https://doi.org/10.37939/jrmc.v28i2.2574

Adaptive Learning Algorithms for Low Dose Optimization in Coronary Arteries Angiography: A Comprehensive Review

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Abstract

Objective: Coronary artery angiography plays a pivotal role in cardiovascular disease diagnosis and treatment, but concerns regarding patient safety due to ionizing radiation necessitate innovative approaches. The article explores the integration of adaptive learning algorithms to optimize low-dose imaging in coronary artery angiography.
Method: Articles are selected based on inclusion criteria that mention studies between the period of 2018 to 2022 emphasizing the detailed algorithmic studies of Low dose optimization of coronary artery angiography and techniques used in it, mentioned total of 175 studies were included in the initial studies that were reduced to ten final selected studies.
Results: The extracted data shows comprehensive data on various techniques that are used for low-dose CAA, advancements in image segmentation, noise reduction, and operator dose reduction highlight the potential of machine learning techniques. Innovative methods such as Model-Based Deep Learning (MBDL) and Self-Attention Generative Adversarial Networks (SAGAN) demonstrate efficient reconstruction capabilities. Application of such algorithms includes automated segmentation, lesion detection, and real-time image analysis, optimizing dose parameters based on patient-specific factors, thus prioritizing patient safety and treatment effectiveness while revolutionizing medical imaging.
Conclusion: This comprehensive review provides valuable insights into the potential of adaptive learning algorithms for low-dose optimization in coronary artery angiography. It underscores the importance of safer imaging practices without compromising diagnostic efficacy. The future lies in exploring adaptive learning algorithms, integrating patient-specific data, and real-time adaptability during procedures. Validation studies and collaboration with healthcare institutions are essential for successful integration into clinical practice.
Keywords: coronary arteries, artificial intelligence, machine learning, neural network, deep Learning.

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Cite this Article: Tariq K, Munir MA, Aftab HT, Naveed A, Yousaf A, Hassan SU. Adaptive Learning Algorithms for Low Dose Optimization in Coronary Arteries Angiography: A Comprehensive Review. JRMC. 2024 Jun. 27;28(2).336-347. https://doi.org/10.37939/jrmc.v28i2.2574.
Received January 07, 2024; accepted June 12, 2024; published online June 27, 2024

1. Introduction

CAA, also known as coronary angiography or cardiac catheterization, is a medical technique used to visualize the coronary arteries and assess blood flow to the heart. It involves the administration of a specialized dye and the use of X-rays[1]. The primary purpose is to aid in the diagnosis and evaluation of various heart conditions, including angina, heart attack, and heart valve disease.[1,2] During the procedure, a slender and flexible tube called a catheter is inserted into an artery, typically in the groin or arm, and carefully guided up to the heart. Contrast dye is then introduced into the bloodstream through the catheter, while X-ray images are captured to generate detailed visuals of the coronary arteries and blood vessels. This allows medical professionals to assess the condition of the arteries and identify any abnormalities or blockages that may be impacting blood flow to the heart.[1]
Coronary angiography is crucial in detecting blockages or narrowing in the coronary arteries, which can impede blood flow to the heart and increase the risk of a heart attack. The procedure also aids in identifying any abnormalities in the structure of the heart or its valves.[1] The radiation dose in coronary artery angiography can vary depending on several factors, including the specific imaging equipment used, the imaging technique, the patient's body size, and the complexity of the procedure. For a standard diagnostic coronary angiogram, the effective dose of radiation typically ranges from 2 to 5 millisieverts (mSv). In more complex procedures, such as interventions like angioplasty or stent placement, the radiation dose may be higher.[2]
The primary objective is to address the challenge of capturing clear images of a dynamic heart, which traditionally requires high doses of X-rays. [2, 3] However, it is well-known that higher doses entail an increased risk of adverse effects, including the development of cancer and alterations to cellular structures. In contrast, the use of low X-ray doses ensures the safety of both medical practitioners and patients involved in the procedure.[2,3,4] The research

aims to explore the effectiveness and advantages of low-dose angiography as a safer alternative, contributing to improved patient care and the well-being of medical practitioners.[4,5]

Low Dose Coronary artery angiography:

Low-dose coronary angiography refers to the use of techniques and protocols to minimize the amount of ionizing radiation exposure to patients during coronary angiography procedures while maintaining sufficient image quality for accurate diagnosis.[6] The as Low as Reasonably Achievable (ALARA) principle underlines the importance of minimizing radiation exposure without compromising diagnostic quality.[9] Hardware and software modifications for coronary angiography systems aim to improve imaging quality, patient safety, and procedural efficiency.[7, 8] Some common modifications and advancements in both hardware and software for coronary angiography systems are shown in Table 1.[7, 8]

