

Implications of Artificial Intelligence in Intravascular Imaging Methods

Implicancias de la inteligencia artificial en los métodos de imagen endovascular

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ABSTRACT

Percutaneous coronary intervention (PCI) is one of the primary revascularization strategies in patients with coronary artery disease (CAD). Several studies support the use of intravascular imaging methods to optimize PCI. However, these methods are underutilized in contemporary clinical practice and face challenges in data interpretation. Therefore, the incorporation of artificial intelligence (AI) is seen as an attractive solution to promote and simplify their use.

AI can be defined as a computer program that mimics the human brain in its ability to collect and process data. Machine learning is a sub-discipline of AI that involves the creation of algorithms capable of analyzing large datasets without making prior assumptions, while deep learning focuses on the construction and training of deep and complex artificial neural networks. The incorporation of AI systems to intravascular imaging methods improves the accuracy of PCI, reduces procedure duration, and minimizes interobserver variability in data interpretation. This promotes their wider adoption and facilitates their use. The aim of this review is to highlight how current AI-based systems can play a key role in the interpretation of data generated by intravascular imaging methods and optimize PCI in patients with CAD.

Keywords: Artificial Intelligence - Percutaneous Coronary Intervention - Intravascular imaging

RESUMEN

La angioplastia transluminal coronaria (ATC) es una de las principales estrategias de revascularización en pacientes con enfermedad coronaria aterosclerótica (ECA). Numerosos estudios respaldan la optimización de la ATC mediante métodos de imagen endovascular; sin embargo, estos métodos son subutilizados en la práctica clínica contemporánea y enfrentan desafíos en la interpretación de los datos obtenidos, por lo que la integración de la inteligencia artificial (IA) se vislumbra como una solución atractiva para promover y simplificar su uso.

La IA se define como un programa computarizado que imita la capacidad del cerebro humano para recopilar y procesar datos.

El aprendizaje de máquinas (*machine learning*) es una subdisciplina de la IA que implica la creación de algoritmos capaces de analizar grandes conjuntos de datos sin suposiciones previas, mientras que el aprendizaje profundo (*deep learning*) se centra en la construcción y entrenamiento de redes neuronales artificiales profundas y complejas. Así, se ha demostrado que la incorporación de sistemas de IA a los métodos de imagen endovascular incrementa la precisión de la ATC, disminuye el tiempo del procedimiento y la variabilidad interobservador en la interpretación de los datos obtenidos, promueve así una mayor adopción y facilita su utilización. El propósito de la presente revisión es destacar cómo los sistemas actuales basados en IA pueden desempeñar un papel fundamental en la interpretación de los datos generados por los métodos de imagen endovascular, lo que conduce a una mejora en la optimización de la ATC en pacientes con ECA.

Palabras clave: Inteligencia artificial - Angioplastia coronaria - Imagen endovascular

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INTRODUCTION

Despite the remarkable advances achieved in preventive strategies and therapeutic approaches in recent decades, atherosclerotic coronary artery disease (CAD) remains the leading cause of morbidity and mortality worldwide. (1) Although percutaneous coronary intervention (PCI) is recognized as a fundamental therapeutic strategy for endovascular revascularization in patients with CAD, its benefit is limited by the need for prior and accurate interpretation of data obtained by diagnostic coronary angiography, which has significant limitations in the assessment of vascular involvement due to its characteristics. In this context, and in line with advances in pharmacological treatment strategies, technologies based on imaging and intravascular physiology have been developed and refined to assess the risk of patients with CAD and to improve their treatment.

So far, several studies have supported the optimization of PCI with stent implantation guided by intravascular imaging methods, such as intravascular ultrasound (IVUS) or optical coherence tomography (OCT). These methods offer considerable benefits by significantly improving stent implantation and reducing the incidence of adverse clinical events during follow-up. (2-5) However, the use of these optimization techniques is currently limited, possibly due to their cost to healthcare systems, the need for operator experience to accurately interpret the data obtained, and the fact that they can significantly increase the overall procedure time. In this context, the incorporation of artificial intelligence (AI) as a tool to facilitate and simplify the use of intravascular imaging and the interpretation of the information obtained is emerging as an attractive strategy. The aim of this review is to highlight how current AI-based systems can play a key role in the interpretation of data generated by intravascular imaging techniques, and thus improve optimization of PCI in patients with CAD.

