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The Role of Artificial Intelligence in Improving Diagnostic Accuracy in Cardiology and Radiology: In-Depth Analysis of Ethical, Legal, and Clinical Implications across Multiple Medical Disciplines

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Abstract

Background: The integration of Artificial Intelligence (AI) within cardiovascular imaging is transforming diagnostic processes across medical specialties, particularly in cardiology, radiology, and oncology. However, the complexities of AI models, notably those utilizing machine learning (ML) and deep learning (DL), raise significant ethical and legal concerns, particularly regarding their interpretability and decision-making transparency.

Methods: This review synthesizes existing literature on AI applications in cardiovascular imaging. It examines the methodologies employed, including supervised and unsupervised learning, deep learning frameworks such as convolutional neural networks (CNNs), and generative adversarial networks (GANs), and the implications for clinical practice. The analysis focuses on AI's ability to detect subtle patterns in imaging data, enhancing diagnostic accuracy and workflow efficiency.

Results: AI technologies have demonstrated remarkable capabilities in identifying cardiovascular abnormalities and improving imaging quality. Applications include real-time detection of coronary artery stenosis from CT angiography and predictive models for cardiovascular events. However, the opaque nature of AI decision processes complicates clinical acceptance, as healthcare professionals often lack insight into the rationale behind AI-generated outputs.

Conclusion: While AI holds promise for advancing diagnostic capabilities in cardiovascular care, the prevailing "black box" issue necessitates the development of explainable AI frameworks. Enhancing transparency and interpretability is crucial for fostering trust among clinicians and ensuring ethical implementation in clinical settings. Addressing these challenges is essential for the responsible integration of AI technologies into healthcare practices, ultimately improving patient outcomes.

Keywords: Artificial Intelligence, Cardiovascular Imaging, Diagnostic Accuracy, Machine Learning, Explainability

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1. Introduction

The widespread incorporation of AI in cardiovascular imaging presents significant legal and ethical issues. The growing intricacy of AI models, especially those using machine learning (ML) and deep learning (DL), presents the difficulty of the "black box," a phrase that denotes the lack of transparency in AI decision-making processes [1]. This task highlighted issues regarding the explicability and openness of AI systems, which are crucial for their ethical implementation and therapeutic acceptability [2]. Despite significant progress in AI-driven cardiovascular imaging, current evaluations mostly concentrate on technical improvements and clinical results, neglecting the decision-making processes of these AI models and the mechanisms that inform their outputs [3]. This gap highlights the essential need for thorough evaluations that examine these sophisticated technologies as well as their ethical and practical ramifications due to their ambiguous nature. Our objective is to provide doctors, researchers, and policymakers with an enhanced comprehension of AI's capabilities and constraints in cardiovascular healthcare.

2. A comprehensive examination of artificial intelligence

Artificial Intelligence entails the creation of computer algorithms that do intricate tasks emulating human cognitive processes. Machine learning (ML), a fundamental aspect of AI, allows systems to learn from data, enhance performance, and provide predictions [4]. Improvements in computer power and large data have accelerated the use of machine learning in healthcare [5]. The proliferation of smart devices and electronic medical records has increased data accessibility, hence improving the efficiency of machine learning algorithms despite the complexity of the data. Machine learning training may be categorized as either "supervised" or "unsupervised." In supervised training, a machine learning model is trained on a variety of inputs linked to a known output, which is monitored either according to an objective classification measure or by a domain expert [6]. Conversely, unsupervised training pertains to the creation of a model to investigate the patterns or clusters that are not delineated within datasets. The model is supplied just with unlabeled input data and does not acquire the ability to correlate data with an outcome [7].

Deep learning (DL), a subset of machine learning (ML), is an essential subject in artificial intelligence (AI). Deep learning is designed to analyze data using extensive artificial neural networks that consist of several processing layers, analogous to the function of real neurons [8]. It has attained remarkable outcomes in complicated tasks requiring high-dimensional data, such as voice and picture recognition, as well as self-driving vehicles [9, 10]. Deep learning methods use many layers of concealed neurons to produce progressively abstract and nonlinear representations of the foundational data. This technique, termed "representation learning," is a crucial component of deep neural networks. After the collection of these representations, final output nodes are often used as inputs for logistic regression models or support vector machines (SVMs) to execute the final regression or classification tasks. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two significant types of deep learning models used for supervised learning [9]. The fundamental difference between CNNs and RNNs is in their differing architectural configurations. In addition to these methodologies, a variety of deep neural network topologies is available.