Table 1: Hardware and software modifications for low dose angiography systems.7, 8

	Hardware Modifications
Flat-Panel Detectors:	Upgrading to flat-panel detectors improves image resolution and sensitivity, reducing the need for higher radiation doses.
Advanced X-ray Tubes:	High-frequency X-ray generators and rotating anode X-ray tubes with improved heat dissipation capabilities allow for longer and more complex imaging procedures.
C-arm Design:	Modern C-arm designs with improved maneuverability and flexibility enable better positioning for coronary angiography procedures, enhancing procedural efficiency.
Real-Time 3D Imaging:	Incorporating 3D angiography capabilities allows for more detailed visualization of coronary anatomy and can assist in precise interventional guidance.
Dual-Energy Imaging:	Dual-energy imaging systems provide enhanced tissue characterization, aiding in the differentiation of soft tissues and improved visualization of contrast agents.
Radiation Dose Monitoring Systems:	Integrated dose monitoring systems provide real-time feedback to the medical team, allowing for dose adjustments during the procedure and promoting adherence to ALARA principles.
Automatic Exposure Control (AEC):	AEC systems optimize radiation exposure by adjusting X-ray parameters based on the patient's anatomy, reducing unnecessary radiation.
Reduced Focal Spot Size:	Smaller focal spot sizes contribute to improved image sharpness and clarity, particularly in small vessels like coronary arteries.

Artificial Intelligence in Low Dose CAA:

AI is transforming low-dose coronary angiography, revolutionizing medical imaging, and improving patient care. By using advanced algorithms and machine learning, AI optimizes imaging for coronary angiography, balancing diagnostic quality with reduced radiation exposure.[10] AI-driven dose reduction strategies follow the ALARA principle, reducing risks from excessive radiation.[9] AI-powered image reconstruction enhances the clarity and precision of low-dose angiography images, providing valuable insights into cardiac anatomy and pathology.[10] Real-time dose monitoring and automated image analysis streamline the procedure, allowing for prompt adjustments and accurate diagnoses.[10] Integrating AI into low-dose coronary angiography improves imaging efficiency and enhances patient safety during essential cardiovascular procedures.[10]

Purpose and objective:

Low-dose angiography refers to a type of medical imaging that uses a lower dose of radiation than traditional angiography, which reduces the potential risks and side effects associated with radiation exposure.[11] However, low-dose angiography can also result in lower-quality images, making it more difficult for doctors to accurately diagnose and treat patients.[12]

Deep learning, a subset of artificial intelligence, involves the use of algorithms and neural networks to analyze large amounts of data and identify patterns. In the context of low-dose angiography, deep learning can be used to enhance the images produced by the imaging technology, allowing doctors to more accurately identify and diagnose medical conditions. Specifically, deep learning algorithms can be trained to recognize specific features of low-dose angiography images, such as blood vessels, and enhance those features to produce clearer and more detailed images. This can help doctors identify and diagnose conditions such as heart disease, stroke, and peripheral artery disease more accurately, leading to improved patient outcomes [11, 12]

Mode of CAA	Software Modifications
Iterative Reconstruction Algorithms:	Advanced reconstruction algorithms reduce image noise and artefacts, allowing for lower-dose imaging without sacrificing diagnostic quality.
Motion Correction:	Software-based motion correction techniques compensate for patient and cardiac motion, improving the accuracy of coronary angiography images.
Image Enhancement Filters:	Software filters enhance image contrast and sharpness, aiding in the visualization of fine vascular details.
Quantitative Coronary Angiography (QCA) Software:	QCA software provides precise measurements of vessel dimensions, helping clinicians in planning and assessing interventional procedures.
Integrated Navigation and Fusion Imaging:	Software solutions that integrate navigation and fusion imaging enable more accurate guidance during interventions, enhancing procedural success.
Real-Time 3D Reconstruction:	Software capable of real-time 3D reconstruction aids in the visualization of complex vascular structures and assists in planning interventions.
Dose Reporting Software:	Automated dose reporting software provides detailed radiation dose information for each procedure, promoting transparency and compliance with safety standards.
Electronic Health Record (EHR) Integration:	Seamless integration with EHR systems allows for efficient documentation of angiography results, enhancing workflow and data management

2. Materials & Methods

The study aimed to investigate the current landscape of adaptive learning algorithms for low-dose optimization in coronary artery angiography. A thorough search was conducted using a carefully crafted search string, encompassing key terms related to adaptive learning algorithms, machine learning techniques, low-dose optimization, coronary artery angiography, and comprehensive or systematic reviews. The inclusion criteria ensured the selection of peer-reviewed research articles, systematic reviews, and meta-analyses published within the specified timeframe (2018-2022), focusing explicitly on adaptive learning algorithms for low-dose optimization in coronary artery angiography. The criteria also emphasized the importance of addressing radiation dose optimization, coronary artery angiography, and reporting accuracy and performance metrics.

