Automatic Calcium Detection in Echocardiography based on Deep Learning: A Systematic Review

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Abstract. The diagnosis of many heart diseases involves the analysis of images from Computed Tomography (CT) or echocardiography, which is mainly done by a medical professional. By using Deep Learning (DL) algorithms, it is possible to create a data-driven tool capable of processing and classifying this type of image, to support physicians in their tasks, improving healthcare efficiency by offering faster and more accurate diagnoses. The aim of this paper is to perform a systematic review on DL uses for automated methods for calcium detection, identifying the state of this art. The systematic review was based on PRISMA methodology to identify relevant articles about image processing using Convolutional Neural Networks (CNN) in the cardiac health context. This search was conducted in Scopus and Web of Science Core Collection, and the keywords considered included (1) Deep Learning, (2) Calcium Score, (3) CT-Scan, (4) Echocardiography. The review yielded 82 research articles, 38 of which were in accordance with the initial requirements by referring to image processing and calcium score quantification using DL models. DL is reliable in the implementation of classification methods for automatic calcium scoring. There are several developments using CT-Scan, and a need to replicate such methods to echocardiography.

1 **Keywords:** Neural network, Deep Learning, Computer Vision, Classification, Artery Calcification, Echocardiography

1 Introduction

Cardiovascular diseases are the main cause of mortality and a major contributor to disability increasing, representing one-third of world's deaths in 2019 [1]. The prevalence of all cardiovascular disorders in the same year doubled from 271 million in 1990 to 523 million in 2019. Also, the number of cardiovascular fatalities progressively increased from 12.1 million in 1990 to 18.6 million in 2019 [2].

Vascular calcification is of great interest in terms of risk factors and subsequent effects. As referred on [3], the presence of Coronary Artery Calcium (CAC) is strongly correlated with coronary artery diseases and may perform a powerful indicator on prediction of cardiovascular occurrences and death. Aortic Valve Sclerosis (AVS) or Aortic Valve Calcification (AVC) is generally understood to refer to the development of calcific structures that are contained inside the aortic valve leaflets and do not affect the aortic annulus or coronary artery ostia [4]. Aortic Stenosis (AS) is nowadays the most prevalent primary heart valve disease and a significant contributor to cardiovascular mortality [5].

Digital images are essential for the early detection of anomalies or diseases in any system of the human body thanks to advancements in biomedical imaging. The heart system is regarded as one of the most vulnerable systems. Due to the lack of exposure to the complexities of pertinent technology, cardiology is perceived as a complex field of practice. Through imaging modalities such as CT-scan, Magnetic Resonance Imaging (MRI), Angiogram, Electrocardiogram (ECG), and others, medical imaging is a powerful diagnostic tool that offers information about anatomical structures [6].

Cardiovascular calcifications are often seen during regular CT-scans or echocardiograms. One of the major concerns about the use of CT for CAC detection is the ionizing radiation exposure to the patient [7]. It is fundamental to weight whether the information obtained from this method offers an improvement in predictive ability over the radiation risk factor and the higher costs associated with it.

According to the European Society of Cardiology, echocardiography is the first-line approach for diagnosing and following the treatment of aortic stenosis, due to its portability, high temporal resolution, absence of radiation and low cost [8]. The echocardiogram (also known as an echo) is arguably the tool used the most frequently in the field of the cardiovascular system. It is utilized primarily because it may diagnose and treat cardiac illnesses early on. It is a quick, painless, and affordable method that can accurately display the pressure gradient of heart lesions. The Echo is regarded as being safe because it employs sound waves rather than radiation [6].

Every aspect of cardiovascular imaging, from acquisition to reporting, has been impacted by Artificial Intelligence (AI). Examples of AI-based applications include automated acquisition, segmentation, and report production; coronary calcium quantification; computed tomography and magnetic resonance imaging measurements; and diagnosis of coronary diseases. Related to echocardiography, AI can reduce observer variation and offer an accurate diagnosis [9].