Convolutional Neural Networks (CNNs) mimic fully linked neural networks, consisting of neurons with modifiable weights and biases. Their efficacy arises from the ability to create local connections among pictures or signals [10]. These localized connections use nonlinear activation functions, enabling the conversion of representations into higher, more abstract forms. Moreover, the use of shared weights across layers, layer pooling, and the incorporation of many hidden layers facilitate the acquisition of complex functions. Conversely, RNNs are proficient at handling sequential data, including voice and language. RNNs include an extra concealed state vector, allowing them to maintain "memory" of past data observations, making them particularly effective for jobs containing sequential information [11, 12].

In recent years, generative AI (GAI), a subset of artificial intelligence, reached its zenith with the emergence of novel language and picture models exhibiting unparalleled capabilities. GAI models are now capable of generating pictures or videos from textual input, modifying images based on text prompts, and producing text that engages in comprehensive dialogues. These models are also readily accessible, thus contributing to the rise in popularity of GAI among the general population. Consequently, this enabled non-technical people to explore application cases across many sectors and specializations. Generative Artificial Intelligence (GAI) may be traced back to the development of two particular types of networks: transformers, which are sophisticated variants of recurrent neural networks (RNNs), and generative adversarial networks (GANs), which use two distinct convolutional neural networks (CNNs) that are trained concurrently in an adversarial framework.

Although RNNs are proficient at managing sequential data via a hidden state that encapsulates prior inputs, they encounter difficulties with long-range dependencies and parallel processing. The transformer addresses these constraints by implementing self-attention methods, enabling the model to assess the significance of each word in a sequence about all other words, rather than depending only on the sequential processing characteristic of RNNs. The design of the transformer obviates the need for recurrent connections, allowing it to process all tokens in a sequence concurrently. This parallelism greatly improves performance and enables the model to more effectively capture long-term interdependence. The use of multi-head self-attention in the transformer enables the model to concurrently concentrate on several segments of the sequence, resulting in a more profound and intricate comprehension of context. Transformers facilitated the extraordinary capabilities and esteemed prominence of Large Language Models (LLMs) such as ChatGPT today [13].

Generative Adversarial Networks (GANs) are very proficient at producing realistic data across several domains, including photos, video, and audio. Generative Adversarial Networks (GANs) include two neural networks—a generator and a discriminator—that are concurrently trained in a competitive framework. The generator tries to create data that emulates the actual data distribution, while the discriminator seeks to differentiate between real and created data. This adversarial mechanism compels the generator to provide progressively credible outputs, eventually yielding the creation of very realistic data [14].

3. Artificial Intelligence used in cardiovascular imaging

Artificial intelligence can examine large volumes of visual data to detect nuanced patterns and abnormalities that may be missed by human specialists. AI-driven algorithms can precisely measure coronary artery stenosis from CT angiography in real time [15]. Neural networks may be trained with suitable data to identify early indicators of heart failure from chest X-rays [16]. Such applications may facilitate earlier and more precise diagnoses, allowing for faster treatments and improved patient outcomes. In addition to diagnostic functions, AI is enhancing imaging operations. Automated image capture, reconstruction, and segmentation activities reduce human error and accelerate the interpretation process [17]. Moreover, AI-driven prediction models may detect individuals at elevated risk for cardiovascular events using imaging data, facilitating proactive risk management measures [18].

Generative AI (GAI) is transforming cardiovascular imaging by improving image quality, automating intricate tasks, and enhancing diagnostic accuracy across multiple modalities [19]. In Cardiac MRI (CMR), GAI significantly accelerates image reconstruction and minimizes motion artifacts, with techniques developed by Ghodrati et al. [20] facilitating free-breathing scans, thereby increasing patient comfort and scan efficiency. Advanced reconstruction approaches, including variational neural networks (VNNs), provide high-quality imaging from undersampled data, markedly decreasing scan durations while maintaining accuracy [21]. This is especially advantageous for treatments requiring comprehensive volumetric and functional assessment of the heart, enhancing the accessibility and reliability of CMR for clinical decision-making.

In Cardiac Computed Tomography (CCT), GAI-based methodologies have shown considerable potential in enhancing picture quality and diagnostic precision. AI-driven algorithms, shown by Itu et al.'s approach for Fractional Flow Reserve CT (FFR-CT), have significantly decreased analysis duration while preserving excellent predicted accuracy, demonstrating AI's capacity to improve non-invasive coronary artery disease (CAD) assessment [22]. These AI-driven innovations are enhancing clinical processes and delivering more consistent and trustworthy diagnostic information, hence improving patient outcomes in cardiovascular care.

Notwithstanding these advantages, the intricacy of AI models, especially deep learning techniques, presents considerable hurdles [23, 24]. In the realm of AI in radiology, "Black box" denotes scenarios in which the decision-making process of the AI model is obscure or not readily comprehensible to humans. This indicates that while the AI may provide outcomes or suggestions, the foundational thinking or processes that resulted in these findings remain opaque. Such indicators might present difficulties in clinical environments since physicians may lack complete comprehension or confidence in the AI's outputs, thereby affecting patient care [25, 26]. Comprehending and explaining AI's judgments is essential for clinical acceptability and ethical implementation [27].