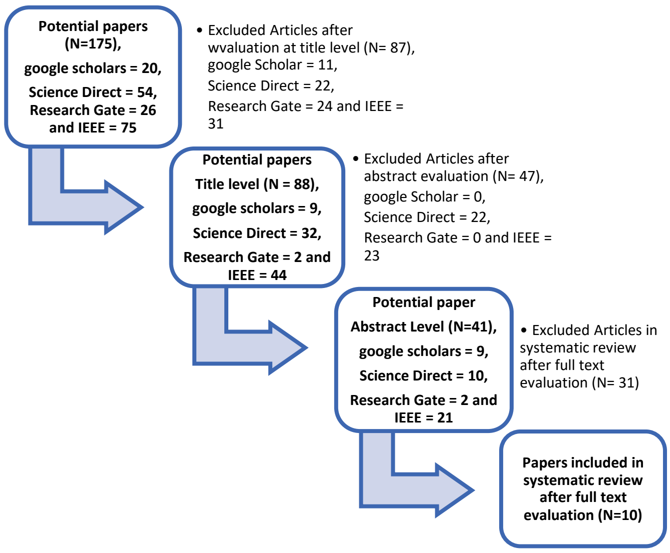

Figure 1: PRISMA Diagram for Research Process

3. Literature Review

Challenges in conventional Angiography:

Traditional coronary angiography techniques, although highly effective, are associated with inherent challenges, particularly the risk of ionizing radiation.2 High radiation doses not only pose potential harm to patients but also contribute to the growing apprehension within the medical community.[3] Efforts to address this challenge have led researchers to investigate novel technologies and methodologies for dose reduction while preserving image quality.4 Associated challenges are mentioned in Table 2.[4]

Theoretical Foundation for Adaptive learning Algorithms:

Adaptive learning algorithms, rooted in machine learning and artificial intelligence, offer a paradigm shift in the optimization of medical imaging.[13,14,15]

Table 2: Challenges in conventional angiography systems.

Challenges in Conventional Angiography Systems	
Problems	**Description**
Ionizing Radiation Exposure	Conventional coronary angiography relies on X-rays, which involve ionizing radiation. This exposure is a concern due to its potential harmful effects. Low-dose protocols aim to minimize radiation without compromising image quality, utilizing advancements in technology and dose optimization techniques.
Image Quality and Diagnostic Accuracy	Lowering radiation dose often leads to decreased image quality, which can impact diagnostic accuracy. Advances in detector technology, image processing algorithms, and optimized protocols aim to maintain sufficient image quality while reducing radiation exposure.
Invasive Nature of the Procedure	The need for catheterization and contrast agents in coronary angiography is inherently invasive. However, refining techniques, such as using smaller catheters and optimizing contrast injection protocols, can contribute to minimizing the invasiveness of the procedure.
Patient-specific Factors	Variability in patient size, anatomy, and pathology can affect the amount of radiation needed for adequate imaging. Tailoring imaging protocols to individual patient characteristics, known as personalized or adaptive imaging, helps optimize dose levels.
Equipment and Technology	Upgrading to newer angiography systems with advanced technologies, such as flat-panel detectors, can improve image quality and allow for dose reduction. These systems often have dose-monitoring features to track and manage radiation exposure

These algorithms can dynamically adjust imaging parameters based on individual patient characteristics, procedural nuances, and diagnostic requirements. [13] By leveraging advanced computational techniques, adaptive algorithms hold the promise of tailoring radiation doses to the specific needs of each patient, thereby mitigating unnecessary exposure. [13] Artificial intelligence (AI) has become a collective term for applications that perform complex tasks that previously required human intelligence.[14] Machine learning (ML), a subfield of AI, performs complex tasks by learning from experience. [14] Training of an ML algorithm creates an ML model, which represents what was learned by the ML algorithm to make predictions on new data. [13, 14] Most common ML applications in cardiac imaging can be broadly subdivided into two categories: supervised learning and unsupervised learning. [13,14] In supervised learning, categorized data are used to classify unseen data. An example of supervised learning is the training of ML algorithms to predict a patient's response to certain treatments. In unsupervised learning, ML algorithms are trained to find patterns or conclusions through unlabeled training data. [13, 14, 15] A well-known unsupervised learning method is clustering in which data/patients are grouped based on similarity, for example, to identify distinct clinical subgroups of patients that may benefit from targeted therapy. [13, 14, 15]

