Short Communication

Interventional Cardiology

Radiology artificial intelligence in the screening and diagnosis of cardiovascular disease: A mini review

Pei-Lun Han[1], Kang Li[1,2,3], Zhi-Gang Yang[1*]

[1]Department of Radiology and West China Biomedical Big Data Center, West China Hospital, Sichuan University, Chengdu, China

[2]Med-X Center for Informatics, Sichuan University, Chengdu, China

[3]Shanghai Artificial Intelligence Laboratory, Shanghai, China

*Author for correspondence:
Zhi-Gang Yang, Department of Radiology and West China Biomedical Big Data Center, West China Hospital, Sichuan University, Chengdu, China, E-mail: yangzg666@163.com

Received date: 19-Aug-2024, Manuscript No. FMIC-24-145728;
Editor assigned: 21-Aug-2024, PreQC No. FMIC-24-145728 (PQ);
Reviewed date: 06-Sep-2024, QC No. FMIC-24-145728;
Revised date: 13-Sep-2024, Manuscript No. FMIC-24-145728 (R);
Published date: 23-Sep-2024, DOI: 10.37532/1755-5310.2024.16(S24).615

Abstract

Artificial intelligence is introducing revolutionary changes in the field of cardiovascular imaging. Combining deep learning and cardiovascular imaging has achieved promising results for the screening and diagnosis of cardiovascular disease, outperforming conventional techniques and even radiologists in some tasks. Deep learning also aids in cardiovascular image processing, improving the efficiency of image analysis and providing diagnostic decision support to clinicians. In addition, deep learning allows traditional imaging modalities to achieve greater diagnostic potential.

Keywords: Artificial intelligence • Deep learning • Cardiovascular imaging • Screening Diagnosis

Description

Cardiovascular Disease (CVD) is the leading cause of death worldwide, accounting for approximately 32% of all deaths [1,2]. Early clinical screening and diagnosis is important for disease monitoring, individualized prevention, and treatment. Radiology imaging techniques are important tools for CVD screening and diagnosis. In this study, we will mainly focus on a few main approaches, including chest radiography, Computed Tomography (CT), and cardiac Magnetic Resonance Imaging (MRI). Generally, chest radiography is a rapid, inexpensive, and non-invasive medical technology used to evaluate cardiac size as well as pulmonary blood flow [3,4]. Cross-sectional imaging using CT or cardiac MRI is being increasingly used to evaluate cardiac anatomy and physiology. However, the accuracy of chest radiographs in diagnosing CVD is suboptimal because cardiac and hemodynamic changes may not be apparent in the early stage. The interpretation of CT or cardiac MRI images is time-consuming, energy-intensive, and cost-efficient. In addition, human errors are inevitable due to visual fatigue or a lack of experience in clinical practice.

Artificial Intelligence (AI) is capable of performing tasks that require human intelligence. In recent years, AI has achieved remarkable success in the classification and interpretation of medical imaging, which facilitates the screening and detection of CVD [5,6]. Machine learning is the core of AI, as it can solve problems based on training data and programmed algorithms [7]. Deep learning is an advanced machine learning approach that is usually implemented using neural networks to characterize and learn higher-level features [8]. Due to its superior ability to analyze high-level features, medical image interpretation using deep learning is becoming a rising hotspot [9]. Deep Learning (DL) has demonstrated high efficacy in the classification, identification, and segmentation of cardiovascular images, which facilitates the image interpretation process. Considering the importance of early identification, this paper focuses on the application of DL in the screening and diagnosis of CVD. In the following section, we provide a literature study in detail.

Automated screening and diagnosis of CVD could be conducted using deep learning classification algorithms. Our team has previously innovated an attempt to apply neural networks to 3255 chest radiograph images for automatic screening for congenital heart disease, which showed good performance (The Area Under the receiver-operator characteristics Curve (AUC): 0.948) and was superior to that of radiologists [10]. In addition, the diagnostic accuracy of radiologists was improved with the assistance of AI. Wang et al., presented a two-stage approach that utilizes noninvasive cardiac MRI cine imaging for CVD screening, followed by further diagnosis using cine and late gadolinium enhancement imaging for 11 types of CVD in 9719 subjects [11]. Using video-based deep learning algorithms, this approach achieved excellent performance (AUC: 0.988 in internal validation; 0.991 in external validation) and outperformed the experienced cardiologists. These deep learning works have greatly improved the efficiency and scalability of cardiovascular imaging interpretation, thereby contributing to early diagnosis, timely treatment, and improving patient prognosis.