To ensure the dependability of an AI system, it is essential to demonstrate that the system has comprehended the fundamental features and that its judgments are not predicated on extraneous correlations between input and output values in the training dataset [28]. Although one may mitigate the shortcomings of an AI methodology by meticulous selection of its model architecture and training algorithm, mistakes remain unavoidable [29].

The capacity of various AI models to comprehend created models differs markedly. The advent of advanced deep learning techniques is making decision reconstruction more challenging. The resultant models often operate as "black boxes," making it difficult for users to understand the underlying mechanisms [28]. Users comprehend simple input and output values, however, designers grasp the system's architecture and the approaches used to create the models [30]. Conversely, interpretable models are named white boxes, since they allocate weights to each characteristic, facilitating straightforward reading and interpretation; an intermediary category between the two is the gray box. Gray box models provide a degree of understanding of internal data processing [31].

It is essential to recognize that, in practice, a technique cannot always be distinctly categorized as a white, gray, or black box approach. Therefore, to tackle the problem of insufficient explainability, it is essential to develop explanation models for black-box models, which facilitate comprehension of their functioning. Figure 1 illustrates the black box dilemma in contrast to explainable AI.

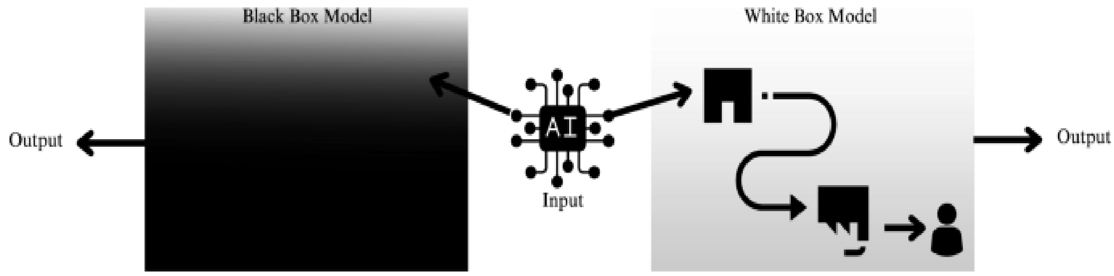

Figure 1. Visual depiction of the black box dilemma in contrast to explainable AI

4. Challenges and constraints related to the nature of AI in cardiovascular imaging

The opacity of AI's decision-making process poses a barrier to evaluating and comprehending its outcomes. Despite the encouraging outcomes of deep learning in cardiovascular imaging, they remain limited, and several difficulties must be addressed to enhance them [32]. Prevalent deep learning architectures, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and recurrent neural networks (RNNs), lack interpretability about their results [33]. In the therapeutic environment, the primary difficulty is sometimes termed a black box. Consequently, the advancement of explainable machine learning systems in the healthcare sector is a paramount concern for computer scientists, policymakers, and consumers [34].

Presently, there is no universally accepted definition of explainability, while there is an agreement on the significance of creating and using interpretable models [35]. Luo et al. [36] introduced a novel data preprocessing method for identifying cardiac illnesses using cardiac magnetic resonance (CMR) imaging, together with an innovative network architecture for estimating left ventricular capacity. Their research indicated that the approach exhibited great precision in forecasting left ventricular (LV) volumes. They identified a notable difficulty often faced in deep learning methodologies—the lack of interpretability for medical professionals. Attaining genuine interpretability in left ventricular volume prediction may, for instance, allow clinicians to pinpoint the exact pixels used in blood volume calculations. They underscored that further research must prioritize attaining interpretability in the direct prediction of left ventricular sizes [36].

Although AI algorithms may identify coronary artery disease, heart failure, conduction anomalies, and valvular heart disease, their lack of transparency raises questions about reliability, interpretability, and possible biases. To guarantee that AI's clinical integration conforms to practical healthcare standards, it is important to comprehend the underlying mechanisms of these algorithms.

As previously detailed, artificial intelligence plays a crucial role in cardiovascular imaging, and comprehending its functionality is vital for successful deployment [37]. Evidence-based medicine has challenges due to the lack of transparency in machine learning models, particularly in medical imaging. In evidence-based medicine, clinical choices are guided by the most reliable evidence from scientific research, integrated with clinical knowledge and patient values. This methodology depends significantly on clear and interpretable data and models, enabling clinicians to comprehend the reasoning behind recommendations or judgments. Nonetheless, machine learning models, especially those used in computer vision imaging, often function as "black boxes," indicating that their underlying decision-making mechanisms are not readily interpretable or explicable. The absence of transparency is a considerable obstacle for evidence-based medicine, as clinicians may find it difficult to trust or comprehend the outputs of these models, hence impeding their successful integration into clinical practice. In the realm of CVS imaging, where precise diagnosis and treatment choices are critical, the opacity of ML models might engender ambiguity or distrust among healthcare practitioners. Clinicians may be reluctant to depend on ML-based advice without a comprehensive comprehension of the model's reasoning process.