Deep learning (DL) is a subfield of ML in which multi-layered neural networks are trained to learn a supervised or unsupervised task.[14, 15] A neuron is a mathematical function that provides an output based on the input.[14, 15] During training, weights of the neurons in a neural network are optimized to map the input(s) to a desired output. Feature selection is an important processing step to select relevant input variables before training an AI algorithm.[14, 15] The selection of features that are most related to the outcomes reduces the complexity of the model and increases training speed. [14] Moreover, noisy and redundant features are eliminated which increases the performance of the model. In contrast to ML, neural networks can automatically select features. [14, 15] Therefore, DL can be trained directly on unstructured data like text, sound, video, and images. DL is a computationally expensive subfield of ML and requires large datasets to avoid generalization errors.[15] The number of neurons, number of layers, and connections between neurons determine the complexity and architecture of DL algorithm.[15] The convolutional neural network (CNN) is a class of DL that is widely used for imaging applications. Trained CNNs can detect and classify distinctive features (e.g., edges of anatomical structures) on images, for example, to classify views of echocardiograms. [15] ML models are evaluated using a variety of metrics, which are selected based on the ML application. Examples of metrics include the F1 score, accuracy, sensitivity, dice similarity coefficient (DSC), area under the receiver operating characteristic curve (AUC), and concordance statistic (C). [15]

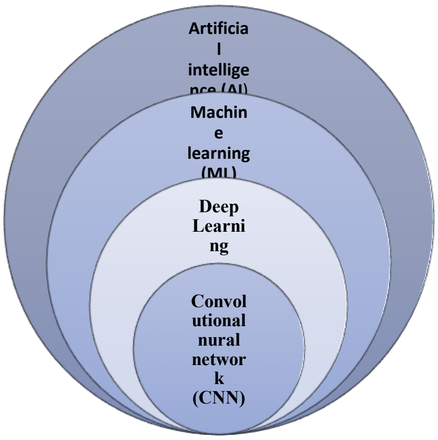

Figure 2: Conceptual framework of artificial intelligence with its subfields machine learning and deep learning

Machine Learning Techniques in Low dose optimization:

Deep learning, reinforcement learning, and ensemble methods are among the innovative approaches that have shown promise in adapting radiation doses during coronary artery angiography.[15] Understanding the strengths and limitations of these techniques is vital for elucidating their potential impact on clinical practice. Image reconstruction techniques for low-dose angiography, several methodologies draw upon diverse theoretical foundations to enhance the quality of medical images while minimizing radiation exposure. [15, 16, 17] Statistical Iterative Reconstruction, wherein iterative methods leverage statistical models to estimate the underlying image from noisy and under-sampled data. Fundamental to this is the application of penalized likelihood approaches, crucial for noise reduction in low-dose images.[17] The Bayesian framework plays a pivotal role in optimizing image reconstruction in low-dose angiography through Bayesian Inference.[16, 17] This mathematical foundation facilitates the modeling of the probability distribution of the underlying image, allowing for the optimization of reconstruction parameters based on new information. Deep learning, contributes significantly to adaptive learning algorithms in low-dose angiography. [16, 17] Neural networks, including Convolutional Neural Networks (CNNs), are instrumental in learning complex patterns within medical images, enabling noise reduction and feature enhancement. [16, 17] Adaptive filtering techniques, such as Wiener filters, form another facet of image reconstruction. These adaptive filters dynamically adjust image processing parameters based on local image characteristics, preserving important details while suppressing noise in low-dose angiography. [16, 17]
The incorporation of objective image quality metrics, such as signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR), provides theoretical frameworks for assessing image quality objectively. These metrics guide the development of adaptive algorithms, facilitating a delicate balance between reducing dose and maintaining clinically relevant image quality. [16, 17] Monte Carlo simulations, rooted in Monte Carlo methods, offer theoretical insights by modeling the transport of radiation in tissues. [16, 17] These simulations contribute to understanding and optimizing the imaging process, shedding light on the intricate relationships between radiation dose, image quality, and reconstruction parameters. [16, 17] Adaptive Control Theory introduces concepts that dynamically adjust imaging parameters in response to changes in the imaging environment or patient characteristics. [16, 17] The adaptability enhances the efficiency of low-dose angiography algorithms, ensuring optimal performance in various clinical scenarios. Finally, framing low-dose angiography as an inverse problem brings in the theoretical foundations of Inverse Problem Theory. [16, 17] This perspective aims to estimate the underlying image from measured data, guiding the development of regularization techniques and algorithms for stable image reconstruction. [16] By synergistically incorporating these theoretical frameworks, adaptive learning algorithms in low-dose angiography continue to evolve, striking a balance between diagnostic accuracy and minimizing radiation exposure. [16, 17, 18]

