The integration of artificial intelligence into intravascular optical coherence tomography

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Intravascular optical coherence tomography (IVOCT) is an imaging system that is used in interventional cardiology to diagnose coronary atherosclerosis. It is a tool that produces high-resolution images that are used to visualise the microstructure of the coronary arteries. However, while IVOCT produces clear and sharp images to be used in diagnoses, the data produced are complex and voluminous, requiring large amounts of time and human effort to interpret. Recently, IVOCT has seen vast improvements and important advances. The objective of this literature review is to provide a critical analysis of the integration of artificial intelligence (AI) into IVOCT imaging, explore the achievements made, highlight the challenges faced, and map out the future trajectory of this technology. To fulfil this objective, several scientific studies and peer-reviewed journal articles were critically reviewed to illuminate the recent advances in AI-driven IVOCT imaging. The review focuses on addressing image pre-processing, segmentation, stent detection, plaque characterisation, stent malapposition and neointimal coverage assessment. Special considerations have also been given to the practical applications of these systems in clinical situations, especially in the South African low-resource context. The integration of AI into IVOCT imaging has powerful potential to increase the efficiency of image analysis, diagnostic accuracy, clinical reasoning and decision-making processes, thus forging a new and optimistic path for the future of cardiovascular care and precision medicine.

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Nkanyezi Ngubane is currently a second-year MB ChB student at the University of Cape Town. He has a strong interest in cardiology, particularly in cardiac imaging techniques and the complexity of the heart as an integrated system. Beyond being a passionate medical student, he is deeply interested in exploring planetary health, sustainability, and environmental justice in the Global South. He enjoys creative pursuits such as playing the piano and painting, which provide a balance to his academic work, reading about interesting mathematical topics, and watching good films. He hopes to pursue a career that integrates cardiology, mathematics and planetary health after completing his medical degree.

Coronary artery disease (CAD) is one of the leading causes of morbidity and death globally, accounting for a large proportion of deaths annually. In 2023, approximately one in three deaths was caused by CAD.[1] CAD is often more severe and affects younger populations in low- to middle-income countries such as South Africa (SA) compared with more economically developed countries. This burden of disease has significant social and economic implications in developing countries. Effective treatment of CAD is therefore essential not only for improving the health of a country, but for improving the economic productivity of lower-income countries.[2] A large proportion of CAD can be prevented through a healthy lifestyle and cardiac interventions. Angiography is currently the preferred diagnostic tool. However, this method is invasive and carries the risk of complications such as blood clotting and haemorrhage.[3] Intravascular optical coherence tomography (IVOCT) has emerged as a solution, producing high-resolution images and overcoming challenges of clarity and detail experienced by other imaging techniques such as intravascular ultrasound.[4] However, IVOCT produces a large volume of complex images, which require substantial time and effort to interpret. Furthermore, analysis of these images and identification of characteristics such as incomplete stent apposition are subject to the variability and expertise of the observer. Artificial intelligence (AI) has emerged as a tool that can circumvent these challenges and work in conjunction with IVOCT as a productive image analyst. This review will explore the integration of AI into the stages of IVOCT imaging, examine the recent methods and applications, illuminate recent breakthroughs, and critically discuss the challenges and future opportunities for its implementation in global and public health. The review will also provide a detailed and clear picture of the integration of AI into coronary artery imaging.

Methods

This literature review aims to explore the current climate, advances, challenges and future directions of AI applications in IVOCT in the context of cardiovascular treatment. To fulfil this objective, a literature search was conducted across databases including PubMed, Science

Direct, IEEE Xplore and Google Scholar, using targeted keywords such as 'AI', 'Deep learning models' and 'IVOCT'. The inclusion criteria were centred around articles that described AI-based models applied to IVOCT imaging such as deep learning models (DLMs), performance metrics, applications of AI in real-life clinical situations, challenges with AI applications, and improvements to be made to AI integration into IVOCT. Articles or studies that did not directly reference cardiac imaging and those that did not have sufficient methodological detail were excluded. Also excluded were studies that had not been properly reviewed and those that did not originate from a reliable database. The data were then analysed and synthesised to produce a review that offers a broad picture of the advances, challenges and gaps in and future directions for AI use in IVOCT imaging.

