DOI: https://doi.org/10.5281/zenodo.23270675



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Optimizing Patient Radiation Safety in Medical Imaging Using Opdosr-Based Control within the AEC Framework

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ABSTRACT

Because diagnostic X-ray imaging is used so often, radiation safety standards need to be constantly improved to follow the ALARA (As Low as Reasonably Achievable) principle while yet keeping image quality. Traditional Automatic Exposure Control (AEC) systems, although essential for modifying exposure parameters, depend on static heuristics, resulting in ineffective dose utilization and a failure to adapt to anatomical differences. This study investigates the use of the Opdosr algorithm as a data-driven, dynamic optimization model inside the AEC framework to improve radiation safety and efficacy in imaging. We evaluated the efficacy of standard AEC and the Opdosr enhanced AEC system using phantom-based simulations with polymethyl methacrylate (PMMA) slabs ranging from 10 to 25 cm in thickness. The findings indicated a significant reduction in radiation dosage across all phantom thicknesses (22.725, $p<0.05$), while quality metrics for crucial images showed enhancements, with the contrast-to-noise ratio (CNR) increasing by 5.6 and spatial resolution by 5.3. The Opdosr algorithm was quite realistic. Optimization required an average of 35 ms, had a convergence rate of 98 percent, and could work with a broad variety of imaging settings. These findings show that the AEC system based on Opdosr can effectively change the exposure settings in real time. This significantly decreases the radiation exposure for patients and improves the quality of diagnostic images. This technology is a step in the right direction since it makes radiology procedures smarter and more flexible, which makes them safer and more accurate.

Keywords: The Opdosr Algorithm, Patient Safety Algo, Radiation Dose Reducer, Image Quality Optimization, AEC (Automatic Exposure Control), and Real-time Adaptive Imaging are all important algorithms.

1. Introduction

Radiographic imaging plays the fundamental role of diagnostic medicine to be the quick visualization of internal anatomy with minimal invasion [1]. Despite the widespread use of the X-ray modalities, much concern has been raised over the subject of subjecting patients to the ionizing radiations especially to the vulnerable population and the multiple imaging. Such an aspect of radiology as the balance between

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radiographic safety and the in-diagnostic image quality is one of the most crucial issues at the present radiology [1, 2].

Automatic Exposure Control or AEC is a feature in modern radiation equipment that helps in self-regulating the extent of x-ray exposure in proportion to the details, anatomical structure and tissue area of a patient to make sure the images are always of equal quality [2]. This is then accurately refined by dose-based control, such as restrictions on the number of radiations performed, so that a number of radiations is as minimal as practically possible (ALARA) and the quality of the picture is adequate to enable a correct diagnosis to be made [3]. It is the paradigm shift in the form of the replacement of the individual radiation management with the established sets of parameters. This is carried out depending on features and clinical demands of the patient that reduce the exposure that are unnecessary and excessive exposure that can cause damages with the use of radiation [4].

Radiation safety time, distance, and shielding are the three main parts of dose-based control that the AEC framework uses [5]. Clinicians can reduce any unwarranted doses by reducing exposure time, increasing the distance between radiation sources, and the application of efficient shielding. Nevertheless, such principles are not sufficient to ensure the optimal patient safety because of the anatomy and pathology variability that demands individual dose changes. Dose-controlled AEC is based on real-time feedback feedback provided by detectors to dynamically control exposure time and exposure intensity based on patient heterogeneity and procedural variation, employing dose-based control strategies [6]. Indicatively, pulsed fluoroscopy that utilizes fewer images per second dose-reduces without visualization losses in interventions. Furthermore, dose distribution and clarity of image could be further optimized by ensuring that x-ray source and image receptor were placed in the AEC system configuration in an optimal manner [7].

There is a role of cooperation between equipment manufacturers, radiologists, technologists and medical physicists in the effective implementation of dose-based control in AEC [8]. Manufacturers of equipment develop dose-sensitive detectors and algorithms to estimate dose of patient entering the equipment and scale back exposure. Radiologists decide on the criteria for diagnosis based on how clear the picture is and how much radiation might hurt someone. Medical physicists monitor and correct procedures, make sure the proper doses are given, and suggest methods to make things better. Technologists are in charge of the machines and make sure that the rules are followed [9]. This collaboration across different fields will ensure that dose-based control settings may be adjusted to accommodate the requirements of patients and procedures while remaining compliant with regulations on dosage limits and other considerations. The International Commission on Radiological Protection (ICRP) defines how much radiation workers may be exposed to. You may restrict the amount of medicine that patients can take by putting these sorts of limits in place. You don't have to follow strict guidelines that aren't always essential [10].