A major problem pertains to mistake detection. AI systems may sometimes diverge from established norms of clinical decision-making [38]. Image classification techniques, especially convolutional neural networks, are notably vulnerable to unforeseen and atypical classification mistakes, resulting in challenges in understanding the causative elements affecting the correlations of these machine learning models [39]. This uncertainty may erode healthcare practitioners' faith in AI predictions, especially when they contradict traditional clinical judgment [40]. To enhance ML systems, it is essential to understand their decision-making processes. AI explainability enables users to comprehend the decision-making processes of an AI model, extending beyond mere enhancement of AI performance [41].

The qualitative study demonstrates that physicians prioritize relevant and readily understandable information from ML models to make informed judgments. Research by Tonekaboni et al. shows that therapists do not inherently favor comprehending the causal factors behind ML decision-making. They favor clear and relevant information on the model's functionality within the realm of healthcare decision-making. This data could involve confidence ratings, the rationale for a choice, and particulars customized to the individual clinical situation [27].

Lang and colleagues have noted that some very successful uses of AI in cardiovascular imaging may lack explainability. This has elicited apprehensions among many professionals who advocate for the cessation of inexplicable models owing to the substantial issues they may provide [38, 42]. In conclusion, while technical specialists may lack a thorough knowledge of machine learning (ML) algorithms, these systems must provide outputs or related information that allow users to evaluate predictions relevant to their clinical decision-making. Despite ongoing attempts to provide methods for contextualizing machine learning predictions according to user requirements, attaining a complete understanding of artificial intelligence predictions continues to be a developing area of study [43].

5. Legal and ethical ramifications

The opacity of AI systems presents considerable legal and ethical dilemmas in healthcare. Trust among clinicians is essential for the incorporation of AI into healthcare operations. The absence of explainability and transparency may result in ethical difficulties and undermine trust in AI for medical care [44]. Ethical concepts, including beneficence (acting in patients' best interests) and non-maleficence (avoiding injury), are pertinent when evaluating the possible hazards of using artificial intelligence (AI) platforms with opaque decision-making procedures. Visibility in algorithmic processes is essential for enhancing understanding [45]. In clinical environments, AI methodologies must provide rationales for their judgments to enhance doctors' trust in the precision of the outcomes [46]. The use of AI models characterized by limited transparency or interpretability creates problems with accountability, patient safety, and decision-making processes. The legal implications of clinician trust are intertwined with responsibility and accountability. When doctors depend on AI-generated diagnoses or treatment suggestions without comprehending the underlying logic, it may exacerbate issues in instances of medical mistakes or negative results. Establishing responsibility is complicated when the decision-making processes of AI are unclear, perhaps leading to inquiries over culpability and legal liability [38].

Regrettably, several AI-driven cardiovascular imaging programs often demonstrate an inexplicable "black box" phenomenon. Assessing the clinical risks and advantages of these opaque models may be difficult, especially when biased decision-making poses a potential threat. The difficulty intensifies when differentiating between explicable and inexplicable AI models [30]. The use of opaque AI in healthcare settings has recently sparked much discussion. Some contend that legislation should impose stronger controls on unexplained models, whilst others assert that such rules may hinder innovation, and clinical uptake, and result in inferior patient outcomes [38]. The replication of clinical trials for technically obscure models is particularly difficult since commercial developers sometimes hesitate to provide their proprietary information [47]. It is crucial to acknowledge that the uncertainty associated with medical treatments is not a novel issue. It is crucial to acknowledge that the specific complexity of AI-driven cardiovascular imaging applications needs rigorous evaluation of the need for separate regulatory approaches. This includes compliance with validation plans and rules established by regulatory authorities, including the FDA, for the implementation of medical AI. [30].

Legal systems regulating inexplicable AI include medical malpractice, complicating physicians' ability to establish standards of care. The evolving environment requires a reassessment of professional standards and protocols. AI-driven care increasingly challenges conventional ethical principles, since automated decision-making affects comprehensibility [38, 48].

A further difficulty with unexplained AI is the notion of informed consent. Clinical specialists assert that informed permission is important before employing AI on patients. They contend that computer-aided detection programs have to be reported in reports, elucidating the rationale for any potential discrepancies. The dissemination of erroneous knowledge to patients and physicians on the hazards associated with AI algorithms may constitute a violation of the duty of care; hence, the sufficiency of information supplied to users is essential for informed decision-making. Regarding information, they question what must be communicated to the patient [49]. These difficulties grow more complex with the use of opaque AI. Patients have the right to comprehend and consent to the operations or treatments proposed by AI algorithms.