Application in CAA:

Adaptive algorithms are essential for enhancing the quality of angiographic images and improving diagnostic accuracy by reducing noise, enhancing contrast, and sharpening edges.[19,20] These algorithms enable clearer visualization of coronary arteries, crucial for accurately assessing vascular structures and identifying issues.[19, 20]

Automated segmentation is another key application of adaptive learning algorithms, saving time for medical professionals by identifying and segmenting coronary arteries in images. This streamlined process enhances efficiency in analyzing coronary artery networks. [19, 20]

Adaptive algorithms are valuable in lesion detection and classification, automatically identifying and classifying abnormalities in coronary arteries. This aids in pinpointing areas of stenosis, thrombosis, or other conditions, leading to quicker and more accurate diagnoses.[20, 21]

Real-time image analysis during angiography benefits from adaptive learning algorithms, allowing informed decisions on the spot, such as optimal stent placement. These insights enhance the precision of interventional procedures.[20, 21]

For dose optimization during angiography, adaptive algorithms dynamically adjust imaging parameters based on patient-specific factors, minimizing radiation exposure while maintaining image quality. This prioritizes patient safety and imaging effectiveness.[35]

Personalized treatment planning involves analyzing angiographic images and patient-specific data to predict intervention success rates and recommend suitable treatment strategies.[20,22] This approach enhances coronary artery disease management efficacy.[20, 22]

Continuous patient monitoring is facilitated by adaptive algorithms analyzing angiographic images over time, tracking disease progression or regression, and guiding treatment adjustments. This proactive monitoring contributes to better patient outcomes. [20, 22]

Integration of 3D imaging techniques with angiography data, enabled by adaptive learning algorithms, provides a comprehensive understanding of coronary artery anatomy. This synergy enhances pre-procedural planning and navigation during interventions, improving the success of cardiovascular procedures. [21]

4. Results

Deep Learning in patient dose optimization:

In the exploration of deep learning applications for patient dose optimization in coronary artery angiography, You A. et al, 2022 [23], delve into the utilization of generative adversarial networks (GAN) and convolutional neural networks (CNN) within the field of ophthalmology. The review of 48 papers underscores the efficacy of GAN in tasks such as segmentation, data augmentation, and de-noising for ophthalmic images. Despite being in early clinical stages, the study reveals promising results, highlighting GAN's potential to enhance various aspects of patient dose optimization in coronary artery angiography. In a related study, Liang and Qiu [24] investigate the impact of an optimized X-ray blanket design on reducing operator radiation dose during cardiac catheterization. Conducted through real-world angiography with 7681 procedures, the research emphasizes the significance of shielding measures in CAA. The optimization of these measures not only enhances patient safety by mitigating radiation exposure but also facilitates the use of lighter radio-protective garments in angiography units, contributing to patient dose optimization.

The work of Gao Z et al, 2022 [25] introduces a vessel segmentation method for X-ray coronary angiography, employing ensemble methods with deep learning and filter-based features. The proposed parameters, multi-scale filtering, and feature maps contribute to effective artery segmentation. Results, evaluated through AUROC and sensitivity, demonstrate the method's effectiveness in extracting coronary vessel trees from X-ray coronary angiography images, aligning with the overarching theme of patient dose optimization through advanced image analysis techniques.

Lu and colleagues[26] contribute to the exploration of machine learning and deep learning in the intelligent diagnosis of coronary atherosclerotic heart disease. Their study includes an assessment of operator dose relative to dose-area product (DAP), revealing a remarkable 94.9% reduction. This underscores the potential of machine learning and deep learning not only in achieving accurate diagnoses but also in significantly reducing radiation exposure for operators during coronary artery angiography.

In a study by Iyer K, Najarian C et al, 2021 [27], AngioNet, a convolutional neural network (CNN), and a fully convolutional network (FCN) are introduced for vessel segmentation in X-ray angiography. The research highlights the effectiveness of CNN in image segmentation and blockage detection, showcasing high performance in brain tumor detection using ultrasound and CT datasets. The results suggest the promising potential of CNN and FCN in enhancing diagnostic accuracy, aligning with the overarching theme of patient dose optimization in coronary artery angiography.