DL models have been employed in many computer vision applications, such as image classification, object detection and image segmentation. From the different types of DL models, CNNs are those typically used on AI-based image analysis tasks. This type of neural networks is suitable for several computer vision tasks based on machine learning, due to their ability to automatically find the best features for the application context. Some studies such as [3], [10]–[14] show that CNNs have been successfully used for medical image segmentation and classification applications.

As referred on [15], for CT-scans there are several studies performed on (semi) automated techniques for CAC quantification; however, only a few applications are fully automated. Furthermore, in the field of echocardiography, the best approach found is a semi-automated model, so there is a need on filling this gap by constructing a fully automated model for calcium detection on this type of images, leading to faster and accurate diagnoses, while minimizing negative impacts on patients' health.

2 State of the art

2.1 Methods

This systematic review is based on PRISMA methodology [16], which means Preferred Reporting Items for Systematic Reviews and Meta-Analyses. PRISMA is focused on assisting authors in better evaluation and reporting of systematic reviews, allowing readers to understand what authors researched and concluded, which improves reporting standards and facilitates peer reviews. In this context, the question this review aims to answer is "What is the state of the art on DL-based models for automatic calcium detection on cardiac images?"

2.2 Data Extraction

The search was conducted on *Scopus* and *Web of Science Core Collection* (WoSCC) databases, in October 2022. Searching keywords have been split into 3 categories: *Concept*, *Population* and *Context*. As shown on Table 1, the search query was built by intercepting all the columns, that is *Concept* AND *Population* AND *Context*. Publication years have also been restricted to the last 4 years (2019-2022) and documents had to be reviews or articles.

Table 1- Keywords selection

<table>
<tr><th>Concept</th><th>Population</th><th>Context</th><th>Limitations</th></tr>
<tr><td>"deep learning"
"neural network"
"computer vision"</td><td rowspan="2">"computed tomography"
"ct-scan"
"echocardiography"
"ultrassound image"</td><td rowspan="3">"aortic stenosis"
"aortic calcification"
"calcium score"
"aortic sclerosis"</td><td rowspan="4">year: 2019-2022

document type: article or review</td></tr>
<tr><td>1.004.076 + 414.288</td></tr>
<tr><td colspan="2">11.268 + 4.078</td></tr>
<tr><td colspan="3">109 + 20</td></tr>
<tr><td colspan="4">80 + 12</td></tr>
</table>

2.3 Results

The search described in the previous section yielded 92 results, 80 from *Scopus* and 12 from WoSCC, which were submitted to some filtering steps, in line with PRISMA methodology. These successive steps are represented in Fig. 1.

Firstly, from those 92 results, the duplicates were removed, resulting in 82 distinct documents. These documents were analyzed and categorized, and the less significant ones were excluded, as they were out of the review scope. At the end of this cleaning process, the initial selection was reduced to 50 documents.

The document set was then refined by analyzing the research's purpose of each document. The main purpose expressed on 22 out of 50 documents is *"calcium quantification"*. Other significant expressed purposes are *"Image Analysis/Detection"* and *"Review"*. These three categories were selected for the current review, and therefore documents stating other objectives were discarded. After this purpose-oriented selection, the final document set included 38 references.

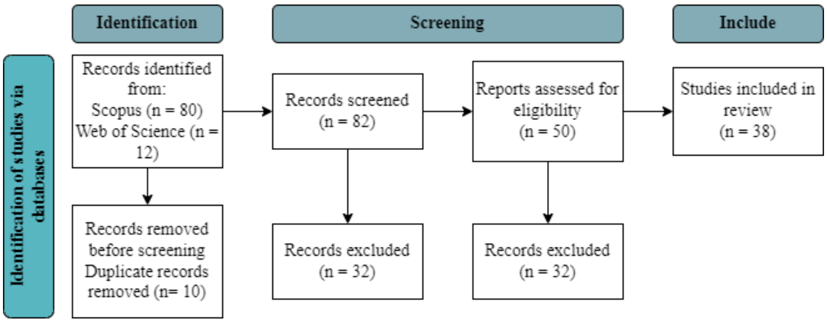

Fig. 1 – PRISMA Workflow diagram

By analyzing the topics addressed on these documents, as represented on the charts depicted in Fig. 2, it can be observed that the primary addressed topics are *Convolutional Neural Network* for ML techniques, *CT-scan* for imaging data types and *Calcium quantification/Risk analysis* in the field of application goals. For the majority of documents, these three topics are presented simultaneously.

