RESEARCH PAPER

Overview of Machine Learning and AI Algorithms is Being Integrated into Coronary Artery Calcium Scoring

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Abstract

Coronary Artery Calcium Scoring (CACS), using the Agatston score in particular, is commonly utilized in early detection and assessment of coronary artery disease (CAD). ECG-gated CT scans have historically complemented the procedure using technologies such as EBCT, MDCT, and DSCT. Although effective, these methods are challenged by accuracy and efficiency. Techniques have been revolutionized with advancements in artificial intelligence (AI), especially with deep learning techniques such as convolutional neural networks (CNNs). These technologies now make it possible to conduct fully automated calcium scoring from gated and non-gated CT scans with increased speed and accuracy. AI also makes it possible to derive complex imaging characteristics, including lesion location and density, improving cardiovascular risk prediction. New models integrating clinical, anatomical, and imaging data are assisting in making more personalized treatment plans. Yet, challenges like data unpredictability, limited clarity of AI algorithms, and data privacy and fairness issues persist. In spite of that, AI incorporation represents a significant leap in cardiovascular imaging, with ongoing exploration and regulation essential for safety and efficacy in clinical practice.

Keywords: Coronary Artery disease; cardiovascular disease; Artificial intelligence; Deep learning; Multidetector Computed Tomography; Electron Beam Computed Tomography

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INTRODUCTION

In specialized CT imaging, coronary artery calcium (CAC) scoring is frequently employed to determine coronary atherosclerotic plaque load and predict cardiovascular disease risk (CVD). (van Velzen et al., 2020). This is one of the best-studied and most available diagnostics in cardiovascular medicine. (Greenland et al., 2018). Since intravenous contrast is not required, CAC is generally assessed noninvasively with the use of electrocardiogram-gated computed tomography (CT) imaging of the heart. Hecht HS et al., 2015). Calcium deposits in the coronary arteries, an indication of vascular calcification and burden of atherosclerotic plaque, are measured in CAC scoring. The progression of Coronary Artery Calcium types is depicted in Figure 1 (Quddus R et al., 2024). Acute coronary syndrome (ACS), myocardial infarction (MI), and even life-threatening coronary thrombosis may be triggered by the breaking or erosion of plaques with time (Nguyen AM et al., 2024). In a 15-year follow-up study in recent times, the mortality among patients with zero CAC was very low and increased progressively with increasing risk classes of CAC scores (1–99, 100–399, and >_400) (Gräni et al., 2018). The Society of Thoracic Radiology (STR) and the Society of Cardiovascular Computed Tomography (SCCT) have now included coronary artery calcium (CAC) scanning in their guidelines and appropriateness criteria for atherosclerotic cardiovascular disease (ASCVD) risk assessment in asymptomatic individuals (Hecht et al., 2018; Greenland et al., 2010). Numerous studies reveal a dose-response relationship between rising CAD burden and cardiovascular risk, and the lack of CAD on CCTA indicates low incidence for cardiovascular events (Al'Aref et al., 2019; Budoff et al., 2008; Miller et al., 2008). The American Heart Association (AHA), American College of Cardiology (ACC), and European Society of Cardiology (ESC) each have practice guidelines for the management of stable angina chest pain that support the use of CCTA as a first or second-line diagnostic tool in symptomatic patients presenting with suspected obstructive CAD (Al'Aref et al., 2019;

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Cho I et al., 2015; Lin FY et al., 2010). But in everyday clinical practice, a substantial majority of patients who received CCTA had minimal or no CAD (Al'Aref et al., 2019; Montalescot G et al., 2013; Fihn SD et al., 2012). In contrast to traditional work-ups with stress testing, coronary CTA enables rapid assessment of patients, with reduced time to diagnosis and discharge.1 through 3 The high negative predictive value for excluding severe coronary stenosis and ACS is the key benefit of coronary CTA (Ferencik et al., 2019). The three CAC scoring methods are the Agatston score, volume score, and mass score (Table 1).

Among them, the Agatston method is most popular and accepted as the gold standard. In regard to the whole area and the maximum calcification attenuation, the Agatston score is a weighted summation of calcified plaques (Gupta, A et al., 2022). Artificial intelligence (AI) provides unique advantages in coronary artery calcium score (CACS) and cardiovascular disease (CVD) risk prediction, with its use in medicine and radiology increasing. AI can potentially extract quantitative CACS from standard chest CT protocols that are not specifically intended for this, including cardiac CT angiography (CCTA), low-dose CT (LDCT), and positron emission tomography (PET)/CT attenuation scans. AI can also upgrade the time-consuming, tedious, and labor-intensive tasks of calcium segmentation and quantification (Aromiwura AA et al., 2024).