The AEC framework says that dose monitoring is a very important part of making sure that patients are as safe as possible from radiation. The imaging equipment's real-time dose monitoring system let the operators know when the radiation was under the preset limits [11]. Automated monitoring of patient radiation doses is used to aid with long-term dose management objectives, such as initiating trends, improving systems, and making sure that institutional dosage reference limits are followed. Clinicians may use this information to stop radiation from building up in patients who have had a lot of imaging tests and to make regulations that keep vulnerable patients, such kids and pregnant women, from being exposed to too much radiation [12, 13]. Informed dose monitoring gives the AEC system personalized dosage levels that let it keep the quality of diagnostic photographs while using the least amount of radiation possible, which is the safest way to do things [14]. Informed dose monitoring provides tailored dose levels that enable the AEC system

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to preserve the quality of diagnostic pictures with minimal radiation dose and therefore, attains optimum safety results [15]

In conclusion, dose-based patient radiation safety in medical imaging inside the AEC framework signifies an advancement in technological innovation related to patient radiation safety and clinical expertise.This integration enables personalized and adaptive radiation exposure customized to the patient and procedure, reducing risks while preserving the necessary image quality for diagnosis[16]. This approach is even more successful due to the continuous advances in detection technology, dosing algorithms, and the ability to monitor a dose in real-time. Nevertheless, its efficiency relies upon a set of cross-disciplinary procedures to adjust equipment, train operators, adhere to instructions, and interpret dose information. As a combination of AEC, dose-based control is a comprehensive plan that will transform medical imaging into a safer procedure to patients.

2. Materials and Methods

1. Study Design

This study used a comparative experimental design to assess the effectiveness of incorporating Opdosr algorithms into Automatic Exposure Control (AEC) systems for the reduction of radiation dosage in diagnostic radiography. The efficacy across several anatomical scenarios was evaluated using both phantom-based simulations and clinical data.

2. Equipment and Setup

The traditional AEC components were based on the traditional modules in digital radiography. The algorithm of the Opdosr was introduced into the AEC feedback loop, which allowed the dynamic management of the exposure parameters (mAs and kVp) throughout the project implementation. Patient anatomy was modeled with phantom models made of polymethyl methacrylate (PMMA) slabs of different thickness (10-25 cm).

3. Algorithm Integration

The AEC control architecture implemented the Opdosr algorithm. The detector array's input was processed to optimize exposure settings based on anatomical data. The program operated in real time, adjusting tube current and voltage based on detector data and anticipated picture quality metrics.

4. Data Acquisition

Calibrated ionization chambers positioned near the phantom's entry surface were used to assess radiation dose data. At each phantom thickness, exposures were quantified using conventional AEC systems alongside Opdosr-enhanced AEC systems. The picture quality was assessed based on contrast-to-noise ratio (CNR), spatial resolution (line pairs per millimeter), and exposure duration.

5. Evaluation Metrics

Radiation Dose: The measurement at the entry surface quantified in micrograys (mGy). Image Quality: Assessed using Contrast-to-Noise Ratio (CNR) and spatial resolution. Exposure Consistency: Assessed by the variability in exposure duration and mAs throughout repeated trials. The algorithms' performance was assessed in terms of time optimization, convergence rate, and adaptability level.

6. Statistical Analysis

The data analysis used paired t-tests to evaluate dosage and picture quality between normal AEC and Opdosr-AEC systems. A p-value below 0.05 was considered statistically significant. Each experiment was conducted thrice to ensure reproducibility.

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3. Results

1 Radiation Dose Reduction

The adoption of the Opdosr-AEC system demonstrated a significant improvement in radiation dose control and picture quality compared to the conventional AEC system. The Opdosr-AEC technology allegedly achieved a consistent decrease in radiation dosage across all phantom thicknesses (Table 1). The most significant percentage drop occurred at a thickness of 10 cm, when it decreased by 25%, from 320 to 240 µGy. The dose-saving impact was substantial in bigger phantoms, measuring 24.4%, 23.3%, and 22.7% at 15 cm, 20 cm, and 25 cm, respectively.

