

Clinical Implementation of AI for CT Dose Optimization and Diagnostic Reliability in Oncology: A Real-World Evaluation

Emilio Russo ^{1*}, Emanuele Stucchi ¹, Eliana Carlucci ¹, Raffaele Tucciariello ², Rosetta D'Andria ¹, Ludmila Omer Carmen ³, Aldo Cammarota ¹

1. 1 Department of Radiology – I.R.C.C.S.-C.R.O.B. - Rionero in Vulture - Italy

2. 2 Medical Physics Unit – I.R.C.C.S.-C.R.O.B. - Rionero in Vulture - Italy

3. 3 Trial Office - I.R.C.C.S.-C.R.O.B. - Rionero in Vulture - Italy

*Correspondence: e-mail: emilio.russo1989@gmail.com

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ABSTRACT

Introduction: CT imaging is essential in oncology, yet its widespread use raises concerns about radiation exposure. Therefore, dose optimization strategies are needed without compromising image quality. Recent advances in iterative reconstruction and AI-based algorithms offer promising solutions.

Methods: This retrospective study was conducted between October 2023 and June 2024 at IRCCS CROB Rionero in Vulture. Examinations were performed on an older-generation Toshiba scanner and two new-generation Canon Aquilion ONE Genesis 320-slice scanners. The study included 14 brain CTs, 28 chest CTs, and 15 triphasic chest-abdomen-pelvis CTs, totaling 174 scans. Dose indicators (CTDIvol and DLP) were recorded and compared between the two CT systems and against diagnostic reference levels (DRLs) available in the literature.

Results: The implementation of AI-based reconstruction techniques led to significant dose reductions. In chest and chest-abdomen-pelvis examinations, CTDIvol decreased by up to 82% and DLP by 70% compared to the older system. For brain imaging, iterative reconstruction was preferred to avoid excessive noise suppression associated with AI approaches, resulting in optimized protocols that preserved diagnostic image quality while enhancing anatomical detail.

Conclusion: Integrating AI algorithms and iterative reconstruction techniques in CT imaging can substantially reduce radiation exposure while maintaining excellent diagnostic reliability.

INTRODUCTION

Computed Tomography (CT) is one of the most widely used medical imaging techniques worldwide due to its ability to provide high-resolution diagnostic images for a broad range of clinical applications. This diagnostic modality, which has grown substantially over the past few decades, results in a significant increase in the population's exposure to ionizing radiation for diagnostic purposes. According to the 2019 NCRP Report No. 184 of the National Council on Radiation Protection and Measurements [1], the use of CT in the United States increased by 20% in just 10 years (2006–2016), even though there has been a gradual reduction in patient doses achieved through the optimization of equipment and methodologies. Furthermore, the European Commission, through its publication Radiation Protection (RP) No. 154 [2], initially presented study results on medical exposure in ten European countries and later provided comprehensive data for 36 countries in Report RP No. 180 [3]. The objective was to highlight and harmonize best practice guidelines across Europe regarding exposure to ionizing radiation. The report reveals significant inter-country differences and an increasing trend in many nations, thus suggesting the need for further national analyses. It also emphasizes that CT accounted for over half of the overall medical radiation exposure of the European population between 2007 and 2010.

At the national level, the Istituto Superiore di Sanità (ISS), The Italian National Institute of Health, as part of its quality assurance program for radiological practices and in coordination with specialized study groups, contributed to defining the Diagnostic Reference Levels (DRLs) for radiodiagnostics, interventional radiology, and nuclear medicine [4]. This effort enabled compliance with the provisions of the new Legislative Decree/ DLvo 101/2020 [5] and established core safety standards to protect against the hazards of ionizing radiation primarily for the long-term risk of radiation-induced neoplasms.

In recent years, numerous approaches have been developed to reduce the radiation dose during CT scans without compromising the diagnostic quality of the images. Techniques such as automatic tube current modulation, optimization of the X-ray tube potential (kVp), iterative reconstruction methods and limiting the scan coverage have all proven effective. However, these methods require continuous oversight by technical and medical physics staff as well as the implementation of a dosimetry audit system [6] to identify potential anomalies or overdoses and ensure patient safety, particularly in oncology centers where series of follow-up examinations are common [7], [8], [9]. In oncological diagnostic programs, dose reduction is crucial due to the frequency of periodic examinations for staging and follow-up studies that have been conducted using triphasic protocols with contrast medium (CM).