Proposals have been suggested to mitigate legal and ethical concerns: one potential answer is the efficient extraction of interpretable characteristics for illness categorization via the use of deep learning techniques. Researchers developed methods for obtaining characteristics from deep learning models that are both precise for illness categorization and comprehensible to healthcare experts. These strategies use deep learning algorithms to find and extract significant and interpretable characteristics or patterns from medical pictures that indicate certain illnesses or disorders [50]. This method enables doctors to comprehend the rationale behind the deep learning model's predictions by elucidating the aspects or attributes of the medical pictures that influence the classification process.

An alternative method involves offering transparent elucidations of neural network outputs after their use in medical photos. GRADCAM, an acronym for Gradient-weighted Class Activation Mapping, is a method used in computer vision and deep learning to see and comprehend the decision-making processes of convolutional neural networks (CNNs). It operates by producing a heatmap that emphasizes the areas of an input picture that are most significant for CNN's classification determination. This heatmap is generated by calculating the gradient of the projected class score relative to the final convolutional layer of the CNN. GRADCAM elucidates the components of the input picture that most significantly influence the network's judgment, offering critical insights into the model's data processing and predictive mechanisms. This might substantially raise the comprehension of the judgments made by these networks and bolster the confidence and acceptance of AI technology among medical practitioners [45]. Zhang et al. illustrated the application of GRADCAM in a cardiovascular setting by utilizing attention supervision within a deep learning model to direct a multi-stream Convolutional Neural Network (CNN) to concentrate on particular myocardial segments for the automated detection of motion artifacts in cardiac T1-mapping [51]. Some critics have proposed that it may be essential to forgo inexplicable AI models. This results from the substantial issues associated with the use of such models, which may be challenging to elucidate or comprehend [47].

The European as well as American Multi-society Statement emphasizes many ethical issues and possibilities associated with AI. A structure has been proposed to provide practical guidance for AI practitioners. Nonetheless, the fast evolution of AI methodologies and instruments complicates the effort to sustain a thorough and current comprehension of the ethical framework [52, 53].

6. Progress in explainable AI methodologies and novel approaches for interpretability

Model-based explanation pertains to models, such as linear regression or support vector machines, that are sufficiently basic for comprehension but smart enough to accurately represent the connection between inputs and outputs [43]. These models are often conventional machine learning models that are less complicated and more interpretable, unlike more intricate models including deep neural networks. Sparsity and simulability are two prominent instances of such models. Sparsity denotes models that constrain several coefficients to be precisely zero. This results in a sparse model in which just a select group of features substantially influences the output, rendering the model's internal structure explicable [54-57]. Simulatability refers to the capacity for a person to internally comprehend the model's calculations and decision-making process. In more straightforward models, such as linear regression, it is easy for an individual to understand the contribution of each attribute to the final result [58].

Unlike model-based clarification, post hoc explanation involves training a neural network and then attempting to clarify the behavior of the resultant black box network, rather than imposing explainability on the neural network itself. Thus, the post hoc analysis is more comprehensible and user-friendly, applicable to any model irrespective of its intricacy [57]. Methods include the examination of acquired features, assessment of feature significance, analysis of feature interactions, and visual elucidation via saliency maps [59-62]. Nonetheless, the limitation of this strategy lies in its restricted ability to encapsulate the whole intricacy of a model. Consequently, the selection between these two options involves a compromise between precision and interpretability, contingent upon the particular context used.

7. Summary

The use of AI in cardiology imaging has substantial promise; nevertheless, it is impeded by the opaque character of many traditional AI models, which creates considerable obstacles to medical decision-making, comprehension, and confidence. Although AI has shown encouraging outcomes in identifying many cardiovascular disorders, the absence of transparency generates apprehensions about its dependability and utilization in evidence-based treatment. To address these problems, it is imperative to create explainable AI (XAI) tools that provide transparent knowledge of AI decision-making processes. These methodologies, such as model based as well as post hoc explanations, might reconcile the disparity between intricate algorithms and the requirement for openness in healthcare environments.

Furthermore, extensive education and training initiatives for healthcare workers are crucial to guarantee the efficient and ethical use of AI in practice. These programs should provide physicians with the understanding and skills needed to comprehend and use AI technologies while considering the ethical ramifications of their application. Furthermore, prioritizing patient engagement and informed permission is essential to preserve autonomy and confidence in AI-driven healthcare. Ultimately, the establishment of strong ethical and legal structures is essential for the secure and efficient incorporation of AI into healthcare procedures. By confronting these obstacles, we can guarantee the responsible use of AI technology, therefore improving patient outcomes and revolutionizing cardiovascular care.