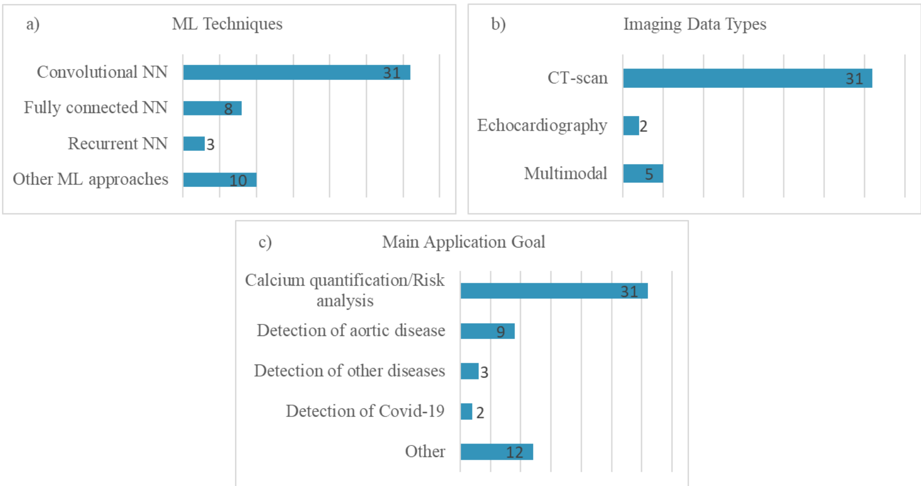

Fig. 2 – Documents distribution by ML techniques (a), imaging data types (b) and application goals (c)

Neural networks were employed in 10 documents, 26% of total selected references, with 87% of them being used for CT-Scan processing and only 13% for echocardiography, as we can see on Fig. 3.

For an easier identification of main keywords aborded by included documents, and existing relationships between them, the diagram shown on Fig. 4 was created by using VOSviewer. This diagram represents the keywords aborded, with different sizes based on occurrences. It reveals the existence of two main keywords, *"Deep Learning"* and *"Artificial Intelligence"*, followed by *"cardiovascular disease"* and *"Ma-*

chine Learning". It also divides topics into three clusters, differentiated by colors. There is evidence of an existing relationship between *"computed tomography"* and *"Deep Learning"*. In contrast, there are no stronger relations evolving echocardiography, meaning that developed DL-based studies applied to it are still scarce.

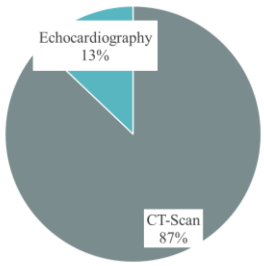

Fig. 3 – Neural Network studies

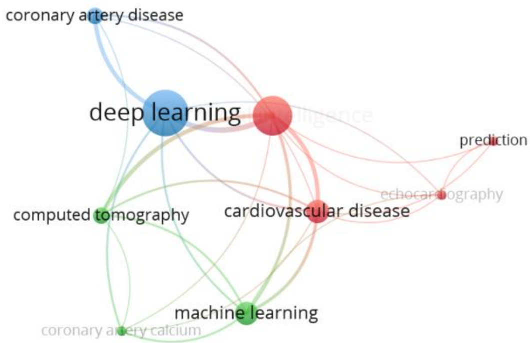

Fig. 4 – Keywords network

2.4 Goals and outcomes analysis

Considering that the main aim of this article is to identify the current applications of AI to calcium detection on cardiac images, the included references were organized by the topics they talk about, as represented on Table 2. It was feasible to recognize the expansion of AI-based models in last few years, after evaluating selected studies.