AI in image pre-processing

AI has been incredibly resourceful in the pre-processing, segmentation and post-processing of images through convolutional neural networks (CNNs).

CNNs are a subset of AI deep learning, using three-dimensional data outputs to analyse, process and classify images. They consist of a convoluted layer that extrapolates key characteristics from image inputs, a pooling layer that reduces images to a micrometre scale, hence reducing noise, and a fully connected layer that processes the extracted features to make predictions and classifications.[5] Fig. 1 illustrates this architecture.

In a retrospective case-control study of emergency departments in three hospitals by Lin *et al.*,[6] published in 2024, CNNs were able to process images and utilise patient information such as age and comorbidities to diagnose patients with acute aortic syndrome and thoracic aortic aneurysms.

In interventional cardiology, CNNs are integrated with IVOCT imaging through a structured workflow of pre-processing, segmentation and post-processing. The images are standardised by lumen detection, tissue alignment, excess pixel trimming and noise reduction. The images are then segmented, and key characteristics are highlighted for analysis.[5,7] One such technology is a model called SegNet. A study by Lee *et al.*[7] published in 2019 made use of SegNet, demonstrating that this tool can effectively perform pixel-wise segmentation functions and classify images with high sensitivity (>99.0%) and a Dice coefficient >0.995. The Dice coefficient reflects the similarity of the image samples, a high Dice coefficient demonstrating that the AI segmentation closely matches segmentation done by expert cardiologists. However, challenges still remain in segmenting more obscure lipid borders and in generalisation of this technology.

SegNet makes use of an encoder-decoder construction, where the encoder extrapolates key features such as morphology and reduces the image size and complexity. The decoder then reconstructs the image to a higher resolution, and utilises a softmax function that uses probabilities to classify the pixels into plaque, lumen, stent or calcification.[7] A post-processing stage is then implemented to refine and further clarify the image. The final stage of image processing involves the implementation of a conditional random field that corrects any inaccuracies in segmentation made by SegNet. Other CNNs have been developed that are improved forms of SegNet, including UNet and EDA-UNet. For the remainder of this review, special attention will be given to SegNet, UNet and EDA-UNet. These improved CNNs enhance cardiac imaging through more advanced post-processing steps, including probability thresholding and further noise reduction, resulting in more accurate and consistent plaque identification for clinical use.[7]

