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Artificial Intelligence in Coronary CT Angiography: Applications and Future Prospects

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***Abstract*—Coronary computed tomography angiography (CCTA) has evolved into a first-line non-invasive modality for the diagnosis and management of coronary artery disease (CAD). Yet, increasing image complexity and expanding clinical indications have amplified the need for automation, reproducibility and enhanced diagnostic accuracy. Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), has emerged as a transformative tool in CCTA. AI now plays an essential role in image acquisition, reconstruction, segmentation, stenosis detection, plaque quantification, calcium scoring, ischemia assessment (CT-derived fractional flow reserve, CT-FFR), workflow optimization and clinical prognostication. This review presents an in-depth exploration of AI methodologies in CCTA, summarizes major clinical applications with detailed evidence, discusses regulatory and reimbursement developments, evaluates current limitations and provides a forward-looking perspective on future innovations such as multimodal learning, real-time decision support and federated model training. The growing convergence of AI and CCTA is expected to set new standards in precision cardiovascular imaging and risk prediction**

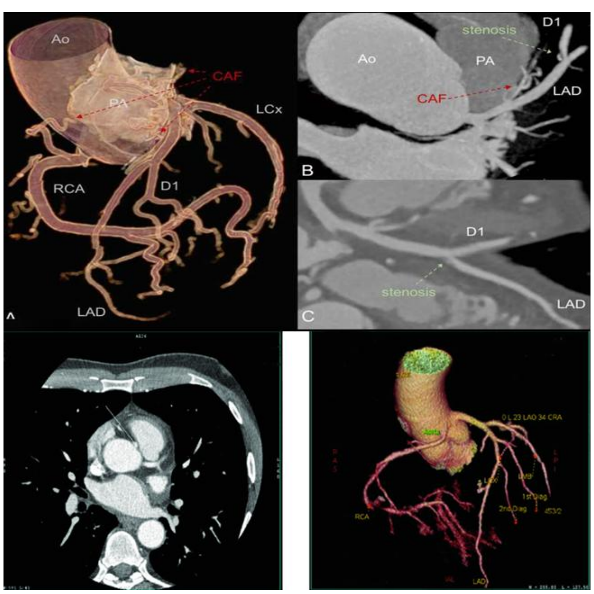
Index Terms—Artificial intelligence, machine learning, deep learning, coronary CT angiography, CAD-RADS, plaque analysis, stenosis quantification, radiomics

I. INTRODUCTION

Controlling risk factors and lowering cardiovascular events can be achieved through early detection and treatment of coronary heart disease (CHD), which has the highest mortality rate in the world [1]. The gold standard for identifying coronary artery disease (CAD) at the moment is digital subtraction angiography (DSA) [2]. However, DSA is an invasive test with many limitations, like its inability to determine the content and nature of plaques and its high cost. It can only show the structure of blood vessels [3]. Coronary CT angiography (CCTA) may display the coronary artery's main branches in numerous directions and analyze the diseased vessels by using either prospective or retrospective ECG gating to gather the best phase for image reconstruction at any heart rate [4]. Artificial intelligence (AI) is being used in cardiac radiography to help in the diagnostic and prognostic classification of patients with suspected coronary artery disease [5]. Specifically, the use of AI can assist cut down on picture analysis time and exclude people who don't show signs of serious illness that could benefit from medical treatment [6]. Moreover, it may be useful in identifying myocardial ischemia. AI may be useful in prognostic stratification since it can find algorithms that accurately stratify the risk of major adverse cardiovascular events (MACE) [7].