Troville and team [28] focus on the implementation of a convolutional neural network (CNN) in fluoroscopic interventional procedures for real-time monitoring and

human recognition. The study utilizes a scattered radiation display system, trained with binary masks for each person in the operating theater. Despite obstructing objects, the CNN produces high-fidelity predictions, indicating its potential in staff dose management, a crucial aspect of patient dose optimization strategies.
Javor D et al, 2021 [28] contribute to the theme by evaluating the radiation dose reduction capabilities of a new C-arm system using AI and deep learning. The C-arm extension algorithm for dose control shows a significant decrease in dose, as demonstrated by data collected from 49 patients. These findings suggest the potential for improved radiation safety with optimized hardware and software in fluoroscopic procedures, contributing to patient dose optimization efforts.
Meng and colleagues [29] present a method for the automatic extraction of coronary arteries using deep learning, employing U-Net, U-Net++, and U-Net 3+. The study, based on 616 invasive coronary angiograms from 210 patients, demonstrates promising results with high Dice scores. Focusing on the angiographies of selected tissues, the research showcases an increase in vascular classification accuracy from 95% to 98.7%, aligning with the overarching theme of patient dose optimization through advanced imaging techniques in coronary artery angiography.
Recovering Structures and preserving details:
The study's results showcased the impressive ability of Self-Attention Generative Adversarial Networks (SAGAN) to uncover underlying structures amid significant uncertainty in coronary artery angiography.[32] The research also emphasized the improved effectiveness of a wavelet-domain deep Convolutional Neural Network (CNN) in reducing noise in low-dose CT images compared to current methods.[33] Particularly, the newly introduced CNN demonstrated superior performance in preserving fine image details within 3 mm slice thickness, outperforming previous networks.[32] The produced images exhibited clearer boundaries and enhanced organ details. Even with a 1 mm slice thickness, the images maintained detailed regions while effectively reducing streaking artifacts.[33, 34] However, it's important to note that denoising 1 mm thick slices resulted in a slight blurring effect, which was linked to the inherent noise in standard CT images of the same thickness.[32] This aspect underscored the difficulty of maintaining precision in the supervised learning process for coronary artery angiography.[33]
Learned or trained networks:
Model-Based Deep Learning (MBDL) emerges as a noteworthy approach. This method, tailored for low-dose CAA, is trained to minimize the cost function and demonstrates comparable noise levels to iterative techniques.[33, 35] Notably, MBDL proves to be cost-effective as it requires no ground-truth information. Following training, the network exhibits the capability to perform reconstruction swiftly, eliminating the need for time-consuming iterative steps.[35]
Additionally, Self-Attention Generative Adversarial Networks (SAGAN), akin to other neural network-based methods, exhibit rapid testing and task accomplishment, requiring less than a second. [35] In a comparative analysis with two denoising methods, BM3D and K-SVD, SAGAN outperforms at lower dose levels, while BM3D excels at the highest dose level. [35] The study encompasses wider anatomic regions and a broader dose range, distinguishing itself from previous network introductions. [35]
The integration of supervised learning networks and unsupervised iterative algorithms is exemplified in SUPER (Supervised-Unsupervised Reconstruction). [35] The amalgamation of FBP-ConvNet, a supervised method, and PWLS-ULTRA (Penalized Weighted-Least Squares), an unsupervised method, gives rise to SUPER-ULTRA (Union of Learned Transforms), along with FBPConvNet þ EP (SUPER-EP).[35] Both configurations exhibit superior performance and convergence compared to their individual model counterparts. This exploration of learned and trained networks showcases promising advancements in the domain of coronary artery angiography deep learning. [35]
Capability of deep learning networks:
In the context of coronary artery angiography with low-dose imaging, supervised learning may encounter limitations due to the network's capacity.[36] Many existing approaches necessitate a substantial number of pre-collected ground truth or high-dose sinogram pairs, presenting challenges related to data availability. [36] Here introduced an innovative unsupervised/semi-supervised deep learning method specifically designed for low-dose angiography. This approach incorporates unlabeled CT sinograms directly into the network training process, enabling the model to consider both the structural characteristics and noise distribution inherent in low-dose angiography sinograms.[36]