1. Traditional CAC Scoring Methods:-

1.1. Agatston Score (AS)

In clinical practice, the most widely used scoring system is the AS. The first suggestion was made by Warren Janowitz and Arthur Agatston in 1990. The AS is acquired with electron beam (EB) CT with a 512 × 512 reconstruction matrix, 3-mm slice thickness, 130-KVp tube voltage, and 630mAs tube current. A 3-mm slice thickness, variable mA based on patient body weight, and 120 kVp have been used to convert the score to multidetector CT (MDCT). The rating considers both the peak coronary calcific density and total area, and is obtained by summing the rating of all the calcified lesions (Figures 2 and 3). Lesions with an area ≥ 1 mm2 and CT attenuation > 130 Hounsfield units (HU) are excluded to avoid image noise (Figure 4). A density weighting factor (DWF) is used to multiply the lesion area to calculate the individual lesion score. A maximal CT attenuation value of a given calcified plaque is applied to derive the DWF (DWF: 130 to 199 HU = 1; 200 to 299 HU = 2; 300 to 399 HU = 3; and ≥ 400 HU = 4).AS (lesion) = Area × DWF 9) In order to determine the overall AS, individual scores—irrespective of location or distribution—are then added up.AS (total) = ∑AS (lesion) (Kumar P et al., 2023). The CAC score enables collaborative decision-making in symptom-free individuals. Following Agatston CAC grading, increased CAC measurements can be used as an additional "biomarker" to improve risk prediction in patients with intermediate CAC values (Top). Identification of high-risk cases for the most aggressive preventive therapy would be a principal role, although some patients would be reclassified downward. Instead, using advanced CAC measures, an entirely new CAC score could be constructed, perhaps enhancing risk prediction in all patients (Bottom) (Figure 5). (Blaha, M.J. et al., 2017).

1.2. Fundamental framework for building a new CAC score

It is necessary to step back and examine fundamental questions about the nature of the CAC score and consider how to refine it. To inform and frame the development of a new scoring system, answers to these questions are essential. First, why does CAC scoring predict coronary risk so well? This topic is addressed by advances in our understanding of the relationship between atherosclerosis and acute coronary events. Whereas the scientific community once was interested in identifying occult obstructive coronary disease, we now understand that the most sensitive predictor of future events in asymptomatic individuals is the total burden of atherosclerosis and not lumen stenosis. For it to be most effective, a new score must be equally easy to play and read quickly.

More precisely, a new CAC score must be at least as repeatable as the Agatston score in terms of observer and scan variability. A new CAC score should ideally be qualitatively reproducible on non-gated chest CT scans. The Society of Cardiovascular Computed Tomography and the Society of Thoracic Radiology have published a new recommendation statement advocating for at least qualitative CAC scoring on all nongated chest CT scans, in response to mounting evidence regarding the value of qualitative CAC scoring on lung cancer screening studies.(Blaha MJ et al., 2017; Hecht HS et al., 2017). The effect of including the number of lesions, max HU, distancebased and territories, and distribution of CAC along territories (diffusivity) in addition to the mass score model was tested, and the effect of mass scores was tested using multivariable Cox models. Cox modeling, which is a machine learning method, provides interpretable results that are able to account for the effect of image features that deep learning cannot. All of the Cox models in our investigation were trained and evaluated using the same data in order to improve comparability. (Hoori A et al., 2024).

2. Artificial Intelligence in Medical Imaging

In recent years, the use of artificial intelligence (AI) techniques in radiology has increased dramatically in a number of fields, including cardiac imaging.(Rogers, et al., 2019; Lim et al., 2020).