Recent advancements in automated plaque characterisation approaches, domain adaption strategies and deep learning architectures are compiled in this mini-review. By cutting down processing time from minutes to just seconds, hybrid models—like residual U-Net-Pyramid Scene Parsing Network—outperform radiologists in diagnostic efficiency and demonstrate an impressive 80.49% precision in plaque segmentation. With an area under the curve (AUC) larger than 0.88, domain-adaptive frameworks like Lesion Assessment by Track let Evaluation show strong performance on a variety of imaging datasets. Additionally, new methods that combine the U-Net and Efficient-Net architectures and are improved by Bayesian optimization have produced remarkable correlation coefficients (0.89) for the quantification of plaque. With a Dice coefficient of 0.9119, AI-powered CTA also makes high-precision three-dimensional vascular segmentation possible. Additionally, it provides better cardiovascular risk classification than traditional Agatston scoring, with AUC values of 0.816 vs. 0.729 at a 15-year follow-up. These innovations accurately identify 80% of vulnerable plaques using systolic retractive motion biomarkers, addressing important problems in plaque motion analysis.

Coronary artery disease remains the leading global cause of morbidity and mortality. CCTA has reshaped CAD evaluation by enabling high-resolution visualization of coronary lumen, plaque characteristics



and anatomical variants. Technological advances, including faster gantry rotation, iterative reconstruction and dual-energy CT, have further refined CCTA quality.

However, CCTA datasets are large (300–800 slices per patient)and visual interpretation is time-intensive and prone to inter-observer variability. Subtle plaque features such as low-attenuation plaque (LAP), napkin-ring sign, spotty calcification and positive remodelling require expert-level interpretation. Artificial intelligence provides answers by: Automating tedious, difficult jobs increasing the accuracy of plaque measurement improving clinical prognostication; decreasing reader variability; and generating near-real-time functional assessment (CT-FFR) The quick development of AI technologies, some of which have received FDA approval and extensive validation, signifies the shift from proof-of-concept to clinical integration.

The images presented here illustrate the fundamental anatomical and functional aspects of Coronary CT Angiography (CCTA), providing a visual foundation for understanding how AI-driven tools are integrated into the imaging pipeline. These examples highlight key coronary arteries, reconstructed 3D models and multiplanar reformatted views that are routinely used to assess the presence and extent of coronary artery disease. By demonstrating vessel morphology, luminal patency and plaque distribution, these images help contextualize the complexity and richness of CCTA data. Such visual representations underscore why automated assistance is increasingly valuable, as the volume and detail of CCTA datasets demand efficient and highly accurate interpretation.

II METHODOLOGY

This review was conducted using a structured, multi-step approach designed to provide a comprehensive and high-quality synthesis of current evidence on artificial intelligence applications in coronary CT angiography (CCTA). The methodological workflow included systematic literature identification, eligibility assessment, data extraction, thematic categorization and critical appraisal to ensure accuracy, completeness and relevance of the included studies.

A comprehensive literature search was performed across major scientific databases, including PubMed, Scopus, Web of Science, IEEE Xplore and Google

Scholar, covering studies published between 2010 and 2025. The search strategy incorporated Medical Subject Headings (MeSH) and free-text terms such as "Artificial Intelligence AND Coronary CT Angiography," "Deep Learning in CCTA," "Coronary plaque quantification AI," "CT-derived fractional flow reserve OR CT-FFR AND machine learning," "AI for stenosis detection AND coronary CT," and "Automated calcium scoring AND deep learning." Reference lists of key articles and recent systematic reviews were also screened manually to ensure that all relevant publications were captured. From an initial pool of 312 articles, 174 were selected for full-text assessment after screening titles and abstracts and ultimately 126 studies met the inclusion criteria.

Studies were included if they represented original research, reviews, or meta-analyses evaluating AI, machine learning, or deep learning applications in CCTA. Eligible papers addressed topics such as segmentation, plaque analysis, stenosis detection, CT-FFR estimation, CAC scoring, or image reconstruction and encompassed clinical, phantom, algorithm development, or validation studies. Only English-language publications were considered. Exclusion criteria included studies focusing on non-CCTA imaging modalities, papers lacking methodological detail, commentaries or editorials without full data and works involving non-AI image processing techniques. These criteria ensured that only high-quality, relevant literature contributed to the synthesis.