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Low-dose CT therefore represents a fundamental means to achieve these objectives, although it comes at the cost of increased image noise, reduced diagnostic quality, spatial resolution and contrast. Optimizing this technique is thus a core mission for diagnostic centers, in accordance with the concept of dose optimization and limitation.

In response to these challenges, the conventional Filtered Back Projection (FBP) algorithm [10], [11], by which the raw CT projection data are processed into volumetric images, over the years have been substituted with more effective Iterative Reconstruction (IR) [12], [13], [14] in order to maintain good image quality while reducing both image noise and radiation dose [15], [16], [17]. Furthermore, in the last years, the introduction of Artificial Intelligence (AI) algorithms [18], [19], [20], [21] is revolutionizing diagnostic imaging by enhancing the quality of the images produced even more [22].

In this study, we present results obtained at the IRCCR CROB (Rionero in Vulture – PZ) between October 2023 and June 2024 in the Diagnostic Imaging Department (D.I.D.), deriving from optimization processes applied to CT examinations performed with two new-generation Canon Aquilion ONE Genesis 320-slice scanners. Both scanners are equipped with iterative as well as AI-based reconstruction algorithms and use identical acquisition protocols.

Specifically, we report dose outcomes for a limited number of patients undergoing recurrent follow-up examinations for brain, chest, chest-abdomen-pelvis in oncological patients with and without contrast medium, comparing the Volumetric Computed Tomography Dose Index (CTDIvol) and the Dose Length Product (DLP) [23] with those obtained with the previous CT scanner, Toshiba Aquilion 64-slice model, previously in use at the Institute, equipped with the FBP algorithms. Dosimetric data derived from the same patients whose executed investigations on both CT scanner generations are compared and percentage variations are reported. Furthermore, new dosimetric data were compared with the corresponding reference values from the ISTISAN 20|22 report.

MATERIALS AND METHODS

This study, conducted at the D.I.D. of the IRCCS CROB – Rionero in Vulture was divided into two phases.

Phase 1:

The initial phase aimed to identify the appropriate clinical protocols for the anatomical regions under examination, followed by the selection of the optimal reconstruction algorithms (iterative or AI-based) available on the Canon scanners. The choice of specific reconstruction kernels involved the radiology staff, integral to selecting reconstruction pro-

ocols by evaluating the quality of the reproduced images to ensure accurate reporting. Based on these evaluations, the reconstruction method (either the iterative or the AI-based, both available on the new Canon Aquilion ONE Genesis 320-slice CT scanners) and the specific reconstruction kernel were chosen. Identifying optimal reconstruction protocols also allowed for adjustments to the acquisition parameters to further optimize patient dose.

Phase 2:

In the retrospective phase, we evaluated the percentage variation in the radiation dose received during periodic diagnostic examinations in patients who had previously been scanned on the older generation Toshiba CT system—whose protocols had been optimized in earlier studies—and compared these with examinations performed on the newly installed equipments. This phase involved a dose analysis of patients who underwent scans on the two new-generation Canon Aquilion ONE Genesis 320-slice scanners for the brain, chest, and chest-abdomen-pelvis (with and without CM). Triphasic examinations (arterial, venous, and delayed phases), as well as non-contrast chest scans for monitoring pulmonary micronodules in oncological patients, represent the most common CT examinations performed in our Institute. The dose analysis considered 14 patients for the brain site, 28 for the chest examination and 15 for triphasic exams on the chest-abdomen-pelvis, all of whom had previously been examined with the older Toshiba Aquilion 64-slice CT scanner, which is now out of use. A total of 174 CT data scans have been analysed.