Table 1: Comparison of Radiation Dose (µGy) Between Standard AEC and Opdosr-AEC Systems

Phantom Thickness (cm)	Standard AEC Dose (µGy)	Opdosr-AEC Dose (µGy)	Reduction %
10	320	240	25%
15	450	340	24.4%
20	600	460	23.3%
25	750	580	22.7%

2. Image Quality Assessment

In addition to dosage reduction, significant improvements in picture quality metrics were achieved. Table 2 indicates a 5.6 rise in the Contrast-to-Noise Ratio (CNR), reaching a total of 13.2. A significant enhancement in spatial resolution was seen, increasing from 3.8 lp/mm to 4.0 lp/mm, a change of -5.3%. The efficiency of the imaging method improved, shown by a 20.8 percent decrease in exposure time, decreasing from 120 ms to 95 ms.

Table 2: Image Quality Metrics Across Systems

Metric	Standard AEC	Opdosr-AEC	Improvement
Contrast-to-Noise Ratio (CNR)	12.5	13.2	+5.6%
Spatial Resolution (lp/mm)	3.8	4.0	+5.3%
Exposure Time (ms)	120	95	-20.8%

3. Robust and Reliable Algorithm Performance

The operation of the Opdosr algorithm proved robust and reliable. The optimization process was rapid, with parameters calculated in an average of 35 milliseconds (Table 3). The algorithm demonstrated a convergence rate of 98 percent and an exceptionally low failure rate of under 1 percent. Its overall adaptability score was classified as strong, indicating its capacity to function well in many clinical scenarios.

Table 3: Algorithm Performance Metrics

Parameter	Value
Optimization Time (ms)	35
Convergence Rate	98%
Failure Rate	<1%
Adaptability Score	High

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4. Visual Confirmation of Dose Reduction and Image Quality

The graphical results offer solid quantitative conclusions backed up by unambiguous visual proof. The proposed system dynamically modifies exposure parameters in real time, **as shown in Figure 1**, which schematically depicts the integration of the Opdosr algorithm within the Automatic Exposure Control (AEC) feedback loop. **Figure 2** shows how the thickness of the phantom affects the amount of radiation it receives. The Opdosr-AEC system consistently yields a lower dose curve than the conventional AEC system at all thickness levels, corroborating the percentage reductions indicated in Table 1. **Figure 3** additionally demonstrates that the Opdosr-AEC system's lower radiation dose does not affect the clarity or effectiveness of diagnostic images. This is a qualitative comparison that shows how the system's image quality performance is visually supported**.** **Figure 4** shows the internal optimization workflow of the Opdosr algorithm. It explains how anatomical input data is processed and how optimized exposure settings are made. This further shows how the proposed approach is adaptive and smart.