RATIONALE FOR ARTIFICIAL INTELLIGENCE

AI can be defined as a computer program that resembles the human brain in its ability to collect and process data. (6) This concept was first coined in 1956 during the Dartmouth Summer Research Project (7) and generated explosive interest in the 1970s to be implemented in biomedical sciences. (8)

Machine learning (ML) is a sub-discipline of AI that involves the creation of algorithms capable of analyzing large datasets without making prior assumptions and learning to identify rules and patterns among variables for prediction and classification. (9) The versatility and great potential of these algorithms are due to their ability to incorporate a wide set of variables from various medical modalities, ranging from clinical parameters to two- and three-dimensional imaging data, taking into account the

multidimensional nonlinear interactions between them. ML approaches can be broadly classified into three categories: supervised learning, unsupervised learning, and semi-supervised learning. (10) Supervised learning is the most common approach in ML, where the system establishes associations from training data obtained from examples that already have an outcome identified by a specialist. The algorithm embeds the specialist's knowledge within the model. In this method, from the given input features, the system outputs a suitable regression or classification analysis of clinical and imaging data. On the other hand, in situations where training data is unavailable or insufficient, unsupervised learning is used to discover hidden structure of data. (10) Finally, semi-supervised learning begins with a small set of labeled data and augments the training data size by gradually labeling unlabeled data. (10) (Table 1).

Deep learning (DL) is a sub-discipline of ML that focuses on the construction and training of deep and complex artificial neural networks. These networks are designed to mimic the learning process of the human brain. Unlike conventional neural networks, which may have only a few hidden layers, deep neural networks have multiple hidden layers, which allow the network to learn hierarchical and abstract features of input data, which make them especially effective for image processing tasks. Convolutional neural networks (CNN) represent a specialized type of artificial neural network specially designed for processing and analyzing the spatial structure of data that has a grid-like topology, such as an image. Several studies have used CNN to automatically characterize atherosclerotic plaques present in the coronary arteries, employing a variety of approaches. (11-13)

Thus, a suitably trained AI system can comprehensively analyze diverse data and provide a diagnosis by interpreting information in a novel way. This makes it an appealing tool for its incorporation into image-based biomedical techniques to improve risk prediction and personalize clinical decisions.

IMPLEMENTATION OF AI IN INTRAVASCULAR IMAGING METHODS

Visualization of the cross-sectional anatomy of the coronary arteries using intravascular imaging methods has high sensitivity in identifying and characterizing atherosclerotic plaques by extracting tissue-specific parameters from the backscattered ultrasound signal. (14,15) In this context, when considering IVUS as a strategy to optimize revascularization by PCI, multiple clinical studies have shown that it reduces adverse clinical events at follow-up compared to standard angiographic guidance. (2-4)

Limitations of IVUS include its limited axial resolution, which makes it difficult to accurately identify thin-cap fibroatheroma (TCFA), and its limited lat-

Table 1. Machine Learning categories.

Category	Description	Subtype	Examples
Supervised learning	Labelled data and results	Classification: Uses an algorithm to assign data into specific categories, reaching conclusions on how to appropriately label those categories within the dataset	Logistic regression, Bayesian networks, Random Forest, Ridge regression, Elastic Net regression, LASSO (Least Absolute Shrinkage and Selection Operator) regression and artificial neural networks.
		Regression: Analyzes the relationship between dependent and independent variables. It is commonly used to make projections	
Unsupervised learning	Detects crucial relationships and similarities in unlabelled datasets	Clustering: Groups unlabeled data based on their similarities or differences	Hierarchical clustering, K-means clustering and Principal component analysis.
		Dimensionality reduction: Reduces the number of data inputs to a manageable size while also preserving the integrity of the dataset; used when the number of features, or dimensions, in a given dataset is too high	
Semi-supervised learning	A combination of supervised learning and unsupervised learning		It includes both labeled and unlabeled results and classes, and is used in image and speech recognition systems.
Reinforcement learning	Based on behavioral psychology, uses a reward function		Utilizes specific reward criteria and is used in medical imaging, analysis and disease detection.

eral resolution which may hinder the proper identification of coronary vascular dissections and atheroma plaques, as well as the correct positioning of stent struts. Considering these limitations, ML-based algorithms offer opportunities to optimize IVUS performance.