Image segmentation using deep learning is a promising tool for interpreting cardiovascular function. Cardiovascular Magnetic Resonance (CMR) is considered the gold standard for assessing cardiac structure and function due to its outstanding soft-tissue contrast and temporal resolution [12,13]. However, the image processing of CMR is time-consuming and requires high technical expertise from doctors. Deep learning can be used to automatically segment the left and right ventricles and atrium of CMR images, allowing for the further calculation of the sizes of the heart chambers, and the accuracy is close to that of clinical experts [14]. Goyal et al., provided an accurate and fast machine learning-based algorithm (Neosoft) for dynamic left ventricular volume measurement [15]. This machine learning model can automatically generate the time-volume curve of the left ventricle within 2.5 ± 0.5 min, which is significantly faster than manual analysis (43 ± 14 min per patient). In addition, Karr et al., demonstrated that DeepLabV3+DCNN, using three versions of the ResNet-50 backbone, can be employed for automated left ventricular chamber quantification and subsequent strain analysis, which is useful for the early identification of cardiotoxicity [16]. Similarly, AI-derived cardiac parameters were also reported to show good performance in the diagnosis of acute myocarditis [17]. These advanced AI technologies allow for fast, accurate, and fully automated analysis of cardiac structure and function, and are not influenced by human factors, which can prompt the diagnosis of CVD. The implementation of deep learning algorithms also enables traditional imaging modalities to play a greater diagnostic potential. Coronary angiography is the established clinical standard for the measurement of Fraction Flow Reserve (FFR) for the diagnosis of coronary artery disease, but it is invasive. Based on the FFR obtained from invasive pressure-wire pullback along a vessel, deep learning algorithms, along with fluid dynamics, support Coronary Computed Tomography Angiography (CCTA) in providing a comparable estimation of FFR values. T Tang et al., compared the diagnostic value of CT FFR in 159 vessels from 103 patients with suspected coronary artery disease, using invasive FFR as the reference standard [18]. The AUC for CT FFR was 0.9, which is significantly higher than that of CCTA (AUC: 0.75). Similar conclusions were obtained by Norgaard et al., and Driessen et al. [19,20]. Yu et al., showed that the per-patient accuracy of CT FFR was 0.85 in identifying hemodynamically in-stent restenosis, suggesting that the deep-learning-based CT FFR provides the same effectiveness and feasibility for patients with stent implantation [21]. In addition, Late Gadolinium Enhancement Cardiac MR (CMR LGE) imaging is the gold standard for noninvasive myocardial tissue characterization, but it requires intravenous contrast agent administration. Zhang et al., presented a CMR virtual native enhancement imaging technology that provides a contrast agent-free approach to replace LGE, enabling faster and more cost-effective CMR scans [22].

Despite the vigorous development of AI, there are still many obstacles to the deployment of AI models at present, primarily including technical, social, economic, and legal challenges [23]. Specifically, technical challenges include the lack of large-scale high-quality data and labels, interpretation of AI-derived results and prospective clinical studies that validate the real-world utility of AI models. In addition, AI applications require substantial financial support, good interdisciplinary cooperation, and a good balance of regulatory safeguards and market forces. Given the ongoing efforts by all sectors of society, we believe that AI will provide efficient assistance to clinicians and patients in the future.

Conclusion

In conclusion, recent studies on deep learning applied to CVD screening and diagnosis have reported good performance, sometimes even surpassing that of radiologists in certain tasks. Deep-learning-based cardiovascular image processing and analysis can accurately and quickly obtain indicators, providing decision support for clinicians. In addition, deep learning enables traditional imaging modalities to realize their greater diagnostic potential. The application of these deep learning models may improve the performance of various diagnostic processes.

Financial Disclosure

The authors have no financial or proprietary interest in the subject matter of this article.

Conflict of Interest

There is no conflict of interest between authors.

Authors Contributions

Data availability were involved in reviewing, writing and revising the article prior to submission.

Data Avalibility

The authors declare that data supporting the findings of this study are available within the article.