The iterative reconstruction algorithm AIDR-3D (Adaptive Iterative Dose Reduction in 3-Dimensions) employs advanced statistical processes to reduce noise by comparing scan data with image models. This selective noise reduction improves the signal-to-noise ratio and diagnostic accuracy without compromising spatial resolution [24]. By repeatedly processing the imaging data, AIDR-3D produces clearer images at a reduced radiation dose compared to traditional filtered back projection methods [25]. In contrast, the AI-based reconstruction algorithms AiCE-DLR [21] (Advanced intelligent Clear-IQ Engine – Deep Learning image Reconstruction), namely AiCE, leverage the classification capabilities of deep convolutional neural networks (DCNN) to differentiate noise from the signal, thereby enhancing image quality by suppressing noise while preserving clinically significant details. Pre-trained on both low- and high-quality CT image datasets reconstructed using iterative filters, these algorithms yield images with more detail and sharper tissue boundaries compared to conventional iterative techniques. The AiCE reconstruction process begins in the raw data domain, where the projections acquired during the scan are analyzed and modified to improve the output signal-to-noise ratio (SNR) and redu-

ce artefacts. The modified raw data are then initially reconstructed to form a base “input layer” that is fed into the DCNN [26]. To ensure that AiCE-DLR performs efficiently even at low doses, its continuous training incorporates low-quality datasets so that the algorithm can generate high-quality images from low-quality inputs while preserving both signal and spatial resolution (see Figure 1). Moreover, AiCE generally offers faster processing times compared to iterative algorithms, thanks to dedicated GPU-based hardware [27], [28]

In this work, we compared the CTDIvol, the DLP, and the total DLP (DLPtot), defined as the sum of the individual DLPs for a given anatomical region in triphasic examinations [23], recorded for each pa-

tient on both generations of CT scanners. In calculating DLPtot, only the DLP values for the chest-abdomen–pelvis regions were considered, while the dose indicators for the brain site were evaluated separately because they refer to a 16-cm PMMA phantom rather than the 32-cm phantom used for chest and chest–abdomen–pelvis regions. In addition, the study presents the percentage variation of the current dose indicators (identified by their median values as suggested by the ISTISAN 20|22 Report) compared to the data recorded on the previous generation CT scanner equipped with traditional FBP reconstruction algorithms. Finally, the dose data obtained were compared with the corresponding DRL values recommended by the ISTISAN report (see Table 1).