Furthermore, the potential of AI in medical imaging to transform clinical practice by facilitating picture acquisition and interpretation, improving image quality, and disease detection has generated a lot of enthusiasm.(Rubin et al., 2019). The AI application has also been shown to improve risk stratification and prediction across a broad array of disciplines and disease phases (Table 2). Using artificial intelligence in cardiovascular imaging via "radiomics" would enhance disease diagnosis and, ultimately, prognosis. All imaging modalities have embraced AI, with it now being used for autonomous measurements and image segmentation, such as the autonomous assessment of coronary artery calcium (CAC). (Abdelrahman et al., 2024). As a helpful add-on tool in clinical use, artificial intelligence (AI) is increasingly being used in diagnostic medicine and radiology to deliver objective and reproducible diagnoses by extracting relevant features from medical imaging information and applying them to classifiers for the automated identification of cardiovascular disease. A type of artificial intelligence referred to as machine learning, or in some cases as deep learning, employs algorithms to merge extensive amounts of data, such as clinical data and coronary anatomical features, to forecast cardiac events as precisely as possible. (Wang W et al., 2019). Through enhanced image generation and more precise diagnoses, artificial intelligence (AI), particularly via machine learning (ML) techniques such as convolutional neural networks (CNNs), has the ability to revolutionize cardiac CT entirely. These AI-based technologies have the capability to significantly streamline the imaging process, allowing radiologists to have increased time to work and deliver results. This acceleration of workflow is important as it allows doctors to initiate patient interventions earlier on, which can have improved outcomes. (ToluAkinnawo OZ et al., 2025).

3. Deep learning in Medical Imaging

A fully automatic branch-level CAC scoring algorithm using DL and involving the left main (LM), left anterior descending (LAD), circumflex (CX), and right coronary artery (RCA) regions was available and tested. The goal was to assess whether the total Agatston scores of the automated model were well correlated with the manual Agatston scoring and whether the vessel labels it provided were concordant with human readers. (David J Winkel et al., 2022). To evaluate whether an automated CACS detector that allows CT calcium score imaging quantification can have an equivalent risk prediction for cardiac risk stratification with a similar degree of convenience to manual measurement, the present study was undertaken.(Wang W et al., 2019).

An aggregation of DL methods integrates a variety of models to enhance the functionality of CAC detection systems. Bagging, boosting, and stacking are some methods that enhance robustness in complex or uncertain situations through counterbalancing the limitations of individual models.(Vivekanandan DD et al., 2024).

3.1.Algorithmic Analysis

The obtained signals were subjected to sophisticated algorithms for anomaly identification and pattern recognition, such as machine learning models and signal processing techniques.(Rana N et al., 2025).

3.2.Outcome Prediction

Most imaging markers of cardiovascular risk, such as radiomics, body fat, plaque morphology, and CAC score, are being integrated into traditional clinical risk factors to develop prediction models that will improve the performance of current risk scores and prognostic tools. AI plays a key role in this process because it enables the combination of imaging and clinical data, as well as the inclusion of additional clinical factors. Several fusion models that merge multiple resources have been developed and effectively used for detecting acute CVD, phenotyping CVD, and assessing CVD risk and severity. (Onnis C et al., 2024).

4. Ethics, Limitations, and Standards of Artificial Intelligence in CAD Imaging

The ease with which machine learning can access data may lead to ethical issues. Big data analysis can be completed in minutes, raising concerns about proper consent and secure PHI storage. For physicians wanting to incorporate these practices, the "black box" nature of AI might cause confusion. To prevent biased outcomes and unintended extrapolation, clinicians need to understand AI's limitations and specific validation (Covas P et al., 2022).

5. Objectives And Scope of the Review

The CACS was postulated by Agatston et al. in 1990, who provided essential information on the ability of (electron-beam) CT to measure CAC. Irrespective of the tremendous technological breakthroughs in CT scanners over the years since then, the longevity of CACS was ensured by the beauty and simplicity of the proposed method. The Agatston score is a radiological entity derived from non-contrast, 3 mm electrocardiogram-gated (ECG-gated) images. It employs a semiautomated calcified plaque quantification based on 1 mm2 and 130 Hounsfield Units (HU) as the lowest cutoffs to differentiate calcified plaques from noise. The weighted sum score of the peak density multiplied by the area of the plaque, summed across all qualifying lesions, is the Agatston score. (Gennari AG et al., 2024).