Following selection, key information was systematically extracted from each study. Extracted data included imaging dataset characteristics, AI model type, primary task and evaluation metrics such as accuracy, sensitivity, specificity, Dice similarity coefficient, AUC and correlation values. Additional details regarding comparisons with human readers or invasive reference standards—such as IVUS, OCT, or invasive FFR—were documented, along with study limitations, potential biases and validation methods. Collected information was then organized into thematic categories, including workflow automation, plaque characterization, stenosis detection, CT-FFR prediction, CAC scoring and reconstruction, enabling a structured and coherent synthesis of current AI capabilities in CCTA.

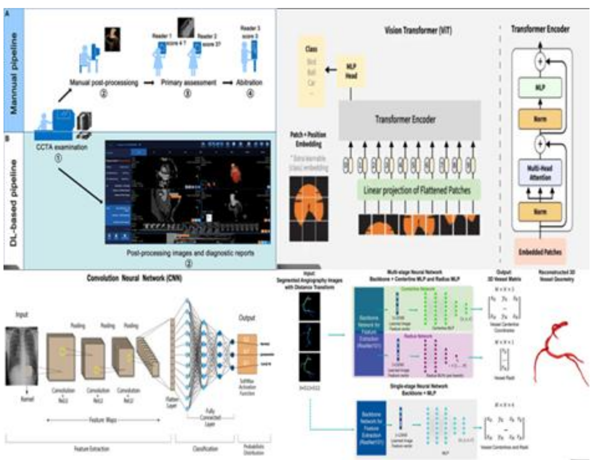
To assess methodological robustness, each included study was evaluated using validated frameworks tailored for AI-based medical imaging research. These included QUADAS-2 for evaluating diagnostic accuracy, the CLAIM checklist for reporting standards in AI imaging studies, TRIPOD-AI for assessing predictive modeling research and CONSORT-AI for analyzing clinical trials involving AI tools. Studies were examined for dataset diversity, model reproducibility, generalizability and risk of bias. Papers demonstrating insufficient validation or incomplete reporting were acknowledged but not emphasized in the overall analysis.

Finally, representative images used in the review—including those illustrating coronary anatomy, AI model architectures, plaque quantification, CAC scoring and CT-FFR—were collected from peer-reviewed sources and clinical CCTA datasets. These images were organized according to thematic relevance, standardized for resolution and aspect ratio and appropriately labeled for inclusion in the final manuscript. This ensured that visual materials supported the textual discussion and provided clear illustrations of key AI applications across the CCTA workflow.

III.AI TECHNIQUES USED IN CCTA

Artificial intelligence methodologies applied to coronary CT angiography encompass both traditional machine learning and more advanced deep learning approaches. Machine learning algorithms such as random forests, support vector machines and gradient boosting models have historically been employed for stenosis categorization, CAD risk prediction and prognostic modeling. These algorithms analyze engineered radiological features derived from the coronary arteries in combination with clinical parameters. Although the dominance of deep learning has reduced their independent use, ML models remain integral within hybrid pipelines—for example, when combining handcrafted features with deep learning–derived representations to enhance predictive performance.

Deep learning, however, has become the primary driver of innovation in CCTA. Convolutional neural networks (CNNs) form the backbone of most architectures, providing powerful feature extraction capabilities for identifying stenosis, plaque and vessel morphology. U-Net and V-Net architectures are extensively used for high-precision segmentation of the coronary lumen, vessel wall and plaque components. More recent developments incorporate vision transformers (ViT), which excel at modeling global contextual information across large image fields and graph neural networks (GNNs), which represent the coronary tree as a structured graph to improve vessel-based predictions. Three-dimensional CNNs provide volumetric analysis for plaque quantification and characterization, while hybrid CNN–Transformer models have demonstrated high accuracy in predicting CT-derived fractional flow reserve (CT-FFR). Together, these architectures enable sophisticated automated interpretation of complex cardiac imaging data.