Table 2 – References distribution by topics aborded

Topic	References	# Doc	% Doc
Deep/Machine Learning	[1], [3], [8], [10]–[15], [17]–[43]	36	95%
CT-Scan	[1], [3], [10]–[15], [17]–[19], [22]–[25], [27]–[39], [41], [42], [44]	31	82%
Aortic Disease/Calcium Score	[1], [3], [8], [10], [12]–[15], [17], [18], [21]–[25], [28]–[42], [45]	31	82%
Computer Vision	[1], [3], [8], [10]–[14], [17], [18], [21], [23], [25], [29], [30], [32], [34]–[39], [42]	23	61%
Neural Network	[1], [3], [10]–[14], [29], [34], [43]	10	26%
Echocardiography/Ultrasound	[8], [20], [21], [43]	4	11%
Heart Failure	[20]	1	3%
Covid-19	[27]	1	3%

Deep Learning on cardiac images - Starting from the most popular topic, Deep Learning was referenced by 95% of the included documents. DL models have several useful applications to cardiac imaging. Fig. 5 represents some types of computer vision (CV) models, such as object detection, image segmentation and prediction, which can be a classification or regression problem.

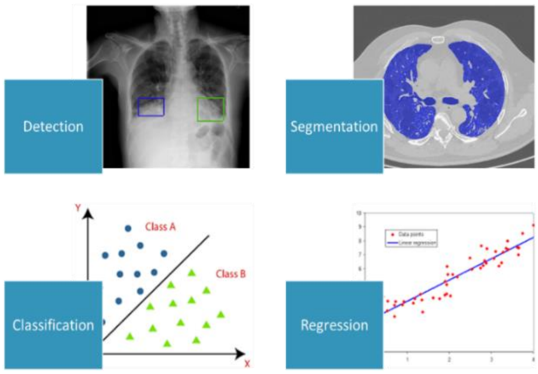

Fig. 5 – Computer Vision models

According to review [44], some examples of convolutional neural network (CNN) uses are: (a) finding a heart in a CT image, returning as output a bounding box indicating the location of the heart; (b) detection of calcium structures, using image segmentation, where the goal is to obtain a "filtered" image showing only the desired object, as represented on Fig. 6.

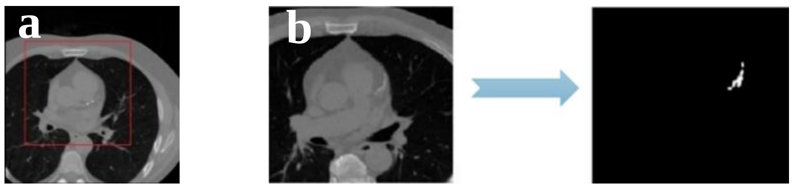

Fig. 6 – Heart identification CT-scan (a) and Calcium detection (b) on CT-scans

Last of all, DL is also helpful for prediction, which can mean classification or regression. When the goal is to determine the presence of cardiac diseases, that is a classification problem. There are two possible solutions: a binary classification model, that will separate images in two classes: "sick" or "not sick", and multiclassification model, where each disease represents a class, and each image will be assigned to a diagnosis: disease "A", "B" or "C". Regression consists of predicting a continuous value. It can be useful on quantifications, such as for calcium score in aortic valve or left ventricular ejection fraction (LVEF).

Calcium score - CAC is a very strong predictor of Cardiovascular Events (CVE), coronary heart disease, stroke, and all-cause mortality [17]. It has been an important biomarker of existing calcium structures in heart valves, which is responsible for many diseases, particularly in aortic valves, such as aortic stenosis or aortic sclerosis, especially in asymptomatic individuals. According to study [27], there is a proven correlation between high coronary calcium score and Covid-19 severity, from oxygenation measure an CT image analysis. There are several studies using AI to automate processes for detection and quantification of calcium in aortic valves. Authors from [3], with their neural network method implementation, have reached 86% of correct classification of cardiovascular risk, concluding that its implementation could increase workflow efficiency for radiologists. Furthermore, a model developed on [13] shows that it is possible to increase calcium scoring accuracy by training a CNN architecture to correct blurred CT images, reducing significatively the assessment variations from 38% to 3.7%.