5.1. Image requirements

The spatial resolution and contrast-to-noise ratio (CNR) of CT images should be superb for AI analysis. Reducing the radiation exposure has to be balanced with this requirement. Current routine CT scanning is already employing new deep-learning image reconstruction methods, which can aid in this direction. Still, radiation levels and image reconstruction methods need to be manipulated. This may mean that various types of CT imaging could be successfully processed, and the image type is not the most important factor. (Yamaoka T et al., 2023)

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6. TRADITIONAL METHODS OF CAC SCORING

6.1. Non-gated chest CT model: internal validation

For the Stanford test set, there was almost perfect agreement (Kappa = 0.84, $P < 0.0001$) when the CAC scores automatically and manually derived were compared with each other using Cohen's

Kappa statistic. In the MESA test set, there was moderate agreement (Kappa = 0.52, $P < 0.0001$)

(Fig. 6). As per current cholesterol recommendations, the statin drug must be initiated once the CAC score is ≥100 in an attempt to reduce the risk of future CVD events. Positive predictive values and sensitivity were exhibited by the non-gated model for binary classification of patients with CAC scores ≥100. (Eng D et al., 2021).

6.2. Non-gated chest CT model: external validation

The non-gated model was externally validated with data from four sites. Substantial agreement existed at site 1 (Kappa = 0.80, $P < 0.0001$), fair agreement at sites 2 and 3 (Kappa = 0.68 and 0.64, respectively; $P < 0.0001$), and fair agreement at site 4 (Kappa = 0.58, $P < 0.0001$) when bucketed CAC values were compared using Cohen's Kappa statistic. At all sites, the diagnostic accuracy for detecting any CAC (≥1) was excellent (sensitivity range: 82–94% and PPV range: 87–100%). The greatest sensitivity and PPV for detecting CAC ≥ 100 were found at Sites 1 and 2.
(Eng D et al., 2021).

7. Electron Beam Computed Tomography (EBCT).

It became known during the 1960s that the pathophysiology behind the development of atherosclerotic plaque was associated with calcium deposition within the coronary arteries. It also became known that fluoroscopy could be utilized in order to visualize calcification. In a groundbreaking study of coronary calcium quantitation, Agatston et al. (1990, researchers identified regions of high attenuation in the heart on EBCT images shortly after the technology had been invented. A calcium score was generated by EBCT-measured coronary calcification in 88 subjects based on the number, area, and attenuation of calcifications. The authors only sought to illustrate that EBCT was better than fluoroscopy for detecting calcification; the predictive value of the calcium score was still uncertain. (Kulkarni et al., 2021). EBCT employs a fixed source/detector assembly in which a rotating electron beam is scanned back and forth across a series of one to four semicircular tungsten targets to generate X-rays.

It is also known as ultrafast computed tomography (CT) (Imatron C-100, C-150) and cine-CT. The imaging chain contains no moving parts, so scanning can be performed in rapid succession over the cardiac cycle or at specified times. (Rumberger JA et al., 1997). The whole heart may be scanned during one or two short breath holds. Standardized methods are now available for employing EBCT to scan, detect, and quantify coronary artery calcium. (Rumberger et al., 1999). Coronary artery calcium is detected by executing sequential, single-slice, 3-mm-thick, 100-ms scans. During as many cardiac cycles as possible, 40 successive heart tomograms synchronized with the heart rate during late diastole can be obtained using this "high resolution" volume scanning mode. Two successive breath holds may be required to obtain scans from the origin of the aorta and the left main coronary artery origin through distal right coronary artery sections, depending on the pulse rate. When the field of view is 300 mm, the in-plane spatial resolution is 0.4 mm2. Coronary artery calcium can be identified without an intravenous contrast injection because the calcification of the arterial walls exhibits comparatively high Hounsfield (H) densities, which are two to ten times higher than those of the surrounding soft tissue. Since high-density intramural coronary calcium deposits lie adjacent to low-density soft tissue and pericardiac fat, it is fairly simple to visually discern calcium to determine the calcium burden of the coronary arteries using EBCT (Rumberger JA et al., 1997). EBCT possesses minimal motion artifacts and superb temporal resolution and is therefore ideal for imaging fast-moving objects such as the beating heart.

8. Dual Source Computed Tomography (DSCT)

The DSCT system being tested has two X-ray tubes and two corresponding detectors. The two acquisition systems are mounted with a 90° angular offset on the rotating gantry. Because of the limited space available on the gantry, one detector (A) scans the entire scan field of view (50 cm in diameter), and the other detector (B) scans a smaller central field of view (26 cm in diameter). (Fig. 7). (Flohr TG et al., 2006). We looked at two methods of combining CTCA and CS. First, we discovered whether a low CS could be applied to exclude significant coronary artery stenoses misinterpreted by CTCA, and whether a high CS could be applied to detect stenoses that CTCA missed. (Leschka, S et al., 2015).