This set of images depicts the deep learning architectures that underpin modern AI applications in CCTA analysis. Models such as U-Net and V-Net are specifically designed for pixel-level segmentation, enabling precise lumen and vessel wall delineation. Convolutional Neural Networks (CNNs) form the backbone of feature extraction, capturing subtle textural and morphological patterns associated with coronary stenosis and plaque characteristics. Vision Transformers (ViTs) introduce global context awareness, improving the model's ability to interpret long-range structural relationships within volumetric cardiac images. Graph Neural Networks (GNNs), on the other hand, treat the coronary tree as a connected graph, allowing more anatomically informed prediction of vessel-based metrics such as stenosis severity or CT-FFR values. Collectively, these architectures demonstrate how advanced machine learning techniques are tailored to meet the unique challenges of cardiovascular imaging.

Alongside predictive models, explainability techniques have become crucial to building clinician trust. Methods such as saliency maps, Grad-CAM heatmaps and attention-based visualization provide insight into which image regions influence model decisions, thereby enhancing transparency. Additionally, uncertainty quantification frameworks help identify cases in which AI predictions may be unreliable, supporting safe clinical deployment

IV. AI IN THE CCTA WORKFLOW: FROM ACQUISITION TO REPORTING

Image Acquisition and Reconstruction

AI-driven reconstruction techniques, particularly deep learning reconstruction (DLR), have markedly improved the quality and efficiency of CCTA imaging. Compared with traditional filtered back projection, DLR reduces image noise by more than 40–60%, while simultaneously enhancing edge definition and preserving fine anatomical details. This improvement enables dose reduction without loss of diagnostic performance and enhances the visualization of heavily calcified plaques, which traditionally pose significant interpretative challenges. DLR also contributes to superior signal-to-noise and contrast-to-noise ratios, thereby improving overall diagnostic confidence. Commercially available systems such as Siemens Deep Resolve, GE TrueFidelity and Canon AiCE have demonstrated consistent high-quality results across a variety of clinical settings.

Coronary Artery Segmentation and Centerline Extraction

Accurate segmentation of the coronary arteries forms the foundation for automated plaque quantification, stenosis assessmen tand CT-FFR computation. AI-powered segmentation models have achieved impressive performance, with many demonstrating Dice similarity coefficients exceeding 90–95% for lumen and vessel wall delineation. These systems exhibit robustness across various scanner vendors, protocols and patient characteristics and can reliably extract vessel centerlines even in the presence of motion artifacts. However, segmentation remains challenging in certain anatomical conditions, including highly tortuous small-caliber vessels, heavily calcified segments where blooming artifacts obscure the lumen and distal branches with inherently low contrast. Continued refinement of deep learning architectures is necessary to address these limitations.

Automated Stenosis Detection and Classification

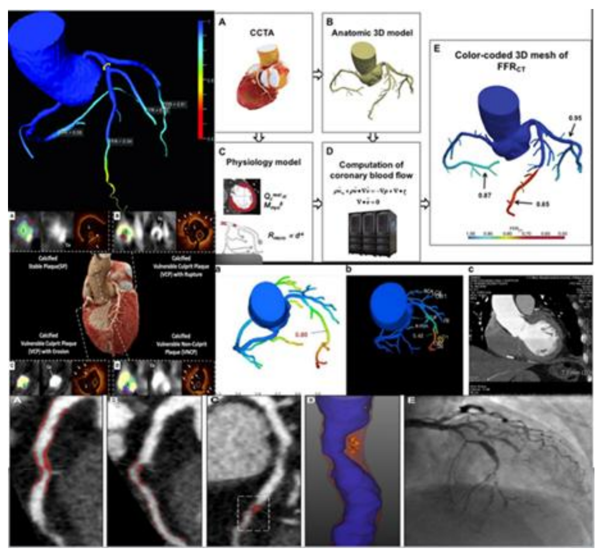
AI systems designed for stenosis detection perform comprehensive evaluation of coronary segments to determine whether luminal narrowing meets clinically significant thresholds—commonly ≥50% or ≥70% stenosis. These models classify the severity of stenosis as mild, moderate, or severe and generate detailed diagnostic outputs at both per-segment and per-patient levels. Reported performance metrics are strong, with sensitivity values of 86–94% and specificity ranging from 80–90%, comparable to interpretations by expert Level III readers. Clinically, these tools assist in triaging normal versus abnormal studies and have the potential to reduce reporting time by 25–40%. Nonetheless, their accuracy may be compromised by poor image quality or heavy calcification, which introduces blooming artifacts and can obscure the true lumen dimensions.