Workflow efficiency improving - As referred in many studies, the implementation of a fully-automated DL model would potentially increase clinical workflow efficiency [3], [8], [15], [18], [21], [26], [37], [43]. In several cases, automated models return higher accuracy than traditional methods. Authors from review [20] affirm that in the field of Heart Failure (HF), when predicting 5-year survival rates for patients with cardiovascular disorders, ML-based AI has been shown to be more accurate (80%) than doctors (60%) in doing so. Another classification problems referenced on review [8] describe DL solutions capable of distinguish between two types of heart diseases from echocardiography images or detect systemic features such as age and sex, which is humanly impossible, with performance scores of 96.2% and 88%, respectively. Also, for quantification issues, deep neural networks are particularly helpful. On assessment of calcium score, it would help radiologists not to have to spend so much time analyzing all the screenings by hand, which is a time-consuming and boring task. When compared with manual assessment, DL-based automated calcium quantification model presented on [15] performed excellent results, supporting viability on its practical implementation. Study [30], which combined different types of examinations on the training dataset for calcium quantification, also returned a better performance against manual scoring. Other quantification problems like Epicardial Adipose Tissue (EAT) volume estimation from CT images described on [32] has demonstrated excellent results, with obtained scores matching manual ones in more than 90%. AI is not a kind of replacer of physicians but can have an important role in improving diagnosis precision.

Radiation exposure reduction - Although CT-scan is primarily used for prediction of cardiovascular diseases and mortality, there is a disadvantage associated with it: radiation exposure and its risks. Because of this, its utilization has been restricted. Trying to solve this problem, ultra-low dose (ULD) CT techniques have been created over the years, trying to decrease the effective radiation dose (ERD), according to study [17]. However, they increase noise, resulting in lower quality images. Deep neural networks may help to get around this problem. According to studies [17], [44], DL algorithms can process “noisy” images obtained by ULD-CT techniques, reducing this noise and improving images quality, which makes the use of low-radiation techniques more feasible, safeguarding patients’ health. As demonstrated on Fig. 7 from [44], an ULD-CT image (A) can be transformed into a noise reduced CT image (B).

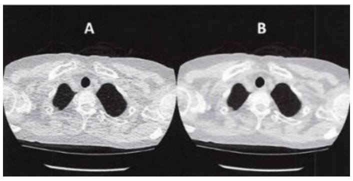

Fig. 7 – Noise reduction with DL

Another way to avoid radiation exposure is the use of echocardiography imaging. Through this method it is possible to detect many types of heart and pulmonary diseases, or assess common metrics like calcium score, without exposing patients to invasive radiation, thanks to use of sound waves instead. It is also advantageous in terms of portability and low costs associated. However, AI implementations in the field of echocardiography are still scarce, due to lower image quality resolution. Despite this, echocardiography performs an essential research method in cardiology, as the large amount of data can get off the existent challenge in quality of images [8].

3 Conclusion

Following PRISMA methodology, this literature review returned 82 distinct references, 38 meeting the desired context, which shows there is still a lot to explore in this scope. The main topics aborded are Deep Learning, calcium score and CT-scan, primarily with the purpose of calcium quantification. Neural Network is a frequently studied topic, showing several applications on cardiac images, from classification of heart diseases to detection and quantification of calcium. 87% of NN included studies were applied to CT-scans, and only remaining 13% to echocardiography.

Developed studies have obtained very high and promising results, some of them with higher performances when compared with manual techniques, proving that AI can be very helpful on increasing clinical workflow efficiency. Diagnoses become faster and more accurate, and clinical professionals can be saved from time-consuming and boring tasks.

Despite its associated risk for patients' health, due to radiation exposure, CT-scan is currently the principal type of image used on automation of cardiac images processing with DL, mainly due to its higher resolution quality. Echocardiography does not expose patients to such radiation, however results in lower resolution quality images. But this is no longer a problem since Deep Learning exists. It is possible to train a deep neural network capable of reducing images noise and improving their quality. Further developments in this field can fill the existent gap on fully automated classification methods for echocardiography, leading to a more frequent and efficient monitoring of patients and reducing physicians' workload.