References

1. World Health Organization WHO Reveals leading causes of death and disability worldwide: 2000-2019.
2. Roth GA, Mensah GA, Johnson CO, et al. Global burden of cardiovascular diseases and risk factors, 1990-2019: Update from the GBD 2019 study. J Am Coll Cardiol. 76(25):2982-3021 (2020).
3. Sachdeva S, Gupta SK. Imaging modalities in congenital heart disease. Indian J Pediatr. 87(5):385-397 (2020).
4. Caro-Domínguez P, Secinaro A, Valverde I, et al. Imaging and surgical management of congenital heart diseases. Pediatr Radiol. 53(4):677-694 (2023).
5. Gill SK, Karwath A, Uh HW, et al. Artificial intelligence to enhance clinical value across the spectrum of cardiovascular healthcare. Eur Heart J. 44(9):713-725 (2023).
6. Dey D, Slomka PJ, Leeson P, et al. Artificial intelligence in cardiovascular imaging: JACC state-of-the-art review. J Am Coll Cardiol. 73(11):1317-1335 (2019).
7. Yang Z, Zeng X, Zhao Y, et al. AlphaFold2 and its applications in the fields of biology and medicine. Signal Transduct Target Ther. 8(1):115 (2023).
8. Romiti S, Vinciguerra M, Saade W, et al. Artificial Intelligence (AI) and cardiovascular diseases: An unexpected alliance. Cardiol Res Pract. 2020(1):4972346 (2020).
9. Chan HP, Samala RK, Hadjiiski LM, et al. Deep learning in medical image analysis. Adv Exp Med Bio. 2020:3-21 (2020).
10. Han PL, Jiang L, Cheng JL, et al. Artificial intelligence-assisted diagnosis of congenital heart disease and associated pulmonary arterial hypertension from chest radiographs: A multi-reader multi-case study. Eur J Radiol. 171:111277 (2024).
11. Wang YJ, Yang K, Wen Y, et al. Screening and diagnosis of cardiovascular disease using artificial intelligence-enabled cardiac magnetic resonance imaging. Nat Med. 30(5):1471-1480 (2024).
12. Leiner T, Bogaert J, Friedrich MG, et al. SCMR position paper (2020) on clinical indications for cardiovascular magnetic resonance. J Cardiovasc Magn Reson. 22:76 (2020).
13. Vasquez M, Nagel E. Clinical indications for cardiovascular magnetic resonance. Heart. 105:1755-1762 (2019).
14. Bai W, Sinclair M, Tarroni G, et al. Automated cardiovascular magnetic resonance image analysis with fully convolutional networks. J Cardiovasc Magn Reson. 20(1):65 (2018).
15. Goyal N, Mor-Avi V, Volpato V, et al. Machine learning based quantification of ejection and filling parameters by fully automated dynamic measurement of left ventricular volumes from cardiac magnetic resonance images. Magn Reson Imaging. 67:28-32 (2020).
16. Karr J, Cohen M, McQuiston SA, et al. Validation of a deep-learning semantic segmentation approach to fully automate MRI-based left-ventricular deformation analysis in cardiotoxicity. Br J Radiol. 94(1120):20201101 (2021).
17. Yuan WF, Zhao XX, Hu FB, et al. Evaluation of Early Gadolinium Enhancement (EGE) and cardiac functional parameters in Cine-Magnetic Resonance Imaging (MRI) on artificial intelligence in patients with acute myocarditis: A case-controlled observational study. Med Sci Monit. 25:5493-5500 (2019).
18. T Tang CX, Guo BJ, Schoepf JU, et al. Feasibility and prognostic role of machine learning-based FFRCT in patients with stent implantation. Eur Radiol. 31(9):6592-6604 (2021).
19. Nørgaard BL, Leipsic J, Gaur S, et al. Diagnostic performance of noninvasive fractional flow reserve derived from coronary computed tomography angiography in suspected coronary artery disease: The NXT trial (Analysis of Coronary Blood Flow Using CT Angiography: Next Steps). J Am Coll Cardiol. 63(12):1145-1155 (2014).
20. Driessen RS, Danad I, Stuijfzand WJ, et al. Comparison of coronary computed tomography angiography, fractional flow reserve, and perfusion imaging for ischemia diagnosis. J Am Coll Cardiol. 73(2):161-173 (2019).
21. Yu KH, Beam AL, Kohane IS, et al. Artificial intelligence in healthcare. Nat Biomed Eng. 2(10):719-731 (2018).
22. Zhang Q, Burrage MK, Lukaschuk E, et al. Toward replacing late gadolinium enhancement with artificial intelligence virtual native enhancement for gadolinium-free cardiovascular magnetic resonance tissue characterization in hypertrophic cardiomyopathy. Circulation. 144(8):589-599 (2021).
23. Koo BK, Erglis A, Doh JH, et al. Diagnosis of ischemia-causing coronary stenoses by noninvasive fractional flow reserve computed from coronary computed tomographic angiograms: Results from the prospective multicenter DISCOVER-FLOW (Diagnosis of Ischemia-Causing Stenoses Obtained via Noninvasive Fractional Flow Reserve) study. J Am Coll Cardiol. 58(19):1989-1997 (2011).