Table 3: Summary of studies using pre-construction methods

Summary Of Studies Using Pre-Construction Methods			
Reference	**Network**	**Data Set**	**Outcome**
You A et all,2022 [23]	GAN & CNN	Search identified 48 reviewed papers	GAN has a generator and a discriminator that perform well in image tasks like synthesis and translation. In ophthalmology, GAN is used for segmentation, data augmentation, de-noising, and more, providing great results. Its use in ophthalmology brings many benefits, even though it is still in early clinical stages. Ultimate goal is vessel detection using GAN and CNN networks can be very useful for CAA.
Liang, D., Qiu, J., 2022 [24]	Hard X-ray blanket as shield	7681 procedures were done with the use of such blanket	X-ray blankets are employed in procedures to shield patients from harm due to high radiation exposure. Optimizing shielding measures can reduce operator doses to levels where lighter radio protective garments can be safely used in Angiography units.
Gao Z et all, 2022 [25]	CNN with dee3p forest & GBDT model		Proposed artery segmentation method in XCA images uses 2 parameters: multi-scale filtering and feature maps. GBDT model: AUROC 0.874, sensitivity 0.902. Deforest model: AUROC 0.867, sensitivity 0.95. Effective for extracting coronary trees.
Lu H et all, 2022 [26]	ML and Deep learning		Operator dose was calculated relative to DAP to determine the dose's impact, resulting in a significant reduction of 94.9%
Lyer K, Najarian C et all,2021 [27]	CNN & FCN over CT angio images		CNN for image segmentation and blockage detection is very effective. Ultrasound and CT datasets were used for brain tumor detection, with ultrasound achieving a DSC of 0.804 ± 0.24 and tumor detection reaching a DSC of 0.856 ± 0.004. CNN and FCN can be effectively utilized after evaluations and uncertainty reduction.
Troville J et all, 2021 [28]	CNN Microsoft Kinect V2		A study focusing on the use of fluoroscopic interventional procedures to reduce patient doses implemented a scattered radiation display system for real-time monitoring. The CNN was trained with 144 binary masks for each of the four persons present in the operating theater, producing high-fidelity predictions despite obstructing objects.
Javor D et all, 2021[29]	AI and deep learning	49 patients, 28 as control and 21 as test group	The study employed a C-arm extension algorithm for dose control, collecting data from 49 patients split into groups A (28 patients) and B (21 patients). The DAP and fluoroscopy time were recorded, showing a significant decrease in dose with the new C-arm system.
Meng Y et al., 2020 [30]	U-Net ++, U-Net 3+ and U-Net	616 ICAs from 210 patients	A set of 616 ICAs from 210 patients was used, with U-Net (DSC: 0.87), U-Net++ (DSC: 0.88), and U-Net 3+ (DSC: 0.89) showing promising results. With some modifications, this method can be applied effectively in clinical operations.
Honolulu H et al., 2018 [31]	CNN & 3D reconstruction	18 patients	Developed 3D CNN with 2 CT coronary angiography settings. Evaluation includes multiple tests and normalization techniques on images. Dice score of 0.829 shows method's suitability for clinical use with patient 3D CNN images.
Monotoya J, Li Y et all, 2018 [32]	3D deep learning	Search identified 48 reviewed papers	Introduces a deep learning method for 3D modeling of cerebral vascular grafts. 3 tissues - nasal cavity, ontic capsule, and osseous - are selected and subjected to angiographies. Vascular classification increased from 95% to 98.7% using the proposed method.
You A et all,2022 [33]	GAN & CNN	Search identified 48 reviewed papers	GAN has a generator and a discriminator that perform well in image tasks like synthesis and translation. In ophthalmology, GAN is used for segmentation, data augmentation, de-noising, and more, providing great results. Its use in ophthalmology brings many benefits, even though it is still in early clinical stages.

Through this method, the network autonomously learns the proper gradient of the low-dose angiography, offering a potential solution to the challenge of data scarcity in supervised learning scenarios. [36]
Another noteworthy solution, proposed by Ding et al., aligns with the iterative reconstruction concept but adopts a deep learning-based regularization approach for low-dose angiography image reconstruction. [36] This method showcased superior reconstruction quality compared to traditional analytical and iterative reconstruction techniques. [36] The study utilized normal-dose CT prostate image data from 100 anonymized scans to which Poisson noise was added to simulate low-dose angiography scans. [36] This innovative approach not only provides an alternative to traditional methods but also demonstrates enhanced performance in low-dose angiography image reconstruction for coronary artery examinations. [36]

5. Limitations

The landscape of AI technologies and solutions is rapidly advancing, with numerous articles being published across various journals and conferences. Despite this scoping review paper's attempt to encompass the reported works on AI technologies for dose optimization in low-dose coronary artery angiography, the sheer pace of advancement makes it challenging to cover all contributions comprehensively. While AI models exhibit promising performance, it is crucial to acknowledge several limitations that may impact the reliability of the studied models, particularly in the context of low-dose coronary artery angiographies.[38]
One notable concern is the potential lack of data heterogeneity and diversity in some image datasets used for developing AI methods. In certain instances, datasets may be captured using the same device and protocol, limiting the generalizability of the studied algorithms. This limitation poses challenges in ensuring that AI models can effectively adapt to diverse imaging conditions encountered in real-world low-dose coronary artery angiography scenarios. [38]
Moreover, the challenge of collecting a sufficient amount of data, coupled with concerns related to personal data protection, serves as a barrier to further improving the performance of AI methods in low-dose coronary artery angiography. This challenge may introduce issues such as overfitting, mirroring similar concerns faced by AI technologies applied in other domains. As AI continues to progress in the realm of low-dose coronary artery angiography, addressing these limitations becomes imperative to enhance the robustness and reliability of AI-driven dose optimization methods.[38]