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References

[1] J.-S. Hong *et al.*, “Automated coronary artery calcium scoring using nested U-Net and focal loss,” *Comput. Struct. Biotechnol. J.*, vol. 20, pp. 1681–1690, 2022, doi: 10.1016/j.csbj.2022.03.025.

[2] G. A. Roth *et al.*, “Global Burden of Cardiovascular Diseases and Risk Factors, 1990-2019: Update From the GBD 2019 Study,” *J. Am. Coll. Cardiol.*, vol. 76, no. 25, pp. 2982–3021, 2020, doi: 10.1016/j.jacc.2020.11.010.

[3] N. Gogin *et al.*, “Automatic coronary artery calcium scoring from unenhanced-ECG-gated CT using deep learning,” *Diagn. Interv. Imaging*, vol. 102, no. 11, pp. 683–690, 2021, doi: 10.1016/j.diii.2021.05.004.

[4] A. Faggiano *et al.*, “Cardiovascular Calcification as a Marker of Increased Cardiovascular Risk and a Surrogate for Subclinical Atherosclerosis: Role of Echocardiography,” *J. Clin. Med.*, vol. 10, no. 8, 2021, doi: 10.3390/jcm10081668.

[5] H. Baumgartner (chair) *et al.*, “Recommendations on the echocardiographic assessment of aortic valve stenosis: a focused update from the European Association of Cardiovascular Imaging and the American Society of Echocardiography,” *Eur. Heart J. - Cardiovasc. Imaging*, vol. 18, no. 3, pp. 254–275, Mar. 2017.

[6] I. Wahlang *et al.*, “Deep Learning Methods for Classification of Certain Abnormalities in Echocardiography,” *Electronics*, vol. 10, no. 4, 2021.

[7] D. Bos and M. J. G. Leening, “Leveraging the coronary calcium scan beyond the coronary calcium score,” *Eur. Radiol.*, vol. 28, no. 7, pp. 3082–3087, Jul. 2018.

[8] M. J. Schuuring, I. Išgum, B. Cosyns, S. A. J. Chamuleau, and B. J. Bouma, “Routine Echocardiography and Artificial Intelligence Solutions,” *Front. Cardiovasc. Med.*, vol. 8, 2021, doi: 10.3389/fcvm.2021.648877.

[9] R. Maragna *et al.*, “Artificial Intelligence Based Multimodality Imaging: A New Frontier in Coronary Artery Disease Management,” *Front. Cardiovasc. Med.*, vol. 8, Sep. 2021, doi: 10.3389/fcvm.2021.736223.

[10] J. Chamberlin *et al.*, “Automated detection of lung nodules and coronary artery calcium using artificial intelligence on low-dose CT scans for lung cancer screening: accuracy and prognostic value,” *BMC Med.*, vol. 19, no. 1, 2021.

[11] J. M. Wolterink, R. W. V. Hamersvelt, M. A. Viergever, T. Leiner, and I. Išgum, “Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier,” *Med. Image Anal.*, vol. 51, pp. 46–60, 2019.

[12] S. Lee *et al.*, “Deep-learning-based coronary artery calcium detection from ct image,” *Sensors*, vol. 21, no. 21, 2021, doi: 10.3390/s21217059.

[13] Y. Zhang, *et al.*, “Motion-corrected coronary calcium scores by a convolutional neural network: a robotic simulating study,” *Eur. Radiol.*, vol. 30, no. 2, pp. 1285–1294, 2020, doi: 10.1007/s00330-019-06447-7.

[14] F. N. Guilenea *et al.*, “Thoracic aorta calcium detection and quantification using convolutional neural networks in a large cohort of intermediate-risk patients,” *Tomography*, vol. 7, no. 4, pp. 636–649, 2021.

[15] M. van Assen *et al.*, “Automatic coronary calcium scoring in chest CT using a deep neural network in direct comparison with non-contrast cardiac CT: A validation study,” *Eur. J. Radiol.*, vol. 134, 2021, doi: 10.1016/j.ejrad.2020.109428.