9. Multidetector Computed Tomography (MDCT)

Increased x-ray tube rotation speed (from 1 sec/rotation to 0.5 sec/rotation) and tube rotation speed number of detectors are the key technological advances of MDCT. Detectors are stacked on the patient's long axis (the z-axis) in MDCT use, and with every rotation of the x-ray tube, four to sixteen CT slices can be collected. Detectors run in alignment along the axial plane of the patient (the X-axis) in standard CT scanners. Multichannel helical CT and multidetector-row CT are synonyms. MDCT design in the majority of instances reduces scanning time to less than one minute and greatly expands volume covered. In conventional CT, electrical cables run through detectors and the x-ray tube, restricting them from rotating more than 180 degrees. MDCT, however, does not have electrical cords within the gantry due to its slide ring technology. These metal conducting rings avoid cable twisting and allow unbroken high-speed rotation of the X-ray tube and detector array. (El-Khoury GY et al., 2004). Though MDCT emits more radiation dosage than EBCT, it is used to enhance spatial resolution and allow 3D reconstruction of coronary anatomy.

10. Clinical Applications and Real-World Deployments

The ability of a clinical test to first recognize an illness and subsequently assist in implementing measures that influence the natural course of the disease and improve outcomes characterizes its value. Coronary artery calcium is special in that it can be visualized by CT and also is a risk factor for CAD (George A et al.,2008). Wang et al. studied a patient cohort with no CAD diagnosis in the Multi-Ethnic study of Atherosclerosis (MESA) study. Myocardial blood flow was measured through MRI at rest and hyperemia induced by adenosine, and multi-detector CT was employed to calculate the Agatston scores for coronary calcification. The research proved that myocardial perfusion reserve in asymptomatic individuals was inversely related to the severity and presence of CAC irrespective of the presence of CAD risk factors (Wang L et al., 2006).

11. Future Directions and Challenges

This approach may determine the most appropriate individuals for CAC scoring, thus alleviating concerns regarding radiation exposure and healthcare costs. Furthermore, advancements in risk assessment algorithms and imaging technology are likely to enhance the accuracy and applicability of CAC scoring across various patient populations. These advancements could enhance the reliability of CAC score results and promote its application as a cardiovascular risk assessment tool. Enabling the integration of CAC scoring into routine clinical practice involves intercooperation from all stakeholders, such as clinicians, researchers, and lawmakers (Majhi L et al., 2022).

Conclusion

Coronary Artery Calcium Scoring (CACS), particularly via the Agatston method, remains a key noninvasive tool for evaluating coronary atherosclerotic burden and cardiovascular risk. Traditional imaging techniques such as EBCT, MDCT, and DSCT have supported accurate calcium quantification. However, limitations exist in precision and applicability, especially for intermediate-risk individuals. Artificial intelligence (AI), including machine learning (ML) and deep learning (DL) methods like convolutional neural networks (CNNs), is revolutionizing CACS by enabling automated, reproducible scoring from both gated and non-gated CT scans. These innovations enhance workflow efficiency and facilitate the extraction of advanced imaging features, improving risk prediction. Notwithstanding these advances, ethical and regulatory considerations—such as data security and model transparency—must be addressed. Ultimately, integrating AI into CACS presents a promising step toward more personalized, efficient, and accurate cardiovascular risk assessment, provided rigorous validation and multidisciplinary collaboration continue.

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Authors involvement-

Shipra Saroj conceptualized the review topic, led the literature search, wrote the section on artificial intelligence, and wrote the initial draft of the manuscript.

Sohel Rana contributed to data extraction and thematic organization of the review.

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Table 1. Methods for Calculating CAC Score (Gupta, A et al., 2022).