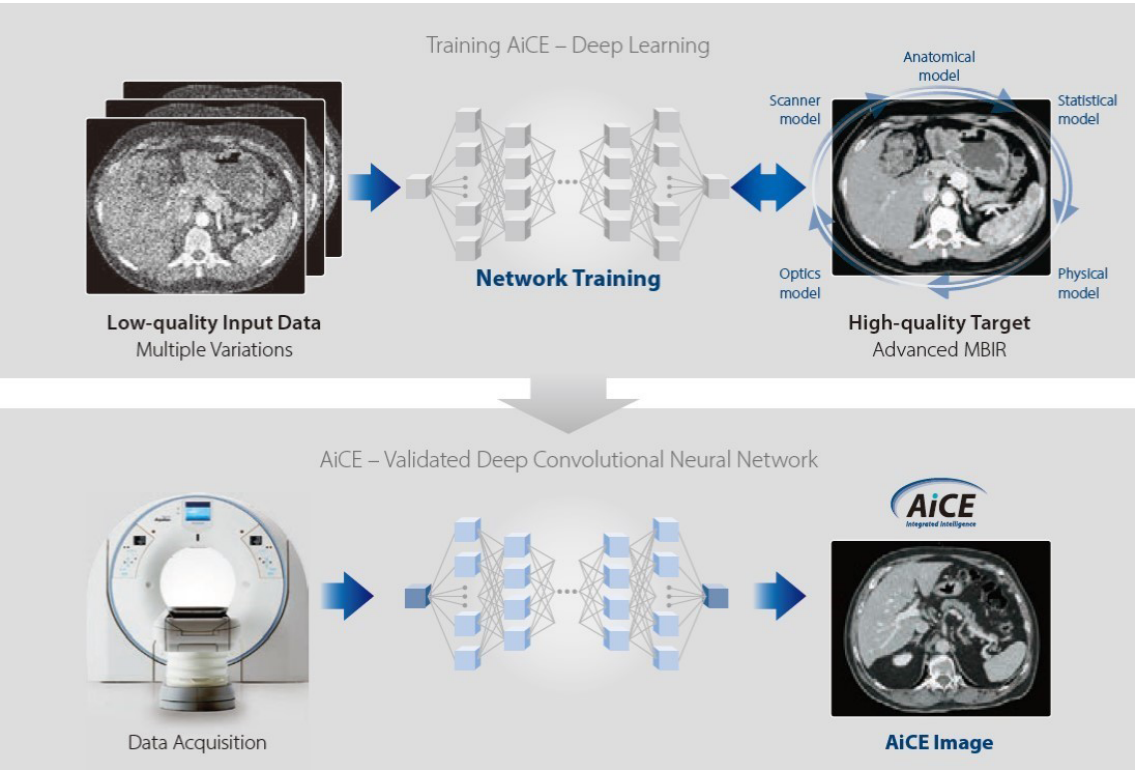


Figure 1. Diagram of how reconstruction through Deep Learning AiCE works

Table 1. DRLs values for adult Computed Tomography in Italian radiological practice – ISTISAN 20|22.

District	CTDIvol (mGy)	DLP (mGycm)	DLPtot (mGycm)
Brain	70	1300	-
Chest	15	600	-
Chest-Abdomen-Pelvis	18	1200	1200



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RESULTS

The active involvement of the medical staff initially led to the identification of the most suitable reconstruction algorithms for the brain, chest, and chest-abdomen-pelvis sites from among those available on the system.

For the brain site, the radiologists preferred the iterative reconstruction kernel AIDR-3D FC26 and rejected the AI-based AiCE Brain LCD Mild kernel, as the latter produced excessive “flattening” of the CT images. This excessive noise reduction resulted in images that were deemed unsuitable for diagnostic reporting. Figure 2 presents a comparison, for the brain site, between images reconstructed with the iterative AIDR-3D algorithm using the FC26 convolution filter and those obtained with the AI-based AiCE Brain LCD Mild algorithm on the same patient.

At the time of commissioning the new equipment, the radiologists positively received the AiCE Lung Standard reconstruction algorithm for the chest region. However, they were less satisfied with the

outcomes from the AiCE reconstruction in the chest–abdomen–pelvis region; the AiCE Body Standard reconstruction exhibited a markedly pronounced flattening effect. Conversely, the iterative AIDR-3D algorithm with the FC8 kernel resulted in pronounced image noise. Through several post-processing trials, the technical staff in collaboration with the radiologists identified that the AiCE Body Sharp Mild reconstruction provided images less “flat” and potentially with a greater amount of diagnostic information. This approach was well received by the radiologists and deemed appropriate for addressing various clinical questions. In this instance, the degree of noise suppression was optimal—providing added value to image presentation—and edge enhancement effects further improved the definition of organ contours, thereby facilitating the differentiation of similar anatomical structures. Figure 3 shows, for the abdominal region, a comparison between images reconstructed using the iterative AIDR-3D FC8 algorithm and the AI-based AiCE Body Sharp Mild algorithm on the same patient.

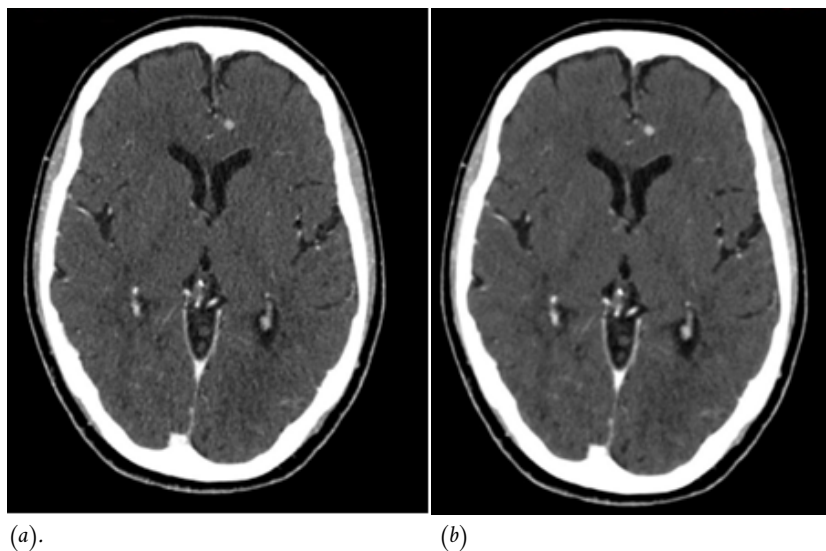


Figure 2. Comparison between 3D AIDR reconstruction with FC26 kernel filter (a) and AiCE with AiCE Brain LCD MILD kernel (b) in the brain district.