[16] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, “Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement,” *BMJ*, vol. 339, p. b2535, Jul. 2009, doi: 10.1136/bmj.b2535.
[17] M. Klug *et al.*, “A deep-learning method for the denoising of ultra-low dose chest CT in coronary artery calcium score evaluation,” *Clin. Radiol.*, vol. 77, no. 7, pp. e509–e517, 2022, doi: 10.1016/j.crad.2022.03.005.
[18] W. Wang, L. Yang, S. Wang, Q. Wang, and L. Xu, “An automated quantification method for the Agatston coronary artery calcium score on coronary computed tomography angiography,” *Quant. Imaging Med. Surg.*, vol. 12, no. 3, pp. 1787–1799, 2022, doi: 10.21037/qims-21-775.
[19] D. H. Yang, “Application of artificial intelligence to cardiovascular computed tomography,” *Korean J. Radiol.*, vol. 22, pp. 1–12, 2021.
[20] F. Yasmin *et al.*, “Artificial intelligence in the diagnosis and detection of heart failure: the past, present, and future,” *Rev. Cardiovasc. Med.*, vol. 22, no. 4, pp. 1095–1113, 2021, doi: 10.31083/j.rcm2204121.
[21] F. Yang *et al.*, “Automated Analysis of Doppler Echocardiographic Videos as a Screening Tool for Valvular Heart Diseases,” *JACC Cardiovasc. Imaging*, vol. 15, no. 4, pp. 551–563, Apr. 2022, doi: 10.1016/j.jcmg.2021.08.015.
[22] D. Eng *et al.*, “Automated coronary calcium scoring using deep learning with multicenter external validation,” *Npj Digit. Med.*, vol. 4, no. 1, 2021.
[23] P. M. Graffy, J. Liu, S. O’Connor, R. M. Summers, and P. J. Pickhardt, “Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort,” *Abdom. Radiol.*, vol. 44, no. 8, pp. 2921–2928, 2019.
[24] C. Xu *et al.*, “Automatic coronary artery calcium scoring on routine chest computed tomography (CT): comparison of a deep learning algorithm and a dedicated calcium scoring CT,” *Quant. Imaging Med. Surg.*, vol. 12, no. 5, pp. 2684–2695, 2022, doi: 10.21037/qims-21-1017.
[25] M. J. Emaus *et al.*, “Bragatston study protocol: A multicentre cohort study on automated quantification of cardiovascular calcifications on radiotherapy planning CT scans for cardiovascular risk prediction in patients with breast cancer,” *BMJ Open*, vol. 9, no. 7, 2019, doi: 10.1136/bmjopen-2018-028752.
[26] S. J. Al’Aref *et al.*, “Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging,” *Eur. Heart J.*, vol. 40, no. 24, pp. 1975–1986, 2019, doi: 10.1093/eurheartj/ehy404.
[27] Y. Takeshita *et al.*, “Coronary artery calcium score may be a novel predictor of COVID-19 prognosis: A retrospective study,” *BMJ Open Respir. Res.*, vol. 8, no. 1, 2021, doi: 10.1136/bmjresp-2021-000923.
[28] W. Wang *et al.*, “Coronary artery calcium score quantification using a deep-learning algorithm,” *Clin. Radiol.*, vol. 75, no. 3, p. 237.e11-237.e16, Mar. 2020.
[29] L. B. van den Oever *et al.*, “Deep learning for automated exclusion of cardiac CT examinations negative for coronary artery calcium,” *Eur. J. Radiol.*, vol. 129, 2020, doi: 10.1016/j.ejrad.2020.109114.