References

1. Wadden, J. J. (2022). Defining the undefinable: the black box problem in healthcare artificial intelligence. Journal of Medical Ethics, 48(10), 764-768.
2. Holzinger, A. (2021). Explainable AI and multi-modal causability in medicine. i-com, 19(3), 171-179.
3. Antoniades C, Oikonomou EK (2024) Artificial intelligence in cardiovascular imaging—principles, expectations, and limitations. Eur Heart J 45(15):1322–6.
4. Lang M, Bernier A, Knoppers BM (2022) Artificial intelligence in cardiovascular imaging: “unexplainable” legal and ethical challenges? Can J Cardiol 38(2):225–33
5. Seetharam K, Kagiyama N, Sengupta PP (2019) Application of mobile health, telemedicine and artificial intelligence to echocardiography. Echo Res Pract 6(2):R41-52
6. Shameer K, Johnson KW, Glicksberg BS, Dudley JT, Sengupta PP (2018) Machine learning in cardiovascular medicine: are we there yet? Heart 104(14):1156–64
7. Sidey-Gibbons JAM, Sidey-Gibbons CJ (2019) Machine learning in medicine: a practical introduction. BMC Med Res Methodol 19:1–18
8. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M et al (2018) Artificial intelligence in cardiology. J Am Coll Cardiol 71(23):2668–2679
9. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U, et al (2019) Deep learning for cardiovascular medicine: a practical primer. Eur Heart J 40(25):2058–2073
10. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 25.
11. O’Shea, K., & Nash, R. (2022). An introduction to convolutional neural networks. arXiv preprint 2015. arXiv preprint arXiv:1511.08458.
12. Salucci, M., Li, M., Chen, X., & Massa, A. (2023). An introduction to deep learning for electromagnetics.
13. Harrer, S. (2023). Attention is not all you need: the complicated case of ethically using large language models in healthcare and medicine. EBioMedicine, 90.
14. Imamverdiyev, Y. N., & Musayeva, F. I. (2022). Analysis of generative adversarial networks. Problems of Information Technology, 22-30.
15. Danilov VV, Klyshnikov KY, Gerget OM, Kutikhin AG, Ganyukov VI, Frangi AF, et al (2021) Real-time coronary artery stenosis detection based on modern neural networks. Sci Rep 11(1):7582
16. Matsumoto T, Kodera S, Shinohara H, Ieki H, Yamaguchi T, Higashikuni Y et al (2020) Diagnosing heart failure from chest X-ray images using deep learning. Int Heart J 61(4):781–786
17. Dikici E, Bigelow M, Prevedello LM, White RD, Erdal BS (2020) Integrating AI into radiology workflow: levels of research, production, and feedback maturity. J Med Imaging 7(1):16502
18. Lin A, Kolossváry M, Motwani M, Išgum I, Maurovich-Horvat P, Slomka PJ et al (2021) Artificial intelligence in cardiovascular imaging for risk stratification in coronary artery disease. Radiol Cardiothorac Imaging 3(1):e200512.
19. Paladugu, P. S., Ong, J., Nelson, N., Kamran, S. A., Waisberg, E., Zaman, N., ... & Tavakkoli, A. (2023). Generative adversarial networks in medicine: important considerations for this emerging innovation in artificial intelligence. Annals of biomedical engineering, 51(10), 2130-2142.