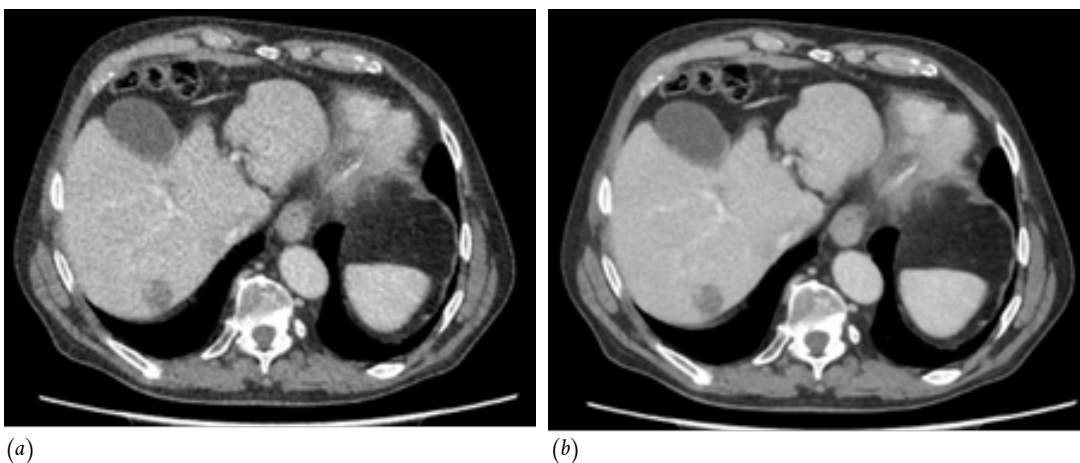


Figure 3. Comparison of 3D AIDR reconstruction with a) FC8 kernel filter and b) AiCE Body Sharp Mild for the abdomen





Table 2 shows the specific reconstruction kernels chosen for the brain, chest and chest-abdomen-pelvis districts.

	Brain	Chest	Chest-Abdomen-Pelvis
Algorithm	Iterative, AIDR3D, FC26	AI-Based, AiCE, AiCE Lung Standar	AI-Based, AiCE, AiCE Body Sharp Mild

The selection of protocols led to the adoption of optimized acquisition algorithms (as shown in Table 2) for use on the new-generation scanners. The brain region posed a particular challenge, as it was necessary to balance dose reduction with diagnostic imaging requirements. This balance was achieved by increasing the tube current from 200 mAs to 250 mAs and reducing the helical pitch from 0.825 to 0.625. In contrast, for the chest and chest–abdomen–pelvis regions, the application of AI significantly enhanced image quality, thereby permitting further dose reduction. This was accomplished by reducing the maximum modulated tube current from 750 to 700 mAs and increasing the image standard deviation (used for current modulation) from 7.5 to 10 HU.

The benefit of applying the AiCE reconstruction algorithm extended not only to diagnostic image quality but also to dose reduction—thus facilitating overall optimization. Table 3 shows the defined acquisition protocols adopted for the Canon Aquilion ONE Genesis CT scanners.

In the brain site, where AiCE was rejected in favor of AIDR-3D, it was necessary to increase the tube current, which in turn raised the CTDIvol. However, by reducing the scan length, the DLP was lowered by approximately 18%. Table 4 shows the median CTDI and DLP values for the brain region, along with a comparison between the data obtained with the two generations of CT scanners.

Table 3. Acquisition parameters adopted for the brain, chest and chest-abdomen-pelvis districts on the Canon Aquilion ONE Genesis CT scanners.

Acquisition Parameters	Brain	Chest	Chest-Abdomen-Pelvis
Tube voltage (kV)	120	120	120
Tube load (mAs)	250	modulated	modulated
Rotation time (s)	1	0.5	0.5
mA [min,max]	-	[100, 700]	[100, 700]
Standard Deviation	-	10	10
Multislice	0.5 mm × 40	0.5 mm × 80	0.5 mm × 80
Slice thickness(mm)	1	1	1
Pitch	0.625	0.813	0.813
Image Matrix	512×512		
D-FOV/Wedge	220 mm / S	400 mm / L	400 mm / L

Table 4. Comparison of the dosimetric indicators for the Brain district.