6. Future Directions

In the evolving landscape of coronary artery angiography, the future of research lies in the exploration of "Adaptive Learning Algorithms for Low Dose Optimization." One promising avenue involves delving into advanced machine learning techniques, such as deep learning and reinforcement learning, to enhance adaptability and performance.[37] Researchers may also focus on integrating patient-specific data, including clinical history and genetics, to tailor low-dose optimization algorithms to individual characteristics. [38]
Real-time adaptabilities during angiography procedures, dynamic adjustments, and immediate responsiveness to changes in patient anatomy or procedure requirements are areas ripe for exploration. [39] A view of the future Cath lab is given in Figure 4.

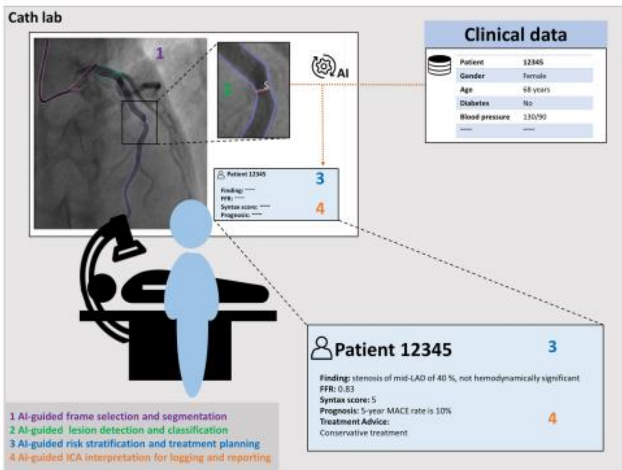

Figure 4: Conceptual framework of the future CATH Lab by the help of Artificial Intelligence

Validation studies and clinical trials are essential for assessing the real-world efficacy and safety of these algorithms, and collaborating with healthcare institutions to implement and evaluate their impact on patient outcomes. [40] The potential of hybrid imaging approaches, combining adaptive algorithms with other modalities, may offer complementary information for enhanced accuracy. [41] Researchers should prioritize the explain ability and transparency of these algorithms, addressing interpretability for healthcare professionals and fostering trust in clinical settings. [42] Establishing quantitative assessment metrics, defining benchmarks, and conducting longitudinal studies on radiation exposure contribute to comprehensive understanding and safety considerations. [43] Additionally, investigating human factors and user acceptance among healthcare professionals and navigating regulatory considerations are crucial elements for successful integration into routine clinical practice. [44] In pursuing these avenues, researchers aim to advance the field, improve patient care, and establish standards for the use of adaptive learning algorithms in low-dose optimization. [45]

7. Conclusion

In the given comprehensive review focusing on dose optimization in low-dose coronary artery angiography, it is observed a prevalent recommendation among researchers for leveraging deep learning-based image reconstruction techniques. Various deep learning methods have been proposed to address image noise reduction either through pre- or post-reconstruction processes. Given the inherent challenge of reduced radiation in low-dose angiography, which can compromise image quality, the integration of artificial intelligence (AI)--based noise reduction techniques is widely advocated.

Despite the continued use of conventional low-dose coronary angiography image reconstruction techniques in current clinical practice, the adoption of AI presents a transformative opportunity for improving image quality. AI-based solutions exhibit diversity in their architectural approaches, offering the potential to overcome limitations associated with network capabilities or insufficient image quality. Noteworthy advancements in AI-based techniques have been reported in the literature, providing effective solutions to challenges previously encountered.

With the integration of AI solutions, the optimization of low-dose coronary artery angiography scans becomes feasible, enabling the acquisition of high-quality images even with reduced radiation. However, it is crucial to underscore the ethical considerations associated with these advancements. The implementation of AI solutions should prioritize safety and ethical acceptability. Radiologists and radiographers must undergo proper education and training to stay abreast of these evolving techniques, ensuring their judicious and ethical use in the context of dose-optimized low-dose angiography procedures.

CONFLICTS OF INTEREST- None

Financial support: None to report.
Potential competing interests: None to report
Contributions:
K.T, M.A.M, H.T.A, A.Y - Conception of study - Experimentation/Study Conduction
K.T, M.A.M, A.N, S.U.H - Analysis/Interpretation/Discussion
K.T, H.T.A, S.U.H - Manuscript Writing
K.T, M.A.M, A.N, A.Y - Critical Review - Facilitation and Material analysis

All authors approved the final version to be published & agreed to be accountable for all aspects of the work.

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