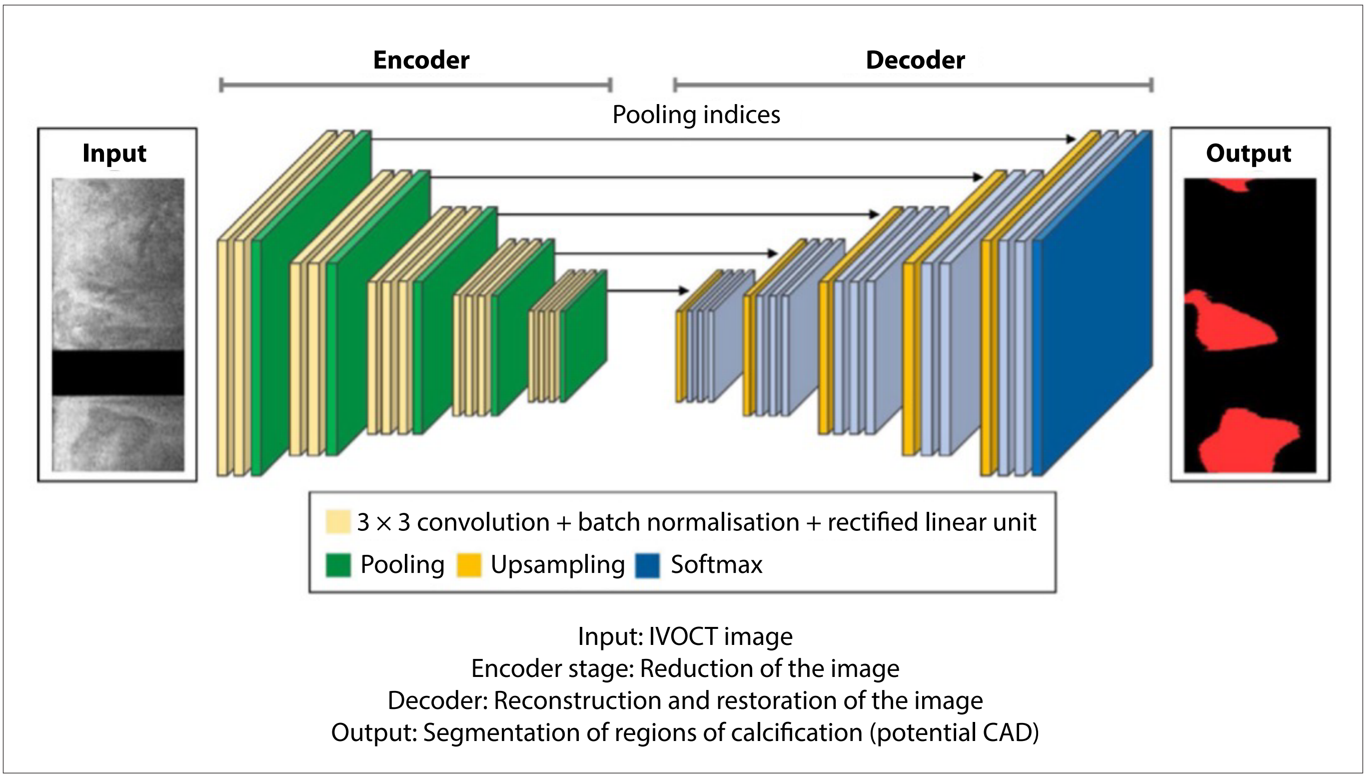

Fig. 1. Architecture of convolutional neural networks, adapted from Lee et al.[7] *(IVOCT = intravascular optical coherence tomography; CAD = coronary artery disease.)*

Plaque characterisation

CNNs also have the specialised ability to characterise plaque types. Different CNNs have been used to characterise plaques, including SegNet, UNet, and the most recent technological breakthrough, EDA-UNet (efficient dual-attention UNet).[8]

EDA-UNet is an improved form of SegNet and UNet, but differs from these CNNs in its highly specialised training. EDA-UNet functions in a similar manner to other CNNs; however, it is trained using real-life clinical scenarios, employing a dual-attention mechanism. This mechanism consists of a channel attention module, which learns the salient features, such as morphological differences between calcification and lipid-rich plaque, and a spatial attention module, which learns the regions of interest, such as regions where plaque may be found.[8] In a study by Liu *et al.*[8] published in 2025, an EDA-UNet model was trained using IVOCT images and assessed in an internal test and an external test. The internal test used IVOCT images from two Chinese hospitals, Beijing Anzhen Hospital and Fuwai Hospital. However, because internal tests suffer from issues of limited cohort size and biases, an external test was carried out using IVOCT images from a Japanese hospital, Osaka University Hospital. The EDA-UNet model outperformed its CNN counterparts at plaque characterisation of all types (fibrous, calcification, lipidous). For example, when assessing lipid plaques, EDA-UNet had an accuracy score of 0.9975 in the internal test and 0.6946 in the external test. Although the accuracy score for the external test is lower than that for the internal test, the external test score is much higher compared with SegNet, with an internal test accuracy score of 0.9973 and an external test accuracy score of 0.6536, and UNet, with an internal test accuracy score of 0.9968 and an external test accuracy score of 0.6564 (Table 1) (p<0.05).[8]