	CTDI (mGy)	DLP (mGycm)
Aquilion One Genesis	61,5	1098,4
Aquilion 64	61,9	1348,7
Variation %	-0,6%	-18.5%



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Table 5 presents the median dosimetric indicators (CTDIvol and DLP) for the chest region, showing percentage variation of -79.0% and -56.4%, respectively. Similar results were observed for the chest–abdomen–pelvis region (Table 6), which displays the median CTDIvol and DLP values for each phase and the total DLP for both Canon systems. For each phase, the percentage variation relative to the values obtained with the older generation scanner was provided. The data indicate that the AI-based reconstruction approach significantly increases the

potential for subsequent dose reduction compared to traditional filtered back projection algorithms—achieving reductions in CTDIvol of around 82% and DLP reductions of approximately 70%. Finally, Table 7 shows the percentage variation between the DRLs from the ISTISAN 20|22 report and the median values obtained from the Canon scanners. (Note that for the chest–abdomen–pelvis region, the median value among the CTDI measurements for the three phases—arterial, portal, and delayed—was considered.)

Table 5. Comparison of dose indicators for the Chest district.

	CTDI (mGy)	DLP (mGycm)
Aquilion One Genesis	4,5	212,5
Aquilion 64	21,6	486,2
Variation %	-79,0%	-56,4%

Table 6. Comparison of dose indicators for the Chest-Abdomen-Pelvis district

	CTDI arterial (mGy)	CTDI portal (mGy)	CTDI-delayed (mGy)	DLP arterial (mGycm)	DLP portal (mGycm)	DLP delayed (mGycm)	DLPtot (mGycm)
Aquilion One Genesis	5,2	4,9	5,2	161,0	362,5	278,6	803,7
Aquilion 64	28,4	28,4	28,4	597,8	1.226,0	916,1	2767,9
Variation %	-81.7%	-82.7%	-81.7%	-73.1%	-70.4%	-69.6%	-71%

Table 7. ISTISAN dose indicators comparison

	Brain		Chest		Chest-Abdomen-Pelvis	
	CTDIvol (mGy)	DLP (mGycm)	CTDIvol (mGy)	DLP (mGycm)	CTDIvol (mGy)	DLPTot (mGycm)
ISTISAN	70,0	1300,0	15,0	600,0	18,0	2100,0
Aquilion One Genesis	61,5	1098,4	4,5	212,5	5,1	803,7
Variation %	-12,1%	-15,5%	-70,0%	-64,6%	-71,7%	-61,7%



DISCUSSION

The results of this study underscore the pivotal role of AI-based reconstruction algorithms —specifically AiCE— in optimizing CT practices in oncological settings. The use of these algorithms led to a drastic reduction in ionizing radiation doses, with percentage decreases relative to the ISTISAN reference values [6] reaching 71.7% for CTDIvol and 61.7% for DLPtot for the chest–abdomen–pelvis region. Similar dose reductions were observed for the chest region (70.0% and 64.6% reductions, respectively), while for the brain region the reductions were more modest (12.1% for CTDIvol and 15.5% for DLPtot). These findings clearly demonstrate the effectiveness of AI in reducing dose without compromising the diagnostic quality of images in various clinical contexts.

However, the integration of such technologies must be preceded by rigorous verification and validation [5]. Data for brain site, for instance, shows how the complexity associated with AI-based algorithms became evident, as these were discarded in favour of iterative reconstructions due to overly aggressive noise reduction that compromised image reportability. This highlights the essential need for continuous involvement of radiologists in every phase of the optimization process to ensure that the images produced are clinically useful and meet diagnostic standards.

Another crucial aspect that emerged is the importance of a multidisciplinary approach that incorporates the expertise of medical physics specialists in the optimization and dose reduction process [5]. Medical physicists play a key role in identifying optimal dosimetry parameters and configuring equipment to minimize patient exposure while maintaining acceptable diagnostic quality. This study demonstrates that only through close collaboration among medical physicists, radiologists, and technicians can effective optimization strategies be implemented.