Calcium scoring method	**Strengths**	**Limitations**
Agatston score Score (*Calculated as plaque area × attenuation weighting factor*)	Most extensively studied and commonly applied method; considered the reference standard- Straightforward postprocessing methodology	Susceptible to fluctuations caused by minor image noise- Requires strict compliance with the original protocol for consistency- Exhibits limited reproducibility between repeated scans
Volume score (*Calculated as plaque area × slice thickness*)	Less influenced by minor variations in image noise- Simple and efficient postprocessing- Demonstrates improved reproducibility across serial scans	Does not incorporate plaque attenuation into the calculation- Lower validation in clinical research compared to Agatston score
Mass score (*Calculated as plaque volume × calibration factor × mean plaque attenuation*)	Provides a more direct measurement of calcium hydroxyapatite content in the plaque- Demonstrates greater resistance to noise-related variability- Offers enhanced reproducibility in repeated examinations	Involves more complex and timeintensive postprocessing- Least validated method, with limited clinical data supporting its use

Table 2. Clinical Application of Artificial Intelligence in Cardiac Imaging.(Abdelrahman et al., 2024)

Category	**Clinical Application**	**Description**	**Clinical Advantage**
Image Acquisition	**Radiation Dose Reduction**	Deep learning-based reconstruction algorithms simulate high-quality images from low-dose CT data	Preserves diagnostic image quality while significantly lowering radiation exposure to patients
	CMR Plane Positioning	AI automatically identifies key anatomical landmarks for precise slice alignment	Produces standardized, reproducible, and diagnostically accurate imaging planes

	CMR Acquisition Time Reduction	DL accelerates cine sequence acquisition through undersampling and image reconstruction	Minimizes scan duration and number of breathholds, especially beneficial for pediatric or uncooperative patients
Image Optimization	**Denoising**	AI-driven models remove noise and correct motion artifacts from raw imaging datasets	Improves clarity and accuracy of image interpretation across modalities
	Non-contrast Image Enhancement	AI enhances soft tissue contrast and visibility in noncontrast images	Avoids the need for gadolinium or iodinebased contrast agents, reducing potential risks for renal patients
Outcome Prediction	**MACE Risk Prediction**	ML models synthesize clinical history, laboratory data, and imaging biomarkers to assess MACE risk	Enhances prediction accuracy beyond traditional risk models and facilitates early intervention
Coronary Artery Disease	**Coronary Calcium Scoring**	Automated or semiautomated CAC scoring from ECGgated and non-ECGgated CT	Enables faster and reproducible risk stratification using widely accessible CT techniques
	Plaque Characterization	DL models classify atherosclerotic plaque types and detect highrisk features (e.g., low-attenuation, napkin-ring sign)	Reduces manual evaluation time and supports early identification of vulnerable plaques
	CT-derived FFR (CT-FFR)	ML calculates fractional flow reserve using coronary CT angiography without invasive procedures	Offers functional assessment of stenosis severity with reduced cost, time, and patient risk
	Epicardial Fat Quantification	AI segments and quantifies pericoronary and epicardial adipose tissue	Provides novel markers for cardiovascular risk, with reduced manual workload
	Myocardial Infarction Assessment	AI detects and segments infarcted regions on noncontrast CMR sequences	Eliminates contrast use, improves workflow, and enhances prognostic accuracy

Myocardial Function	**Volume Analysis**	AI automatically segments ventricular cavities for calculating ejection fraction, EDV, and ESV	Saves time, standardizes measurements, and reduces inter-observer variability
	Myocardial Strain Measurement	AI quantifies strain from cine or tagged MR images, eliminating need for dedicated sequences	Increases adoption and diagnostic depth of strain imaging, even in routine settings
Valvular Heart Disease	**AI-Based Classification**	AI assesses and grades severity of valvular dysfunction from flow velocity and regurgitation data	Streamlines diagnosis, reduces reporting time, and supports early intervention planning
Cardiomyopathies	**Disease Classification and LGE Evaluation**	AI detects hypertrophic, dilated,	Improves diagnostic precision and supports
		or restrictive patterns, and evaluates late gadolinium enhancement (LGE)	long-term prognosis evaluation
Congenital Heart Disease (CHD)	**Image Acquisition & Reconstruction**	AI-assisted protocols optimize acquisition of high-resolution images tailored for complex CHD anatomy	Enhances image quality and reduces scanning/postprocessing time, critical in pediatric populations

