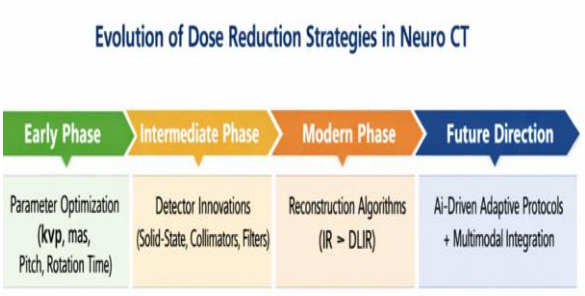
Dose Reduction in Neuro CT: Advances, Strategies, and Future Directions

Aditya Nagrath[1], Kanwaldeep Kaur[2]
[1]*Senior Technologist, PGIMER, Chandigarh*
[2]*Nursing Officer, PGIMER, Chandigarh*

Abstract : Computed Tomography (CT) has become indispensable in neuroimaging, enabling rapid diagnosis of acute neurological conditions. However, its widespread use has raised concerns about radiation exposure and associated malignancy risks. This review synthesizes current strategies for dose reduction in neuro CT, ranging from fundamental acquisition parameter optimization to advanced detector technologies and artificial intelligence-driven reconstruction algorithms. Emphasis is placed on pediatric considerations, shielding, and the critical role of technologists. Research gaps and future directions are highlighted to guide clinical practice and innovation.

Introduction

The exponential increase in CT utilization has revolutionized neuroimaging but simultaneously contributed to rising population radiation exposure. If current dose levels persist, CT may account for nearly 5% of cancers diagnosed annually (19). Although the head is less radiosensitive than abdominal regions, the ALARA principle remains essential. Radiation dose is quantified using CTDIvol and DLP (7). Modern strategies now extend beyond parameter adjustments to detector innovations and deep learning-based reconstructions, aiming to minimize dose without compromising diagnostic confidence.



Fundamental Parameter Optimization

Tube Potential (kVp): Reducing kVp from 120–140 to 100 or 80 achieves substantial dose reductions, especially when paired with advanced reconstruction techniques (5, 15).

Tube Current Modulation (ATCM): Automatic tube current modulation adjusts current in real time based on patient anatomy, ensuring constant image quality at minimized dose (3, 13, 14).

Pitch & Rotation Time: Increasing pitch reduces dose but may compromise resolution, while shorter rotation times reduce motion artifacts and dose linearly (13).

Slice Thickness & Scan Length: Thinner slices improve detail but increase noise and dose. Overscanning beyond the region of interest should be avoided (7).

Detector Technology

Photon-counting detector (PCD) CT systems demonstrate significant radiation dose reduction compared to energy-integrating detectors (EID), eliminating electronic noise and improving spatial resolution (17). Clinical studies confirm dose savings up to 35% with superior image quality (18). Solid-state detectors such as Siemens Stellar, GE Gemstone, and Philips GOS achieve >90% efficiency compared to xenon gas detectors (~50%) (17).

Table 1. Detector Technologies and Dose Efficiency

Detector Type	Efficiency	Example Vendors/Models	Dose Reduction Potential
Xenon Gas Detectors	~50%	Older CT models	Higher dose required
Solid-State Detectors	>90%	Siemens Stellar, Philips GOS, GE Gemstone	20–30% reduction
Photon-Counting Detectors (PCD)	~100%	Siemens NAEOTOM Alpha	Up to 35% reduction

Reconstruction Algorithms

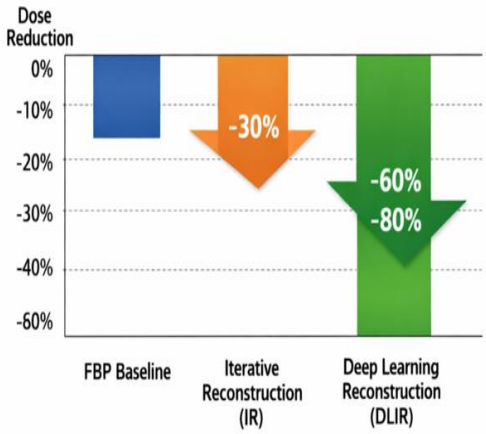
Iterative Reconstruction (IR): IR algorithms (ASiR, MBIR, SAFIRE, ADMIRE) reduce noise and allow ~30% dose reduction in brain CTs while preserving diagnostic confidence (9). However, aggressive noise suppression can produce blotchy or plastic-like textures, limiting subtle lesion detection (6).

Deep Learning Image Reconstruction (DLIR): DLIR uses deep convolutional neural networks trained on low-dose and high-dose CT pairs to remove noise while preserving natural texture. Clinical studies in stroke imaging demonstrated ~40% dose reduction with >50% improvement in SNR compared to IR (2). Phantom studies confirm DLIR improves spatial resolution and detectability even at drastically reduced CTDIvol (11). Unlike IR, DLIR maintains natural FBP-like appearance, enabling dose reductions between 44–83% across clinical settings (6, 12, 4).