OCT has an inherent advantage in the morphological analysis of atherosclerotic plaques due to its high spatial resolution. (16) Compared to IVUS, OCT offers superior resolution, enabling clear visualization of thin fiber layers. However, its ability to penetrate tissues is limited, which lowers its capacity in detecting plaque size, large lipid cores, and external elastic layers. (17) It is important to note that the human eye has limitations, which can lead to the omission of a significant amount of data in the images. Therefore, there is an urgent need to introduce new optimization technologies in intravascular imaging methods to improve diagnostic efficiency and accuracy. AI constitutes a promising option within this framework.

In this scenario, there are DL methods based on adversarial attacks on CNN learning that could be used to transfer knowledge between IVUS and OCT. For example, images acquired with OCT and IVUS could be used to train AI models to increase the resolution of IVUS images. Similarly, IVUS images could be used to train AI models to complement the information of deep atherosclerotic plaque in OCT images. (Figure 1)

INCORPORATION OF AI IN PRE-PROCEDURAL ASSESSMENT

In the assessment before PCI, it is crucial to perform a thorough characterization of the vascular anatomy and atherosclerotic plaque using intravascular imaging methods to adequately select the endovascular technique to be used and the dimensions of the stent to be implanted. In this context, it is essential to identify the following characteristics before PCI, including the morphology and length of the atherosclerotic plaque, the diameter of the coronary vessels, and the predicted outcome of the intervention (Figure 2).

Several studies have explored the feasibility of implementing AI systems to improve accuracy, reproducibility, and speed in the analysis of intravascular imaging methods. In this setting, a multicenter observational study evaluated the accuracy and consistency of an AI system-based approach for automatic plaque characterization using OCT. (18) A post hoc analysis of OCT pullbacks from cohorts of patients with CAD participating in five different clinical trials was performed, dividing these data into two groups: training data set and testing data set. Thus, quantification of plaque burden using a CNN-based DL system for OCT analysis correlated very well with conventional manual pullback measurements (coefficient of determination $R^2 = 0.98$, $p < 0.001$). (18) Furthermore, through an external validation process that included OCT pullbacks different from those previously analyzed, the CNN-based DL system demonstrated an overall diagnostic accuracy of 86.6% (95% CI: 83.7-