[30] S. G. M. van Velzen *et al.*, “Deep learning for automatic calcium scoring in CT: Validation using multiple cardiac CT and chest CT protocols,” *Radiology*, vol. 295, no. 1, pp. 66–79, 2020, doi: 10.1148/radiol.2020191621.
[31] D. J. Winkel *et al.*, “Deep learning for vessel-specific coronary artery calcium scoring: validation on a multi-centre dataset,” *Eur. Heart J. Cardiovasc. Imaging*, vol. 23, no. 6, pp. 846–854, 2022, doi: 10.1093/ehjci/jeab119.
[32] A. Hoori, T. Hu, J. Lee, S. Al-Kindi, S. Rajagopalan, and D. L. Wilson, “Deep learning segmentation and quantification method for assessing epicardial adipose tissue in CT calcium score scans,” *Sci. Rep.*, vol. 12, no. 1, 2022.
[33] B. Jiang *et al.*, “Development and application of artificial intelligence in cardiac imaging,” *Br. J. Radiol.*, vol. 93, no. 1113, 2020, doi: 10.1259/bjr.20190812.
[34] B. D. de Vos *et al.*, “Direct Automatic Coronary Calcium Scoring in Cardiac and Chest CT,” *IEEE Trans. Med. Imaging*, vol. 38, no. 9, pp. 2127–2138, 2019.
[35] G. Singh *et al.*, “End-to-end, pixel-wise vessel-specific coronary and aortic calcium detection and scoring using deep learning,” *Diagnostics*, vol. 11, no. 2, 2021, doi: 10.3390/diagnostics11020215.
[36] M. T. Winkelmann *et al.*, “Fully Automated Artery-Specific Calcium Scoring Based on Machine Learning in Low-Dose Computed Tomography Screening,” *RoFo Fortschritte Auf Dem Geb. Rontgenstrahlen Bildgeb. Verfahr.*, vol. 194, no. 7, pp. 763–770, 2022, doi: 10.1055/a-1717-2703.
[37] J. Lee *et al.*, “Fully Automatic Coronary Calcium Score Software Empowered by Artificial Intelligence Technology Validation Study Using Three CT Cohorts,” *KOREAN J. Radiol.*, vol. 22, no. 11, pp. 1764–1776, Nov. 2021.
[38] N. Zhang *et al.*, “Fully automatic framework for comprehensive coronary artery calcium scores analysis on non-contrast cardiac-gated CT scan: Total and vessel-specific quantifications,” *Eur. J. Radiol.*, vol. 134, 2021.
[39] R. Gal *et al.*, “Identification of Risk of Cardiovascular Disease by Automatic Quantification of Coronary Artery Calcifications on Radiotherapy Planning CT Scans in Patients with Breast Cancer,” *JAMA Oncol.*, vol. 7, no. 7, pp. 1024–1032, 2021, doi: 10.1001/jamaoncol.2021.1144.
[40] J. Lee *et al.*, “Prediction of Coronary Artery Calcium Score Using Machine Learning in a Healthy Population,” *J. Pers. Med.*, vol. 10, no. 3, Sep. 2020.
[41] P. T. Lauzier *et al.*, “The Evolving Role of Artificial Intelligence in Cardiac Image Analysis,” *Can. J. Cardiol.*, vol. 38, no. 2, pp. 214–224, 2022.
[42] J. Waltz, M. Kocher, J. Kahn, M. Dirr, and J. Burt, “The Future of Concurrent Automated Coronary Artery Calcium Scoring on Screening Low-Dose Computed Tomography,” *CUREUS*, vol. 12, no. 6, Jun. 2020, doi: 10.7759/cureus.8574.
[43] C. Antoniades, F. W. Asselbergs, and P. Vardas, “The year in cardiovascular medicine 2020: Digital health and innovation,” *Eur. Heart J.*, vol. 42, no. 7, pp. 732–739, 2021, doi: 10.1093/eurheartj/ehaa1065.
[44] L. B. van den Oever *et al.*, “Application of artificial intelligence in cardiac CT: From basics to clinical practice,” *Eur. J. Radiol.*, vol. 128, 2020.
[45] L. Hahn, K. Baeumler, and A. Hsiao, “Artificial intelligence and machine learning in aortic disease,” *Curr. Opin. Cardiol.*, vol. 36, no. 6, pp. 695–703, Nov. 2021, doi: 10.1097/HCO.0000000000000903.