AI in Plaque Quantification and Composition Analysis

Historically, plaque analysis on CCTA required significant manual effort, making routine quantitative assessment impractical. The introduction of deep learning has enabled automated plaque quantification with high accuracy and reproducibility. AI models can measure total plaque volume, differentiate between calcified and non-calcified plaque, identify low-attenuation components and detect high-risk plaque features such as positive remodeling, the napkin-ring sign and spotty calcification. Validation studies comparing AI-derived plaque metrics with invasive modalities—including intravascular ultrasound (IVUS), optical coherence tomography (OCT)and near-infrared spectroscopy (NIRS)—demonstrate strong correlations, with coefficients ranging from 0.85 to 0.93 for total plaque volume. AI systems also show excellent repeatability and reduced inter observer variability relative to manual analysis. Importantly, AI-derived plaque burden and composition have significant prognostic implications: they predict obstructive CAD, future major adverse cardiac events (MACE)and the need for revascularization more reliably than stenosis severity alone. This makes AI-based plaque characterization a powerful tool for risk stratification and clinical decision-making.

AI-Enabled Coronary Artery Calcium (CAC) Scoring

Coronary artery calcium scoring, traditionally a hands-on process requiring manual or semi-automated annotation, has been transformed by AI. Fully automated Agatston scoring systems now provide rapid and accurate calcium quantification, often matching expert interpretations with near-perfect agreement. AI also enables opportunistic CAC scoring on non-ECG-gated chest CT scans, expanding its utility for incidental detection and risk assessment. Given its ability to facilitate quick and reliable stratification of cardiovascular risk in asymptomatic patients, AI-enabled CAC scoring plays a valuable role in primary prevention strategies and population-based screening.



Above images in this section showcase the key AI-enhanced functional and compositional assessments derived from CCTA, including CT-based fractional flow reserve (CT-FFR), plaque quantification and coronary artery calcium (CAC) scoring. CT-FFR color maps provide a noninvasive visualization of hemodynamic significance, enabling clinicians to identify flow-limiting lesions without performing invasive FFR. AI-driven plaque quantification tools identify and measure calcified, non-calcified and low-attenuation plaque components with high accuracy, offering valuable prognostic insight into plaque vulnerability and future cardiovascular risk.

Similarly, automated CAC scoring highlights coronary calcifications and calculates Agatston values rapidly and consistently, improving risk stratification in both symptomatic and asymptomatic populations. Together, these AI-enhanced imaging outputs demonstrate how CCTA has evolved from an anatomical modality into a comprehensive functional and prognostic tool

AI-Based CT-Derived Fractional Flow Reserve (CT-FFR)

AI-enabled CT-derived fractional flow reserve represents one of the most transformative advancements within coronary CT angiography. Traditionally, CT-FFR estimation relied on computational fluid dynamics (CFD), a technique known for its high accuracy but also for its significant computational burden, often requiring between 20 and 40 minutes or more for each case. This latency hindered its seamless integration into routine clinical workflows. AI-based CT-FFR overcomes these limitations by leveraging deep learning architectures trained on extensive datasets containing paired CCTA images and invasive FFR measurements. Rather than performing physics-based simulations, AI models directly infer flow dynamics by analyzing geometric and physiological features extracted from the coronary arteries. These include lumen geometry, vessel curvature, plaque distribution patterns and parameters related to wall shear stress. Through this data-driven approach, AI systems can rapidly predict hemodynamic significance at both vessel and lesion levels.