Finally, it is important to emphasize that the selection of acquisition and reconstruction protocols cannot be generalized but must be tailored to the specific characteristics of each anatomical region and clinical need. For example, the introduction of AiCE algorithms in the chest and chest–abdomen–pelvis regions enabled dose reduction while enhancing image quality, thereby positively influencing diagnostic interpretation. In contrast, for the brain region, optimization focused on adjusting traditional parameters (such as tube current and pitch), indicating that AI is not a universal solution but rather a complementary tool that must be used judiciously. This study conducted at the IRCCS CROB – Rionero in Vulture, provides compelling evidence for the significant advancements in radiation dose optimization in oncological CT imaging through the implementation of new-generation Canon Aquilion ONE Genesis 320-slice scanners equipped with both iterative and AI-based reconstruction algorithms.

The primary objective was to evaluate the clinical impact of these advanced techniques on dose reduction without compromising diagnostic reliability, in comparison to an older-generation Toshiba scanner utilizing FBP algorithms. Our findings demonstrate a clear superiority of the new-generation reconstruction algorithms in achieving substantial dose savings across various oncological imaging protocols.

Specifically, for chest and chest–abdomen–pelvis examinations, the integration of AI-based reconstruction techniques, particularly AiCE, led to remarkable reductions in radiation exposure decreasing the CTDIvol by up to 82% and DLP by 70% compared to the older Toshiba Aquilion 64. These results underscore the transformative potential of AI algorithms in minimizing the risks associated with ionizing radiation in oncology patients who frequently undergo serial follow-up examinations. The enhanced image quality achieved with AiCE, characterized by improved signal-to-noise ratio and sharper tissue boundaries, facilitated diagnostic confidence even at these significantly reduced dose levels. The positive reception of the AiCE Lung Standard and AiCE Body Sharp Mild reconstruction algorithms by the radiologists for chest and chest–abdomen–pelvis imaging, respectively, highlights the clinical acceptance and diagnostic utility of these AI-driven advancements. Conversely, the experience with brain imaging revealed a more nuanced scenario. The AI-based AiCE Brain LCD Mild kernel was rejected in favour of the iterative one AIDR3D FC26 and the dose reduction limited to decrease the scan length, reaching a variation for the DLP of approximately -18%, while the CTDIvol was substantially the same. Indeed, AiCE Brain LCD Mild kernel was rejected by the radiologists due to excessive noise suppression leading to a “flattening” effect and threatening the diagnostic reportability. In this specific case, FC26 was preferred for maintaining diagnostic image quality and enhancing anatomical details. This observation emphasizes that AI is not a universally optimal solution and that the selection of reconstruction algorithms must be carefully tailored to the specific clinical context and anatomical region, necessitating the active involvement of radiology staff in the evaluation and selection process.

Furthermore, the comparison of the median dose indicators obtained with the Canon scanners with the Diagnostic Reference Levels (DRLs) published in the ISTISAN 20|22 report demonstrated substantial dose reductions below the national benchmarks. For instance, CTDIvol for the chest and chest–abdomen–pelvis regions were reduced by 70.0% and 71.7%, respectively, compared to the DRLs. These findings not only validate the effectiveness of the implemented optimization strategies but also highlight the potential for widespread adoption of similar technology-driven approaches to achieve significant reductions in population radiation exposure from



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CT imaging, particularly in high-utilization settings like oncology centers.

CONCLUSION

The success of this dose optimization initiative underscores the critical importance of a multidisciplinary approach involving radiologists, medical physicists, and technicians. The careful selection of acquisition parameters (tube current modulation, pitch, multislice setting etc...) in conjunction with the optimized reconstruction algorithms is pivotal in achieving the observed dose reductions while preserving diagnostic image quality. The continuo-

us oversight by technical and medical physics staff, along with the implementation of a dosimetry audit system, remains essential to ensure patient safety and the identification of potential anomalies. Ultimately, the authors would like to emphasize the indispensable role of human expertise in guiding and validating the implementation of these technologies to ensure optimal diagnostic scan outcomes. Only through critical analysis and a tailored approach can the full potential of this technology be harnessed, ultimately promoting ever higher diagnostic standards and optimal patient protection.

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