20. Ghodrati V, Bydder M, Ali F, Gao C, Prosper A, Nguyen KL et al (2021) Retrospective respiratory motion correction in cardiac cine MRI reconstruction using adversarial autoencoder and unsupervised learning. NMR Biomed 34(2):e4433
21. Oscanoa JA, Middione MJ, Alkan C, Yurt M, Loecher M, Vasanawala SS et al (2023) Deep learning-based reconstruction for cardiac MRI: a review. Bioengineering 10(3):334
22. Itu L, Rapaka S, Passerini T, Georgescu B, Schwemmer C, Schoebinger M et al (2016) A machine-learning approach for computation of fractional flow reserve from coronary computed tomography. J Appl Physiol 121(1):42–52
23. Kiryati, N., & Landau, Y. (2021). Dataset growth in medical image analysis research. Journal of imaging, 7(8), 155.
24. Strubell, E., Ganesh, A., & McCallum, A. (2020, April). Energy and policy considerations for modern deep learning research. In Proceedings of the AAAI conference on artificial intelligence (Vol. 34, No. 09, pp. 13693-13696).
25. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K (2019) The practical implementation of artificial intelligence technologies in medicine. Nat Med 25:30–6
26. Topol EJ (2019) High-performance medicine: the convergence of human and artificial intelligence. Nat Med 25:44–56
27. Tonekaboni, S., Joshi, S., McCradden, M. D., & Goldenberg, A. (2019, October). What clinicians want: contextualizing explainable machine learning for clinical end use. In Machine learning for healthcare conference (pp. 359-380). PMLR.
28. Gallée L, Kniesel H, Ropinski T, Götz M (2022) Artificial intelligence in radiology - Beyond the black box. RoFo Fortschritte auf dem Gebiet der Rontgenstrahlen und der Bildgebenden Verfahren. 195:797–803
29. Götz, M., & Maier-Hein, K. H. (2020). Optimal statistical incorporation of independent feature stability information into radiomics studies. Scientific reports, 10(1), 737.
30. London, A. J. (2019). Artificial intelligence and black-box medical decisions: accuracy versus explainability. Hastings Center Report, 49(1), 15-21.
31. Nasief H, Zheng C, Schott D, Hall W, Tsai S, Erickson B et al (2019) A machine learning based delta-radiomics process for early prediction of treatment response of pancreatic cancer. NPJ Precis Oncol.
32. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U et al (2019) Deep learning for cardiovascularmedicine: a practical primer. Eur Heart J 40:2058-2069C
33. Salih A, Boscolo Galazzo I, Gkontra P, Lee AM, Lekadir K, Raisi-Estabragh Z et al (2023) Explainable artificial intelligence and cardiac imaging: Toward more interpretable models. Circ Cardiovasc Imaging 16(4):E014519
34. Pesapane F, Volonté C, Codari M, Sardanelli F (2018) Artificial intelligence as a medical device in radiology: ethical and regulatory issues in Europe and the United States. Insights Imaging 9:745–53
35. Preece, A., Harborne, D., Braines, D., Tomsett, R., & Chakraborty, S. (2018). Stakeholders in explainable AI. arXiv preprint arXiv:1810.00184.
36. Luo G, Dong S, Wang K, Zuo W, Cao S, Zhang H (2018) Multi-views fusion CNN for left ventricular volumes estimation on cardiac MR images. IEEE Trans Biomed Eng 65(9):1924–1934
37. Price, I. I., & Nicholson, W. (2017). Artificial intelligence in health care: Applications and legal issues.
38. Lang M, Bernier A, Knoppers BM (2022) Artificial intelligence in cardiovascular imaging: “unexplainable” legal and ethical challenges? Can J Cardiol 38:225–33
39. Afifi, M., & Brown, M. S. (2019). What else can fool deep learning? Addressing color constancy errors on deep neural network performance. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 243-252).
40. Samek W, Montavon G, Lapuschkin S, Anders CJ, Müller KR (2021) Explaining deep neural networks and beyond: a review of methods and applications. Proc IEEE 109(3):247–278
41. Shin, M., Kim, J., & Kim, M. (2020). Measuring human adaptation to AI in decision making: application to evaluate changes after AlphaGo. arXiv preprint arXiv:2012.15035.
42. Rudin C (2019) Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nat Mach Intell 1:206–15

43. Murdoch WJ, Singh C, Kumbier K, Abbasi-Asl R, Yu B (2019) Definitions, methods, and applications in interpretable machine learning. Proc Natl Acad Sci 116(44):22071–22080
44. Sermesant M, Delingette H, Cochet H, Jaïs P, Ayache N (2021) Applications of artificial intelligence in cardiovascular imaging. Nat Rev Cardiol 18:600–9
45. Barredo Arrieta A, Díaz-Rodríguez N, Del Ser J, Bennetot A, Tabik S, Barbado A et al (2020) Explainable Artificial Intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fus 1(58):82–115
46. Slomka PJ, Miller RJ, Isgum I, Dey D (2020) Application and translation of artificial intelligence to cardiovascular imaging in nuclear medicine and noncontrast CT. Semin Nuclear Med 50:357–66
47. Hagen GR (2021) AI and Patents and Trade Secrets. In: Martin-Bariteau Florian, Scassa Teresa, editors. Artificial Intelligence and the Law in Canada. Toronto
48. Reznick, R. K., Harris, K., Horsley, T., & Hassani, M. S. (2020). Task force report on artificial intelligence and emerging digital technologies. Royal College of Physicians and Surgeons of Canada.
49. Cestonaro C, Delicati A, Marcante B, Caenazzo L, Tozzo P (2023) Defining medical liability when artificial intelligence is applied on diagnostic algorithms: a systematic review. Front Med 10:1305756
50. Zheng Q, Delingette H, Ayache N (2019) Explainable cardiac pathology classification on cine MRI with motion characterization by semi-supervised learning of apparent flow. Med Image Anal 1(56):80–95
51. Zhang Q, Hann E, Werys K, Wu C, Popescu I, Lukaschuk E et al (2020) Deep learning with attention supervision for automated motion artefact detection in quality control of cardiac T1-mapping. Artif Intell Med 110:101955
52. Geis JR, Brady AP, Wu CC, Spencer J, Ranschaert E, Jaremko JL et al (2019) Ethics of artificial intelligence in radiology: summary of the joint European and north American multisociety statement. J Am Coll Radiol 16(11):1516–1521
53. Rehani, M. M., & Brady, Z. (2021). Contemporary issues in radiation protection in medical imaging: introductory editorial. The British Journal of Radiology, 94(1126), bjr-20219004.
54. Reznick RK, Harris K, Horsley T (2020) Task force report on artificial intelligence and emerging digital technologies
55. Khoury Lara (2006) Uncertain causation in medical liability. Hart Pub. p 270
56. Frank X (2019) Is Watson for oncology per se unreasonably dangerous?: Making a case for how to prove products liability based on a flawed artificial intelligence design. Am J Law Med 45(2–3):273–294
57. Van der Velden BHM, Kuijf HJ, Gilhuijs KGA, Viergever MA (2022) Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. Med Image Anal 79:102470
58. Lage I, Chen E, He J, Narayanan M, Kim B, Gershman SJ et al. (2019) Human evaluation of models built for interpretability. In: Proceedings of the AAAI conference on human computation and crowdsourcing. pp 59–67
59. Abbasi-Asl R, Yu B (2017) Structural compression of convolutional neural networks. arXiv preprint arXiv:170507356
60. Olden JD, Joy MK, Death RG (2004) An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. Ecol Modell 178(3–4):389–397
61. Petsiuk V, Jain R, Manjunatha V, Morariu VI, Mehra A, Ordonez V et al. (2021) Black-box explanation of object detectors via saliency maps. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. pp 11443–52.
62. Tsang M, Cheng D, Liu Y (2017) Detecting statistical interactions from neural network weights. arXiv preprint arXiv:170504977.