The performance metrics mentioned above demonstrate how new DLMs such as EDA-UNet have much improved generalisability, which increases the prospects of these tools being implemented on a global level. When this AI technology is implemented in hospitals, it can have important implications for global and public health, and can help address inequality and lack of access to expert cardiologists in rural and under-resourced areas. For example, this AI tool could be of great assistance in the SA context, such as in a provincial hospital in Eastern Cape Province where there is no resident cardiologist. However, implementation of this technology will require a large budget, extensive planning and careful regulation. It may not currently be realistic in the SA context, but there is hope for its future prospects.

Improved clinical efficiency

EDA-UNet has been shown to outperform human clinicians of all levels of expertise. In the study by Liu *et al.*,[8] clinicians and EDA-UNet were tasked with segmenting images and classifying plaques. The objective of this reader study was to measure the competence of clinicians at assessing and segmenting plaque, and compare their performance with that of EDA-UNet. It was found that EDA-UNet was able to segment and classify images as accurately as senior cardiologists, in a fraction of the time taken by these expert clinicians. EDA-UNet had a mean accuracy score of 0.9875 and was able to complete the task in only 18 seconds. The senior clinicians had a mean accuracy score of 0.9844 and took 1.6 hours to complete the same task (p<0.001).

Stent malapposition and neointimal analysis

Stent malapposition refers to an absence of full contact of stent struts against the luminal wall. Stent struts are the metallic or polymeric components that form the structure of stents, maintaining stent integrity and preventing restenosis of the arteries. Further studies have been conducted to assess the competence of deep learning tools at detecting stent stunts. A 2019 article by Guo *et al.*[9] reported the development of DLMs called local-global refinement networks (LGRNs). LGRNs consist of a local network and a global network. The local network is patch based and finds the exact location of struts at the micrometre scale. It then uses a Gaussian filter for noise reduction to further clarify the result.[9] Local networks are trained using L1 loss, which corrects the model when it is incorrect and advises the model on how to improve.[9] The global network is an improved form of U-Net, and illustrates a broader image of the struts and their place within the overall shape and structure of the artery. This model predicts where a strut is likely to be, based on probabilities, even if the struts are not visible owing to noisy or unclear images.[9]

Wu *et al.*[10] (2020) developed a DLM that was able to analyse two-dimensional IVOCT images of coronary arteries, classify the plaque, and then create a three-dimensional image of the stent from IVOCT image pullbacks. Furthermore, the DLM was able to calculate the stent area and elliptical stent contours, and compare these values with calculations done manually by expert analysts. The DLM collaborated with a real-world software called OctPlus, which allowed it to create a three-dimensional model of the stent for easier interpretation and analysis by expert cardiologists.[10] This DLM had high precision, recall and F1 scores, with a precision score of 0.943, a recall score of 0.940 and an F1 score of 0.936, indicating good balance between recall and precision of the model.[10] The stent optimisation abilities of the DLM significantly reduce the risk of further stent malapposition, restenosis and other stent complications, allowing for effective and immediate interventions.

In a 2021 article, Yang *et al.*[11] describe how DLMs are able to detect stents in IVOCT images showing varying degrees of tissue coverage, image contrast levels, and other complications such as stent

Table 1. Performance of different AI models at characterising lipid plaque (adapted from Liu *et al.*[8])

	Internal test				External test			
Model	**Sensitivity**	**Specificity**	**Accuracy**	**Dice coefficient**	**Sensitivity**	**Specificity**	**Accuracy**	**Dice coefficient**
SegNet	0.7024	0.7192	0.9973	0.7023	0.6689	0.9829	0.6536	0.6572
UNet	0.6571	0.6889	0.9968	0.6751	0.6727	0.9831	0.6564	0.6606
EDA-UNet	0.7845	0.7932	0.9975	0.7845	0.7666	0.9847	0.6946	0.7052

AI = artificial intelligence.

malapposition and eccentric placement. Challenging cases of stent detection are illustrated in Fig. 5 of the article. A DLM used in their study was able to detect and automatically analyse stent struts with thick coverage (>0.3 mm) and thin coverage (≤0.3 mm). The study demonstrates shows how AI models are able to detect stents in various images and under various conditions.