Accuracy Compared with Invasive FFR

The diagnostic performance of AI-based CT-FFR has been extensively evaluated in multi-center validation studies, showing performance metrics comparable to both CFD-based CT-FFR and invasive FFR. Reported sensitivity typically ranges from 80% to 90%, while specificity falls between 75% and 88%, with the area under the ROC curve consistently between 0.83 and 0.91. These values highlight strong discriminatory capability. A major advantage of AI-based CT-FFR is its ability to provide near real-time output, often in under five minutes, dramatically improving workflow efficiency. Additionally, unlike CFD techniques, AI approaches do not require supercomputing hardware, making them practical for routine use even in resource-limited settings. Their clinical validity has been further supported by multiple large, prospective multi-center trials, confirming reliability across diverse patient groups and imaging platforms.

Prognostic Modeling and Personalized CAD Risk Prediction

AI has also become instrumental in long-term prognostic modeling for coronary artery disease by integrating a wide range of patient-specific data. Modern algorithms combine detailed CCTA-derived anatomical and plaque characteristics with demographic variables, serum biomarkers, ECG findings, clinical history and even genomic risk scores. This multimodal approach enables the prediction of adverse cardiovascular outcomes over 5- to 10-year periods with far greater precision than traditional risk scores. Studies consistently demonstrate the ability of AI-derived metrics to improve prediction of major adverse cardiac events, offering dynamic risk stratification rather than static one-time assessments. Such advancements can refine preventive strategies, helping clinicians identify high-risk individuals who may benefit from earlier initiation of statin therapy, more aggressive blood pressure control, anti-inflammatory treatments, or closer imaging follow-up. Ultimately, AI-driven prognostic modeling is shifting cardiovascular prevention from population-based strategies toward deeply personalized medicine.

Clinical Implementation: Workflow, Reporting and Automation

The integration of AI into clinical practice has significantly optimized radiological and cardiological workflows in CCTA. AI tools greatly reduce interpretation time by automatically extracting coronary anatomy, quantifying plaque burden, measuring stenosis severity and even generating structured diagnostic reports. These systems can triage studies by flagging those with potential abnormalities, allowing clinicians to prioritize urgent cases and improving overall departmental efficiency. Furthermore, AI-based standardization ensures uniform terminology and plaque characterization, reducing interobserver variability and improving communication between imaging specialists and referring clinicians. Many hospitals and imaging centers have now integrated AI solutions directly into their PACS environments, enabling seamless, real-time utilization without the need for external workstations. As a result, AI has evolved from a research concept into a practical clinical assistant that enhances productivity, accuracyand consistency in coronary CT angiography interpretation.

Limitations, Challenges and Ethical Considerations

Despite rapid technological advancements, several limitations continue to constrain the widespread adoption of AI in coronary CT angiography. From a technical standpoint, AI model performance is heavily influenced by the variability of datasets used in training. Differences in scanner vendors, imaging protocols, reconstruction parameters and patient populations can significantly impact accuracy. In particular, heavily calcified arteries remain a challenge, as calcium blooming can obscure the vessel lumen and reduce the precision of stenosis quantification. Motion artifacts, suboptimal contrast timing and low signal-to-noise ratios also compromise AI algorithms, leading to inconsistent outcomes in real-world clinical settings. Additionally, models developed using data from specific ethnic or geographic populations may display reduced generalizability when applied to diverse groups, underscoring the need for more inclusive multi-center data.