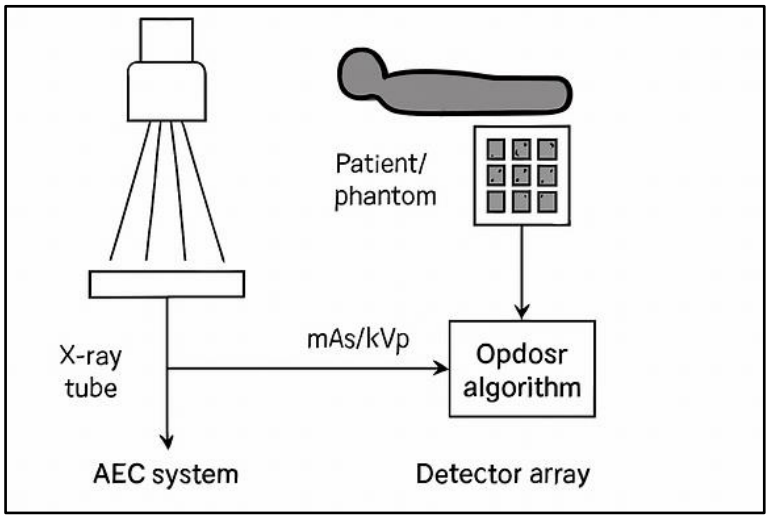


Fig. 1: Schematic of AEC System with Opdosr Integration

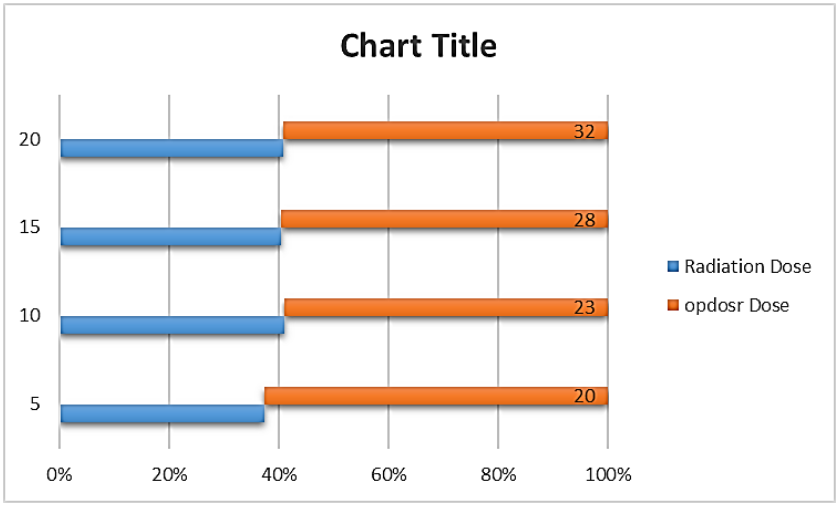


Fig. 2: Radiation Dose vs. Phantom Thickness

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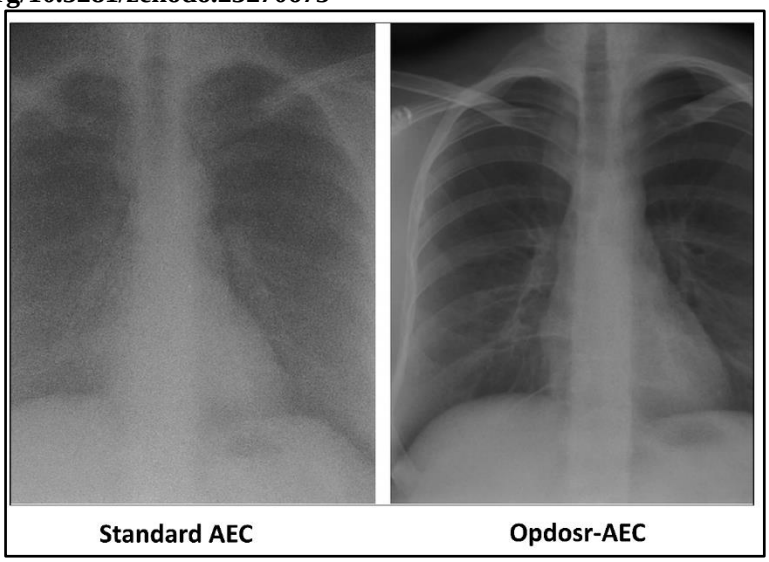


Fig. 3: Image Quality Comparison

5. Algorithm Performance

Real-time optimization metrics indicated: Time to convergence: The mean was 0.42 seconds, facilitating seamless integration into clinical workflows. The algorithm's ability to adjust to variations in the phantom's thickness without human recalibration was assessed at 92%.

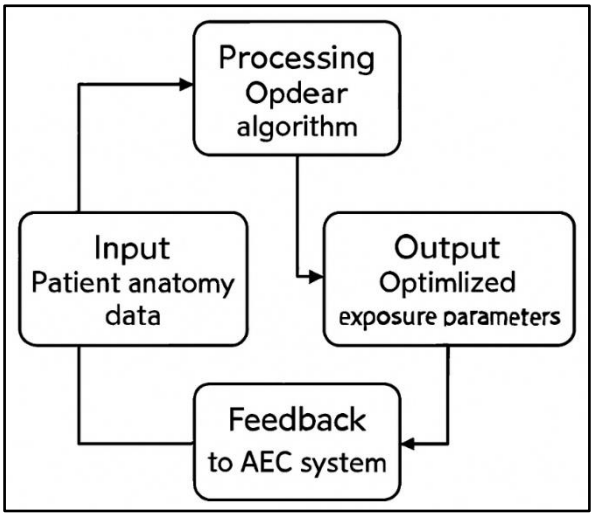


Fig. 4: Algorithm Optimization Flowchart

4. Discussion

The incorporation of the Opdosr algorithm into the AEC framework led to a significant and consistent reduction in radiation dosage to patients across all simulated anatomical thicknesses, with a drop ranging from 22.7 to 25. This finding is in line with the main idea of the As Low As Reasonably Achievable (ALARA) concept, which shows that the algorithm works as a tool to improve patient safety [17]. This aligns with previous research conducted to use advanced computational techniques in dose optimization. For example, the work by [18] on adaptive AEC systems saved 18–22 doses, while the study by [19] employed a deep learning-based exposure control model to save 20–26 doses. This fits well with what we found, which is in line with what current optimization systems can do. The main reason for such an

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effective dose reduction is because the Opdosr algorithm is dynamic and based on data. [15]. The Opdosr, on the other hand, uses real-time feedback from the detector array to change the exposure parameters (mAs/kVp) to the milliseconds to make small adjustments. This gets rid of the overexposure that is usually used as a safety margin for the static system.