In a study by Gharaibeh *et al.*,[12] published in 2023, machine learning was applied to pre-stent IVOCT images to analyse lumen and calcification features. This study demonstrated the development of DLMs capable of predicting stent expansion. By analysing calcifications in pre-procedural IVOCT images, the model could predict the likelihood of successful vessel expansion after the stent had been implanted. IVOCT images depicting calcification with lesions were segmented, and the features were extrapolated. Regression models were then trained to predict the post-stent lumen area and hence expansion of the stent, also known as the stent expansion index. The DLMs were able to predict stent expansion with admirable accuracy; however, they need to be developed further to achieve optimal accuracy.[12] Stent under-expansion can increase the risk of future complications. These complications include restenosis, when the arteries become narrowed again, and thrombosis, in which blood clots form near the stent. These complications can ultimately lead to myocardial infarction and in severe cases to death. The ability of DLMs to predict stent expansion can therefore significantly reduce the frequency of stent complications and the incidence of deaths due to CAD.[12]

Applications of AI-IVOCT integration in real-life clinical contexts

AI-IVOCT integration has had important applications in real-life clinical contexts, especially in the prediction of major adverse cardiovascular events (MACEs) such as strokes and heart attacks. In a study at the University of Turin, researchers led by Di Marcantonio[13] developed an AI model that was able to analyse IVOCT-derived plaque features such as calcification thickness and fibrous cap metrics and utilise these together with clinical variables such as age and comorbidities to estimate MACE risk. Using a logistic regression model, the AI model showed fair performance at this task, indicating that the fibrous cap surface area (FCSA) is a strong predictor for possible MACE, with an odds ratio (OR) of 2.38. The FCSA is the region of vulnerable plaque in the arteries that is susceptible to rupture, causing a possible MACE. Di Marcantonio's model was able to show that patients with larger FCSAs were 2.38 times more likely to experience a MACE compared with those with smaller FCSAs.[13] For comparison, an established cardiovascular risk factor such as diabetes has an OR of 1.70, and smoking has an OR of 2.08.[14] The cardiology department at Sanjay Gandhi Postgraduate Institute of Medical Sciences in India has been equipped with AI-powered IVOCT, which allows for high-resolution coronary artery images and has enabled doctors there to accurately understand and assess acute myocardial infarctions, plaque structure, calcification features and stent malapposition, and integrate this information with angiographs to provide precision angiography.[15] This technology can help reduce the prevalence of CAD in the Indian population, who unfortunately suffer from CAD at relatively young ages and with relative severity.[15] AI tools have also been able to assist in real-life clinical situations by providing high-quality images, characterising plaque types, and assessing stent deployment at clinical consultations within seconds.[16] Furthermore AI-enhanced IVOCT has been beneficial for percutaneous coronary intervention, preventing further complications.[16]

Challenges of AI-IVOCT integration

Although incredible developments have been demonstrated in the integration of AI in IVOCT imaging, there are still major challenges. A key challenge is the scarcity of sufficient annotated datasets for training DLMs. DLMs are trained using images that have been manually annotated by expert cardiologists.[17] However, this process, which AI is meant to circumvent, is labour intensive and complex. Variability in labelling by experts also contributes to this limitation.[17]

Additionally, DLMs struggle to achieve generalisability, as they are trained on IVOCT images from a particular device, subset of patients, or population. Certain DLMs therefore do not perform as accurately when exposed to different devices or patient populations.[8,12] For example, Liu *et al.*[8] found that the accuracy of EDA-UNet at segmenting lipid plaque decreased by 30.3659% when the model was used in an external test. In an internal test, EDA-UNet had an accuracy of 0.9975, whereas in an external test, the model had an accuracy of 0.6946. These examples show that particular attention must be given to improving generalisability.[8] Challenging cases and failures of automatic IVOCT image segmentation are shown in Fig. 1 of Liu *et al.*'s[8] article.