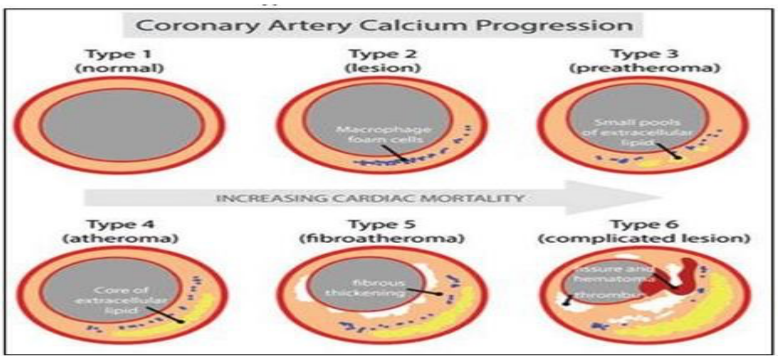

Figure 1 : Pathophysiology of coronary artery calcification progression (Quddus R et al., 2024)

Figure 2: Example of Agatston and volume score calculation. The illustration displays a single 3 mm² calcified plaque with a maximum CT number of 175 HU. The area of the lesion is multiplied by the

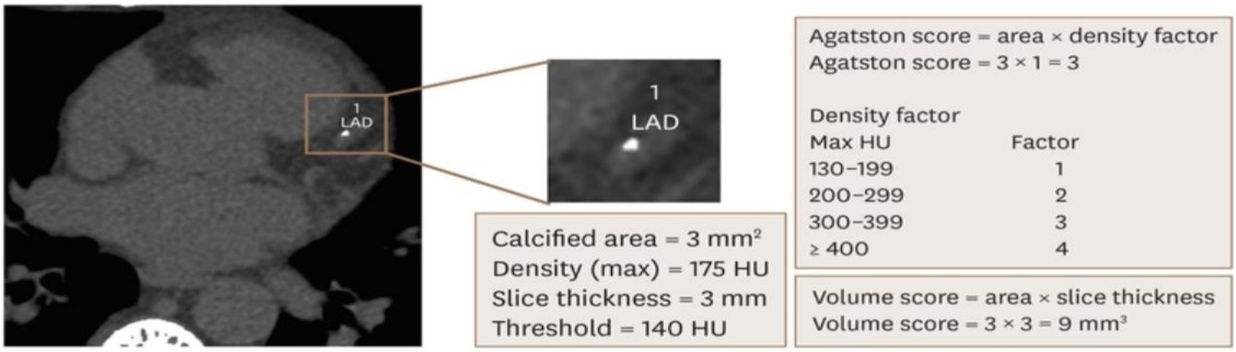

Figure 3 : Calcium score for the heart. (A) A non- contrast ECG gated axial CT scan of the coronary arteries shows that the anatomic region of the proximal segments of the left circumflex (blue) coronary arteries, the proximal segment of the RCA (red), and its branch has several calcified plaque. The aortic

density factor to determine the Agatston score. Predetermined cutoff values are used to calculate the density factor. The calculated area multiplied by slice thickness yields the volume score. The final result is produced by adding the scores for each individual lesion. (Kumar P et al., 2023)root's calcification are shown by the white spots. (B) The CT workstation's measurement table shows each coronary artery's Agatston, volume, and mass calcium scores as well as the overall score. 130 HU is the cutoff point for determining the Agatston score. 0.81nis the mass calibration factor. (Kumar P et al., 2023)