دور الذكاء الاصطناعي في تحسين دقة التشخيص في أمراض القلب والأشعة: تحليل معمق للآثار الأخلاقية والقانونية والسريرية عبر تخصصات طبية متعددة

الملخص

الخلفية :يُحدث دمج الذكاء الاصطناعي (AI) في التصوير القلبي الوعائي تحولاً في عمليات التشخيص عبر التخصصات الطبية، لا سيما في أمراض القلب والأشعة والأورام. ومع ذلك، فإن تعقيد نماذج الذكاء الاصطناعي، لا سيما تلك التي تستخدم التعلم الآلي (ML) والتعلم العميق(DL) ، يثير مخاوف أخلاقية وقانونية كبيرة، خاصة فيما يتعلق بقابليتها للتفسير وشفافية اتخاذ القرار.

الطرق :تُجمّع هذه المراجعة الأدبيات القائمة حول تطبيقات الذكاء الاصطناعي في التصوير القلبي الوعائي. وتتناول المنهجيات المستخدمة، بما في ذلك التعلم المُشرف وغير المُشرف، وأطر التعلم العميق مثل الشبكات العصبية الالتفافية (CNNs) والشبكات التوليدية التنافسية(GANs) ، وتداعياتها على الممارسة السريرية. يركز التحليل على قدرة الذكاء الاصطناعي على اكتشاف الأنماط الدقيقة في بيانات التصوير، مما يُعزز دقة التشخيص وكفاءة سير العمل.

النتائج :أثبتت تقنيات الذكاء الاصطناعي قدرات مذهلة في تحديد الشذوذات القلبية الوعائية وتحسين جودة التصوير. تشمل التطبيقات الكشف الفوري عن تضيق الشرايين التاجية من تصوير الأوعية المقطعية التاجية والنماذج التنبؤية للأحداث القلبية الوعائية. ومع ذلك، فإن الطبيعة الغامضة لعمليات اتخاذ القرار في الذكاء الاصطناعي تُعقّد قبولها سريرياً، حيث يفتقر المتخصصون في الرعاية الصحية غالبًا إلى فهم المبررات وراء مخرجات الذكاء الاصطناعي.

الخلاصة :على الرغم من أن الذكاء الاصطناعي يحمل وعدًا بتطوير قدرات التشخيص في رعاية القلب والأوعية الدموية، إلا أن مشكلة "الصندوق الأسود" الحالية تستلزم تطوير أطر ذكاء اصطناعي قابلة للتفسير. يُعد تعزيز الشفافية وقابلية التفسير أمرًا حيويًا لتعزيز الثقة بين الأطباء وضمان التنفيذ الأخلاقي في البيئات السريرية. معالجة هذه التحديات ضرورية للتكامل المسؤول لتقنيات الذكاء الاصطناعي في الممارسات الصحية، مما يُحسن في نهاية المطاف نتائج المرضى.

الكلمات المفتاحية :الذكاء الاصطناعي، التصوير القلبي الوعائي، دقة التشخيص، التعلم الآلي، القابلية للتفسير