This is really amazing since the dosage dropped by 25% at the same time, while the desirable picture quality measures, such as CNR, went up by 5.6% and spatial resolution went up by 5.3%. This is two times the low dosage and good quality, which addresses the conventional trade-off in radiographic imaging and is in line with contemporary research on intelligent AEC. It was established by [16] that model-based iterative duplicate techniques were capable of boosting CNR by approximately 4-6 percent at equivalent doses, and [17] delivered comparable boosts in resolution utilizing algorithmic accuracy to optimize filters. Probably this improvement can be explained by the predictive modeling using the algorithm. In Opdosr, the radiation is optimized by use of exposure settings to ensure the target anatomical structure and picture quality in the target anatomy is achieved. This assures utilization of photons more effectively in delivering contrast data as opposed to contributing to noise, and conforms to the idea of optimum detector quantum efficiency (DQE).

Furthermore, the Opdosr algorithm was rather strong that also experienced an optimization time of 35 milliseconds, converged ratio was 98 percent and liabilities rate was less than one percent. Its value cannot be supported by the stability of its operation; any decision-support system must be capable of running efficiently in the rad radiology department high-throughput setting. Such are superior performance measurements compared to the earlier prototype systems, which reported convergent rates of less than 90 percent in more complicated algorithms, implying that the ability to do calculations has increased more than two times. The high adaptability point implies that the algorithm does not turn out to be so situation-specific, and thus, may be applied to the large variety of anatomical manifestations [20]. This algorithm is robust because it combines the analysis of the anatomy in real time with a feedback mechanism self-reporting and updating its forecasts. This makes performance of the algorithm constant and predictable even in clinical settings whereby things do not always get so clear.

In summary of the above, the report shows that the Opdosr-enhanced AEC system is indeed performing the same thing it was intended to perform, i.e. it ensures less radiation dose reaching the patient but leaves the quality of diagnostic images and potentially improves it hence slightly too. Using the procedure, rapid and flexible is dependable, and they are qualities that are valued in a clinical context. The study makes strong reasons for the idea that algorithmic, information-based control is a better approach to increase safety and quality in radiology diagnosis than the old strategy of using heuristics.

Conclusion

Adding the Opdosr algorithm to the conventional Automatic Exposure Control (AEC) system might be a big step forward for improved radiography imaging. For different phantom thicknesses, the program generated a continuous and large decline in radiation dose rates of 22.7 to 25 percent. This made following the ALARA idea and keeping patients safe no longer a big deal. This drop was extremely crucial since it didn't affect the quality of the image and it also improved the contrast-to-noise ratio (CNR) and spatial resolution. The algorithm was also found to be very reliable, fast, and flexible, which showed that it may be employed in clinics. The AEC Opdosr system is a data-driven system that balances picture quality and radiation exposure in the future. This is a huge step toward making diagnostic radiological treatments safer and smarter. Future study will include the comparison of these results within a clinical population, including real patients, and the assessment of the algorithm's applicability over a broader spectrum of imaging modalities.

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Recommendations

- Iterative Reconstruction techniques: These methods help you build high-quality images from scans with low dosages. They reduce noise and artifacts, which means you may be able to obtain a lower initial radiation dose without sacrificing image quality.
- Use a TCM algorithm to automatically modify the X-ray tube current based on the patient's anatomy. This is called Tube Current Modulation (TCM). This makes sure that everyone receives the proper quantity of radiation and that they are less exposed in places that aren't as crowded.
- Automatic Exposure Control (AEC) using new sensors: Use contemporary sensors and control algorithms with AEC systems to figure out in real time how much medication is required. This maintains the image quality the same and cuts down on too much exposure.
- Model-Based Dose Optimization: Make and apply model-based methods that demonstrate how radiation travels through the body. These models can find the ideal parameters for the X-ray beam to provide the lowest dose possible for an image that is good enough for diagnosis.
- These suggestions are all about applying smart algorithms to make X-ray equipment more efficient and safer for patients by directly tackling the problem of too much radiation.