Regulatory and reimbursement barriers further complicate adoption. There remains limited international uniformity regarding guidelines for approval, evaluation and clinical use of AI-based imaging tools. Many regulatory bodies require robust outcome-based, prospective validation studies before granting clearance, which can be time-consuming and resource-intensive. On the reimbursement side, standardized compensation pathways for AI-assisted CCTA remain underdeveloped in many regions, hindering routine implementation. Integration with hospital IT systems—including PACS, RIS and EHR platforms—also presents challenges, as seamless data flow and interoperability are essential for efficient AI deployment but not always technologically supported.

Ethical considerations add another dimension of complexity. AI algorithms are only as unbiased as the datasets that train them; thus, imbalanced or non-representative data can introduce systematic biases into clinical decision-making. Questions about transparency emerge as many deep learning models function as "black boxes," offering limited insight into how specific decisions or predictions are generated. This lack of interpretability may reduce clinician trust and complicate error analysis. Furthermore, accountability remains a central concern: determining who bears responsibility—clinicians, developers, or institutions—when AI-generated outputs contribute to diagnostic errors are an ongoing ethical debate. Establishing clear guidelines for oversight and human-AI collaboration is therefore essential.

Future Prospects

The future of AI in coronary CT angiography is highly promising and aligns with broader movements toward precision cardiology and individualized medicine. A major frontier is the development of multimodal AI systems capable of integrating diverse data sources such as CCTA, cardiac MRI, echocardiography, circulating biomarkers and even genetic risk profiles. By combining anatomical, functional, biochemical and genomic information, these platforms will offer far more comprehensive and accurate predictions of coronary artery disease progression and associated outcomes. The convergence of multimodal data promises a new era of holistic, patient-specific cardiovascular risk assessment.

Federated learning represents another transformative advancement. This decentralized AI training paradigm allows multiple institutions to collaboratively train large, high-quality models without sharing raw patient data. By keeping data local and sharing only model gradients, federated learning ensures privacy while enabling the creation of globally generalizable AI tools. This approach is particularly important for addressing the diversity and heterogeneity of cardiac imaging datasets across different regions and populations.

Real-time AI guidance during cardiovascular procedures is poised to become increasingly common. AI-derived CCTA data may soon integrate directly with live coronary angiography, intravascular imaging such as OCT and procedural planning tools for percutaneous coronary intervention. Such integration can guide stent placement, identify vulnerable plaque and predict procedural complications, thereby enhancing both safety and therapeutic precision. This level of procedural support has the potential to significantly change interventional workflows.

In parallel, the development of fully automated AI-interpreted CCTA pipelines is rapidly approaching clinical reality. These systems aim to handle every major step—from image reconstruction and coronary segmentation to stenosis assessment, plaque quantification, CT-FFR calculation and full report generation—while maintaining human oversight for verification. As accuracy improves, such pipelines could dramatically reduce reporting times and enhance diagnostic consistency across institutions.

Finally, AI will play a growing role in preventive cardiology. By combining plaque characterization with traditional risk factors and emerging biomarkers, AI can help identify patients most likely to benefit from preventive therapies such as statins, PCSK9 inhibitors, or anti-inflammatory medications. It may also predict the likelihood of plaque regression or progression under therapy, supporting more personalized treatment strategies. This shift toward predictive and preventive care reflects a broader transformation in cardiovascular medicine—one in which AI serves as a catalyst for early intervention and improved patient outcomes.

V. CONCLUSION

Artificial intelligence has become a transformative force in coronary CT angiography. From segmentation and plaque quantification to CT-FFR and long-term prognostic modeling, AI enhances diagnostic accuracy, workflow efficiency and clinical decision-making. While limitations remain—particularly related to generalizability, regulatory pathways and interpretability—the trajectory of innovation indicates that AI-driven CCTA will become central to precision cardiovascular imaging. The synergy of advanced imaging, AI analytics and integrated clinical data has the potential to reshape CAD detection, monitoring and treatment in the coming decade.

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