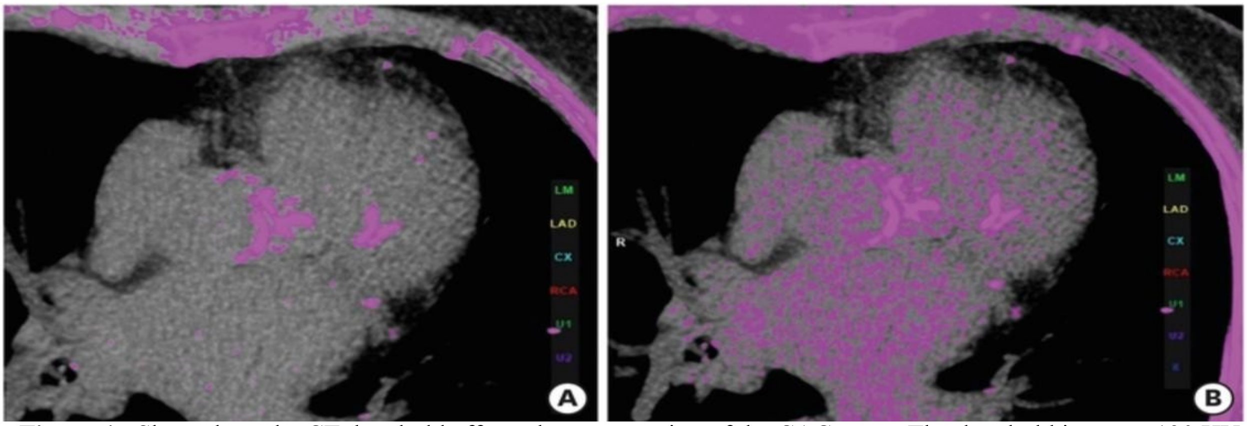

Figure 4 : Shows how the CT threshold affects the computation of the CAC score. The threshold is set at 130 HU in (A) and 110 HU in (B). Image noise significantly increases when the threshold is lowered by 20 HU, which may change the final score. (Kumar P et al., 2023)

Figure 5 : Moving Beyond the Agatston Score (Blaha, M.J. et al., 2017).

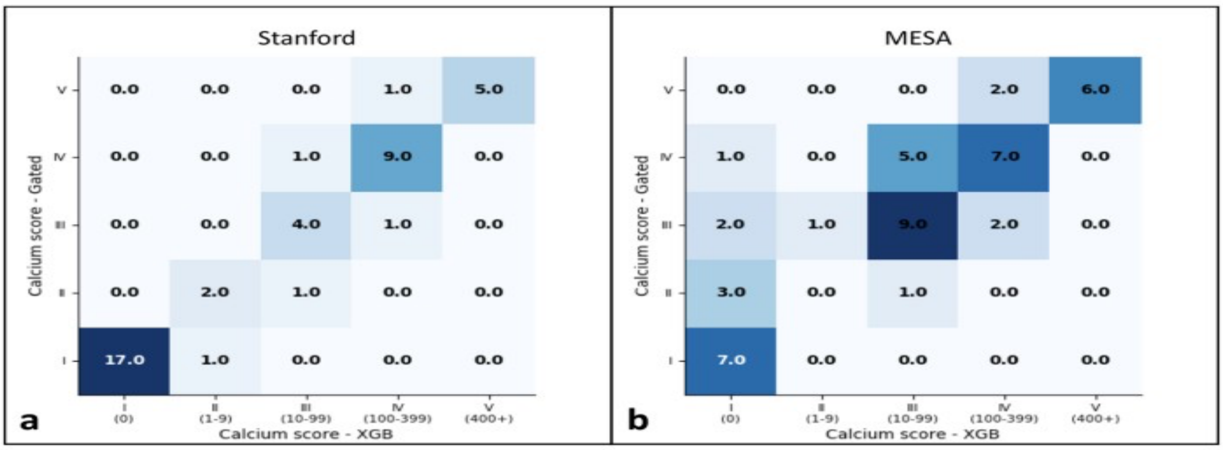

Figure 6 : Internal and MESA datasets are used to compare automated and manual CAC grading on non-gated chest CT exams. Confusion matrices comparing automated scoring of non-gated chest CT tests to ground truth scores for the Stanford (a) and MESA (b) test sets. In each matrix, the x-axis represents the model prediction and the y-axis represents the ground truth scores. (Eng D et al., 2021)

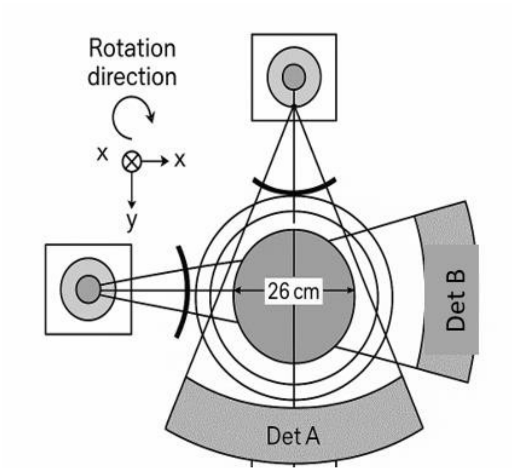

Figure 7. Dual-source computed tomography (DSCT) system engineering and implementation. With a diameter of 50 cm, one detector (A) cover the whole scan field of view, but due to gantry space

constraints, the other detector (B) is only able to cover a narrow, center field of view.(Flohr TG et al., 2006)

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