

Physica Medica 117 (2024) 103195

Contents lists available at ScienceDirect

Physica Medica

journal homepage: [www.elsevier.com/locate/ejmp](http://www.elsevier.com/locate/ejmp)



ELSEVIER



A fully automated machine learning-based methodology for personalized radiation dose assessment in thoracic and abdomen CT

Eleftherios Tzani, John Stratakis, Marios Myronakis, John Damilakis\*

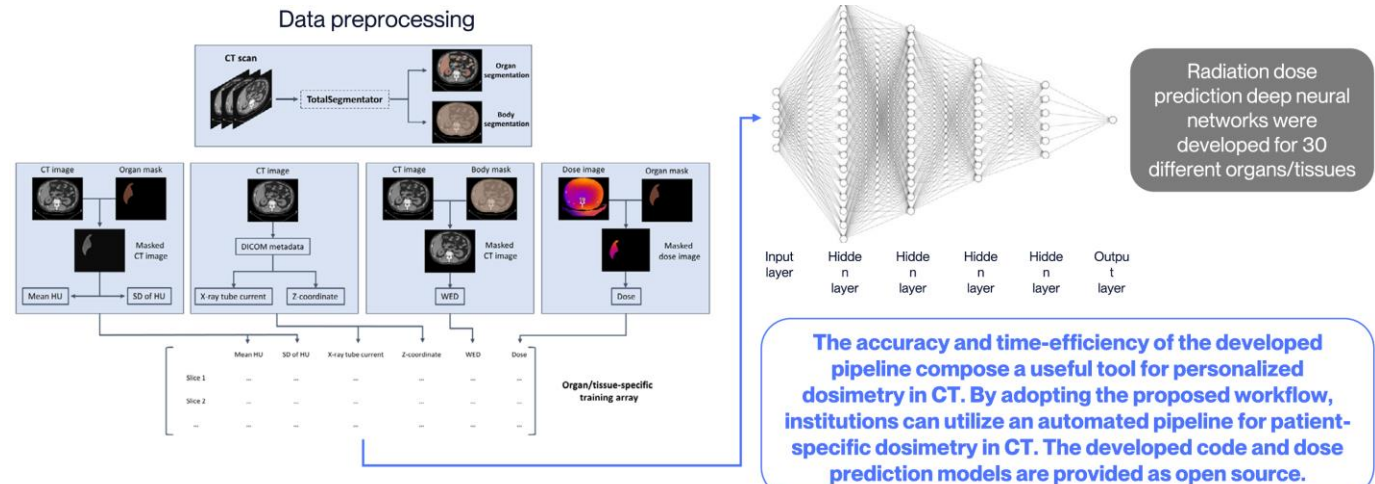
Department of Medical Physics, School of Medicine, University of Crete, P.O. Box 2208, Heraklion, Crete 71003, Greece

Tzani and Damilakis *European Radiology*  
<https://doi.org/10.1007/s00330-024-11002-0>

EUROPEAN SOCIETY OF RADIOLOGY  
 European Radiology

COMPUTED TOMOGRAPHY

A machine learning-based pipeline for multi-organ/tissue patient-specific radiation dosimetry in CT



# An automated ML-based methodology for CT

## Evaluation of the segmentation models

Segmentation models	Jaccard score			Dice score		
	Mean	SD	Range	Mean	SD	Range
Lungs	0.92	0.03	0.83-0.95	0.96	0.02	0.91-0.97
Liver	0.93	0.06	0.59-0.97	0.96	0.03	0.74-0.98
Spleen	0.89	0.06	0.58-0.94	0.94	0.04	0.73-0.97
Stomach	0.81	0.12	0.43-0.94	0.89	0.08	0.60-0.97
Kidneys	0.90	0.09	0.60-0.97	0.94	0.05	0.75-0.98
Patient	0.90	0.06	0.76-0.96	0.95	0.03	0.86-0.98

SD = standard deviation



# An automated ML-based methodology for CT

Organ doses estimated with the dose prediction DNN model and MC simulations

	DNN (mGy)*	MC (mGy)*
Lungs	12.0 (4.1)	12.7 (5.1)
Liver	18.1 (4.6)	18.1 (4.5)
Spleen	18.3 (4.5)	18.7 (4.2)
Stomach	17.7 (4.4)	17.7 (4.1)
Kidneys	18.6 (4.3)	18.4 (4.0)