Table 2. Detector Technologies and Dose Efficiency

Feature	Iterative Reconstruction (IR)	Deep Learning Image Reconstruction (DLIR)
Noise Reduction	30–60% dose reduction, but texture may appear "plastic"	44–83% dose reduction, natural FBP-like texture
Image Texture	Unnatural, blotchy at aggressive settings	Preserves natural appearance
Clinical Confidence	Good for routine scans, limited for subtle lesions	Superior lesion detectability, higher SNR
Computational Demand	Moderate to high	High (requires GPU/AI infrastructure)
Pediatric Application	Limited	Strong evidence for 80 kVp protocols

Figure 2. Dose Reduction Impact of DLIR vs IR



Shielding and Gantry Tilting

Tilting the gantry to avoid direct irradiation of the eye lens reduces dose by ~75% (16). Bismuth-coated

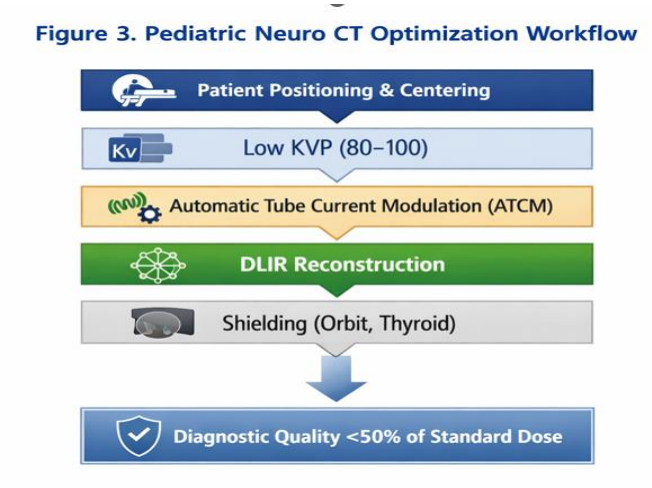
shielding of the orbit reduces superficial dose by 25–50% without compromising diagnostic quality (10).

Table 3. Practical Technologist Strategies for Dose Reduction

Strategy	Dose Impact	Notes
Patient Centering	7–56% reduction	Off-centering increases dose significantly
Gantry Tilting	~75% reduction to eye lens	Essential in neuro CT
Bismuth Shielding	25–73% reduction to superficial organs	Orbit and breast shielding
Limiting Scan Length	Direct reduction	Avoid over-scanning
Slice Thickness Adjustment	Noise & dose reduction	Thicker slices reduce noise, trade-off with resolution

Pediatric Considerations

Children are uniquely vulnerable to ionizing radiation due to longer life expectancy and rapidly dividing tissues. DLIR applied to 80 kVp pediatric CTs drastically outperforms standard-dose IR, halving radiation exposure while improving edge sharpness and detectability (8, 15).



Discussion

The literature demonstrates a clear evolution in dose reduction strategies:

From hardware to software: Early reliance on acquisition parameters and detector efficiency has transitioned to advanced reconstruction algorithms (7, 17, 18).

Iterative Reconstruction (IR): IR enabled ~30% dose reduction in neuro CT while preserving diagnostic confidence, but aggressive noise suppression produced blotchy textures that limited subtle lesion detection (9, 6).

Deep Learning Image Reconstruction (DLIR): DLIR overcame these limitations by preserving natural FBP-like texture while achieving unprecedented dose reductions between 44–83% (6, 2, 11, 12, 4). Clinical outcomes in acute stroke imaging showed DLIR reduced effective dose from 2.5 mSv to 1.5 mSv while improving SNR by over 50% (2).

Technologist's role: Practical measures such as patient centering, scout accuracy, gantry tilting, and shielding remain critical but are often underemphasized in literature. Gantry tilting reduces lens dose by ~75%, while bismuth shielding reduces superficial organ dose by 25–50% (16, 10).

Pediatric protocols: DLIR applied to 80 kVp pediatric CTs halved radiation exposure while improving edge sharpness and detectability,

underscoring its importance in radiosensitive populations (8, 15).

Despite these advances, challenges remain in balancing dose reduction with diagnostic confidence, particularly in subtle low-contrast lesion detection.

Conclusion

Dose reduction in neuro CT has progressed from basic acquisition adjustments (3, 5, 13, 14, 15) to advanced detector technologies and AI-driven reconstructions. Iterative methods enabled significant progress, but DLIR now represents the gold standard, achieving unprecedented dose reductions while preserving diagnostic confidence (6, 2, 11, 12, 4). Hardware innovations such as photon-counting detectors, shielding strategies, and technologist-driven optimization reinforce patient safety (17, 18, 16, 10).

Addressing research gaps—including validation across diverse populations, standardized protocols, texture fidelity studies, multimodal integration, and updated Diagnostic Reference Levels (DRLs)—will ensure neuro CT continues to deliver life-saving diagnostic accuracy at the lowest possible radiation burden (19).

Research Gaps

1. Validation across diverse populations: Most DLIR studies focus on adult cohorts; pediatric and geriatric validations remain limited.
2. Standardization of protocols: Variability in vendor-specific implementations (CARE Dose, Smart mA, SURE Exposure) complicates cross-institutional comparisons.
3. Texture fidelity in DLIR: While DLIR preserves natural appearance, long-term radiologist acceptance and diagnostic accuracy studies are needed.
4. Integration with multimodal imaging: Research is required on combining DLIR with perfusion CT and advanced neurovascular protocols.
5. Dose Reference Levels (DRLs): Updated DRLs for neuro CT incorporating AI-based reconstructions are lacking.

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