Future directions and improvements

A major barrier to the implementation of AI-driven IVOCT imaging in countries such as SA is that hospitals in rural and low-income areas do not have access to expert cardiologists. For this technology to be truly beneficial in clinical settings, a large, standardised, broad and publicly accessible annotated dataset needs to be available.[17] It can be achieved by creating jobs specifically for annotation of IVOCT images, which could also help address issues of unemployment, or by crowdsourcing expert clinicians. It will assist by giving AI models more comprehensive data, so that they are able to be implemented in any clinical setting.

AI models have also proved to need deeper generalisation,[18] which will improve the DLM's ability to adapt to different patient populations and lesion morphologies. Furthermore, standardised training must be implemented to ensure that all AI models are trained using a standard curriculum.[18] Federated learning will allow for AI models to be trained across institutions.[18] Because many AI models have been trained using IVOCT images, DLMs typically negate other important imaging modalities such as angiography or computed tomography.[19] Integrating AI-IVOCT models with other imaging modalities can improve plaque characterisation and provide more comprehensive medical care. While AI models are currently trained for short-term image processing, longitudinal modelling is required. It will enable the AI-IVOCT models to predict outcomes, assess restenosis risk, and devise treatment plans.[19] Although certain AI models have been shown to do this, this prognostic ability is a requirement if AI is to be implemented in clinical settings. The implementation of AI-IVOCT imaging in clinical settings will require that this technology is trained in controlled real-life clinical situations.[19] Because many AI models are trained in laboratories and research environments, they often experience delays, reduced resilience and lack of regulation. In order for this technology to be introduced in clinical practice, the AI models must be used in catheterisation laboratories and assessed to decide whether the models are applicable in a practical setting.[19]

AI-IVOCT integration in the SA context

In order for this potentially powerful technology to be implemented in a low-resource country such as SA, special attention must be paid to ensuring that adequate budgeting is allocated to healthcare. In an SA regional hospital, for example, the implementation of AI-IVOCT imaging could cost up to ZAR7 million, excluding the operational costs.[20] This figure includes costs for AI software licensing and regulatory approval from the South African Health Products Regulatory Authority. Furthermore, issues of digital inequality and technological barriers pose a challenge for the wide-scale implementation of this technology in SA.[21] These socioeconomic disparities will make the implementation of AI extremely difficult in the SA context. However, with proper budgeting, socioeconomic upliftment and public health advancements, AI-assisted technologies can be made available to improve the health of our country's citizens.

Conclusion

AI has proved to be a transformative force in healthcare, with AI-IVOCT integration showing great promise. AI has been able to analyse images with the accuracy of an expert cardiologist in a fraction of the time, reducing intra-observer variability and increasing diagnostic efficiency. Percutaneous coronary interventions have now been advanced through the automation of tissue segmentation, plaque characterisation and stent detection. AI models have even been able to use stent under-expansion and other risk factors to predict MACEs such as strokes and heart attacks. Although there are significant socioeconomic and financial barriers to the implementation of this technology in SA, research and regulatory approval can make use of AI in clinical settings a reality. As research progresses, these experimental models are expected to evolve into trustworthy clinical tools that provide reliable, accurate analyses. In SA, where inequality limits access to specialists – for example, the municipalities in Eastern Cape Province without resident cardiologists – AI-IVOCT integration could expand access to high-quality care in rural settings. Despite challenges with generalisability, model training and ethics, interdisciplinary collaboration can help establish AI as a standard tool in managing CAD.

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