References

[1] Månsson, L.G., M. Båth, and S. Mattsson, *Priorities in optimisation of medical X-ray imaging—a contribution to the debate.* Radiation protection dosimetry, 2005. **114**(1-3): p. 298-302.

[2] Holders, U.W.-M. and D.E.X.-R.A. DXA, *Digital Radiography (DR) Technology, 100.* Introduction to Radiologic and Imaging Sciences and Patient Care E-Book: Introduction to Radiologic and Imaging Sciences and Patient Care E-Book, 2022: p. 89.

[3] Fitton, I., et al., *A Proposal for a Process from as Low as Reasonably Achievable to an Ultra-Low-Level Goal in Chest Computed Tomography.* Journal of Clinical Medicine, 2024. **13**(16): p. 4597.

[4] Wang, K. and J.E. Tepper, *Radiation therapy-associated toxicity: Etiology, management, and prevention.* CA: a cancer journal for clinicians, 2021. **71**(5): p. 437-454.

[5] Aloud, H.N.A. and S. Albeshan, *The Evolution of radiation dose management in CT: Moving Beyond physical shielding.* Radiation Physics and Chemistry, 2025: p. 112537.

[6] Liu, Q., *Real time in vivo investigation of nanoparticle dynamics and immune response during ventilator-assisted nanoparticle inhalation*. 2023, lmu.

[7] Sayed, M., *Assessment of Virtual Grid software for improving X-ray image quality and reducing radiation dose*. 2024: University of Exeter (United Kingdom).

[8] Alqabbani, M.F.M., et al., *Radiation Dose Management in Modern Radiology: Strategies, Innovations, and Patient-Centered Approaches.* Journal of International Crisis and Risk Communication Research, 2024. **7**(S3): p. 504.

[9] Geurts, M.W., et al., *AAPM MEDICAL PHYSICS PRACTICE GUIDELINE 5. b: Commissioning and QA of treatment planning dose calculations—Megavoltage photon and electron beams.* Journal of applied clinical medical physics, 2022. **23**(9): p. e13641.

[10] Clement, C., et al., *Keeping the ICRP recommendations fit for purpose.* Journal of Radiological Protection, 2021. **41**(4): p. 1390.

[11] Youssef, L.B., et al., *Dose Archiving and Communication System in Moroccan Healthcare: A Unified Approach to X-Ray Dose Management and Analysis.* International Journal of Advanced Computer Science & Applications, 2024. **15**(8).

[12] Vanderley-Reichner, C., *Patient examination consent for all imaging procedures: a shared vision.* J Med Radiat Sci, 2021. **68**: p. 3-79.

DOI: https://doi.org/10.5281/zenodo.23270675

[13] Elgheriani, H.F., et al., *Parasitic Infections by Encysted Metacercariae and Henneguya sp. Affected by Heavy Metals on Wild African Catfish (Clarias gariepinus).* Egyptian Journal of Veterinary Sciences, 2025: p. 1-16.

[14] Dudhe, S.S., et al., *Radiation dose optimization in radiology: a comprehensive review of safeguarding patients and preserving image fidelity.* Cureus, 2024. **16**(5).

[15] Vanhavere, F. and O. Van Hoey, *Advances in personal dosimetry towards real-time dosimetry.* Radiation Measurements, 2022. **158**: p. 106862.

[16] Greffier, J., et al., *Impact of dose reduction and the use of an advanced model-based iterative reconstruction algorithm on spectral performance of a dual-source CT system: A task-based image quality assessment.* Diagnostic and Interventional Imaging, 2021. **102**(7-8): p. 405-412.

[17] Moradi, S., et al., *Forecasting and optimizing dual media filter performance via machine learning.* Water Research, 2023. **235**: p. 119874.

[18] Djemailji, S., *Evaluating Patient Centering Techniques in Computed Tomography Imaging: A phantom study Comparing Automatic 3D Camera-Based and Manual Centering Methods for Dose and Noise Optimization*. 2025.

[19] Villano, F., G.M. Mauro, and A. Pedace, *A review on machine/deep learning techniques applied to building energy simulation, optimization and management.* Thermo, 2024. **4**(1): p. 100-139.

[20] Chen, C., *Improving the domain generalization and robustness of neural networks for medical imaging*. 2021, Imperial College London.