\*Mean values (SD), DNN = deep neural network, MC = Monte Carlo





# Generative Adversarial Networks (GANs)

Physica Medica 122 (2024) 103381

Contents lists available at ScienceDirect

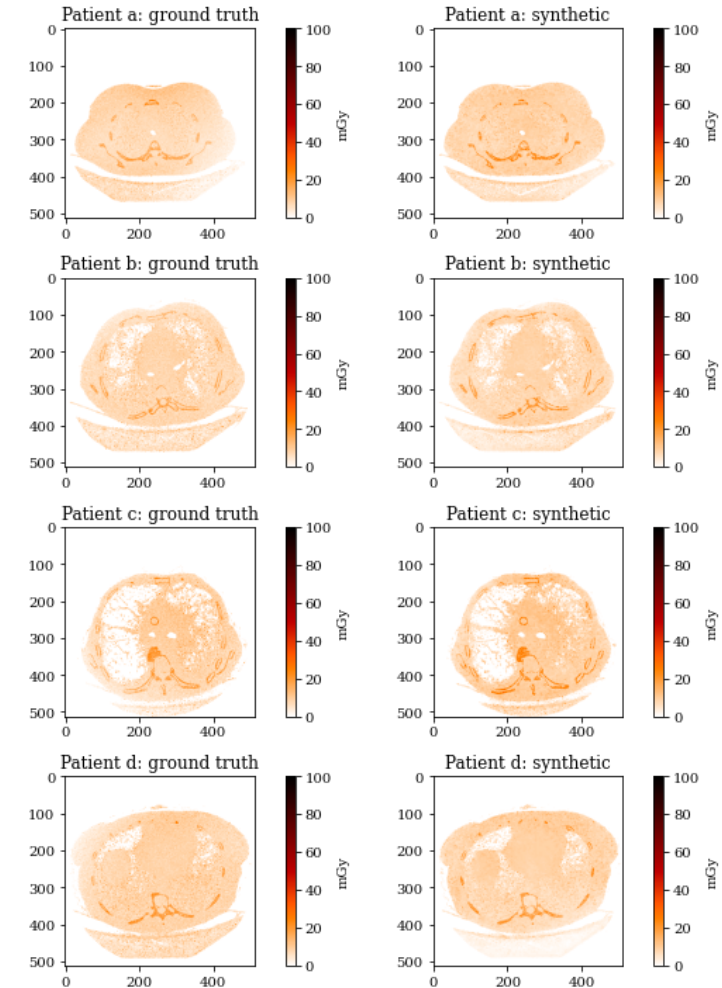
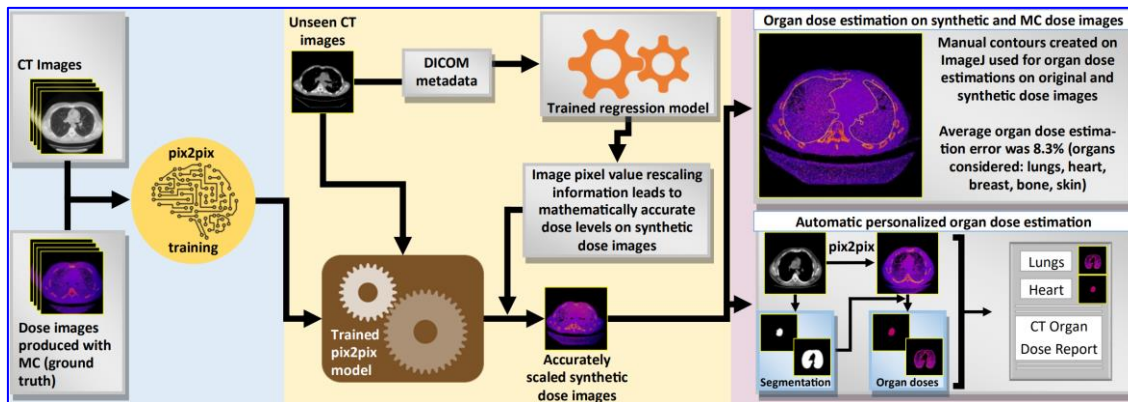
**Physica Medica**

journal homepage: [www.elsevier.com/locate/ejmp](http://www.elsevier.com/locate/ejmp)

Original paper

Is deep learning-enabled real-time personalized CT dosimetry feasible using only patient images as input?

Theocharis Berris<sup>a</sup>, Marios Myronakis<sup>a</sup>, John Stratakis<sup>b</sup>, Kostas Perisinakis<sup>a</sup>, Apostolos Karantanas<sup>c</sup>, John Damilakis<sup>a,\*</sup>



# i-Dose: a new web-based platform

DEPARTMENT OF MEDICAL PHYSICS  
SCHOOL OF MEDICINE - UNIVERSITY OF CRETE

## iDose

Personalized organ dose estimation from radiological examinations

SINFONIA

Welcome to iDose

Username

Password

Login

Register new user

Terms & Conditions

iDose.med.uoc.gr  
A part of medphys-tools.med.uoc.gr

UNIVERSITY OF CRETE  
Medical Physics Tools

CoDE

CT-RAD

AUTO WED

iDOse

Sinfonia is a four-year research project developing tools for comprehensive risk appraisal for detrimental effects of medical exposure during management of patients with lymphoma or brain tumour.





This project has received funding from the Euratom research and training programme 2019-2020 under grant agreement No 945196.

Department of Medical Physics, University of Crete  
Contact: Prof. John Damilakis, Project scientist  
email: john.damilakis@med.uoc.gr

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## UNIVERSITY OF CRETE

### Medical Physics Tools

- **CoDE**  
Conceptus Radiation Doses and Risks Estimation from Imaging with Ionizing Radiation
- **CT-RAD**  
Personalized Computed Tomography Organ Dose Estimation (MEDIRAD project)
- **AutoWED**  
Automated Calculation of Water-equivalent Diameter based on AAPM TG220 report (DICOM image-based)
- **iDOse**  
Personalized organ doses estimation from radiological examinations on patients with lymphomas and brain tumors (SINFONIA project)

<http://ctdose-iqurad.med.uoc.gr/>

# **Key areas of focus: Ethical & legal considerations**

## **Main ethical and legal considerations**

- **Risks for privacy and security**
- **Risks associated with lack of transparency**
- **Risks of biases**
- **Gaps in regulations (e.g., in the field of AI accountability/liability)**
- **Gaps in certification of AI products**

# **Key areas of focus: E&T for radiological protection personnel**

## **Key strategies to integrate AI education into RP curricula**

- **AI-powered virtual assistants**
- **Hands-on simulations**
- **Modular training programs**
- **Collaborative learning with AI experts**

# AI presents unique challenges and amazing opportunities

## Challenges/Issues

- Bias and discrimination
- Lack of transparency
- Dependence
- Lack of regulation
- Security and privacy concerns

## Technical solutions and tools (examples)

- Federated Learning, Swarm learning
- Generative AI
- OCR DL
- Explainable AI
- Low code/no code AI

## Benefits

- Improved, fast workflows
- Available at all times
- Reduction of human error
- Reduction of cost
- Informed patient care

*Thank you!*