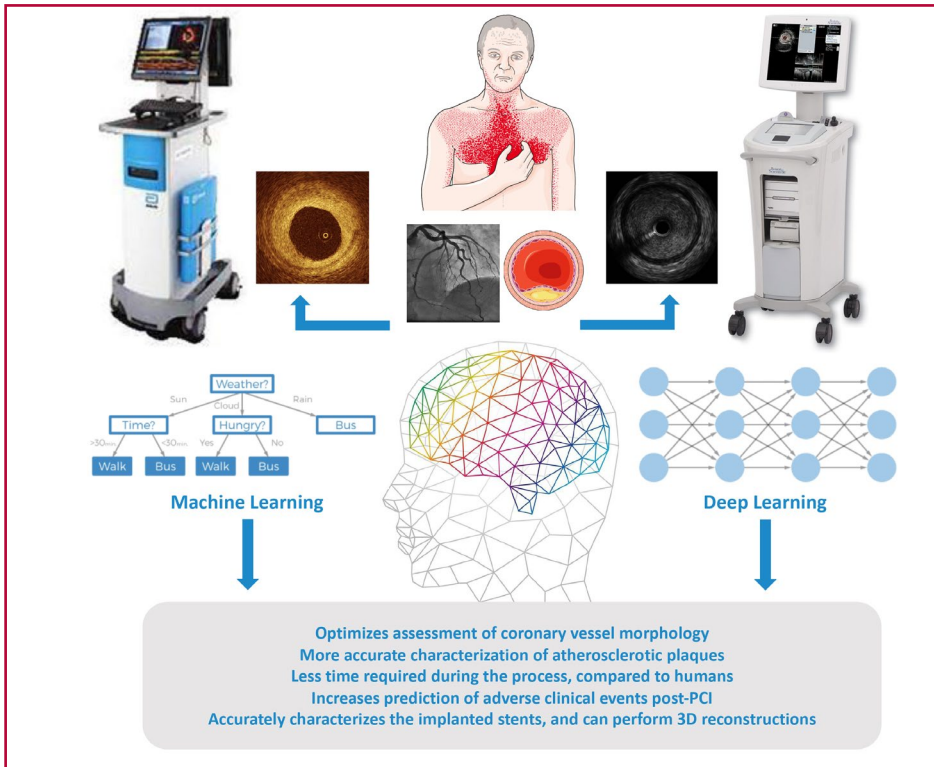


Fig. 1. Benefits provided by artificial intelligence in intravascular imaging methods.

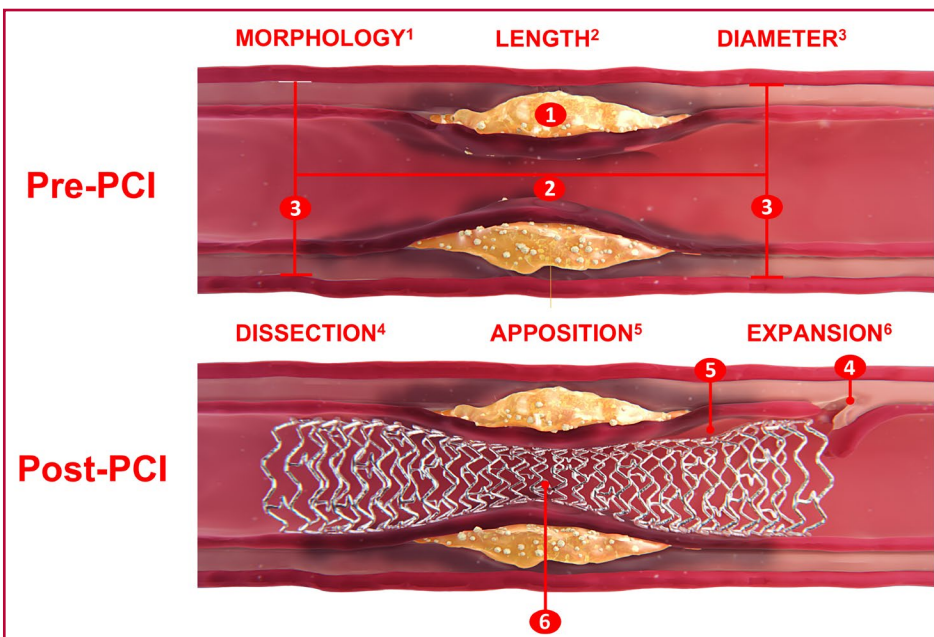


Fig. 2. Artificial intelligence parameters for optimizing percutaneous coronary intervention.

89.1). The software performed the best in fibrous plaques (97.6%; 95% CI: 93.4-99.3%), followed by lipidic plaques (90.5%; 95% CI: 85.2-94.1%) and calcifications (88.5%; 95% CI: 82.4-92.7%). (18) Of note, one of the challenges associated with this type of study is the lack of histological validation, since the initial classification is often based on expert observations.

The incorporation of AI models in the characterization of the coronary arteries by means of OCT has improved the interpretation of atherosclerotic plaques and increased the predictive ability of adverse clinical events during follow-up. In this context, a retrospective observational study analyzed OCT pullbacks in the nonculprit vessel of patients with acute coronary

syndrome. (19) In this analysis, AI was used to determine the optical flow ratio (OFR) as a surrogate parameter of coronary physiology derived from OCT, as well as to identify the lipid-to-cap ratio (LCR), a novel morphologic OCT index that integrates the lipid burden of the atherosclerotic plaque and the cap thickness over the diseased segment. (19) In this regard, determination of OFR and LCR using an AI system demonstrated superior discriminatory ability to predict nonculprit vessel-related major adverse cardiovascular events (NCV-MACE) compared with predictions based on minimum luminal area (MLA) determination and identification of TCFA. The combination of $LCR > 0.33$ and $OFR \leq 0.84$ resulted independent risk factors for NCV-MACE during follow-up. (19) Table 2 presents studies in which AI was used as a strategy to optimize OCT.

IVUS is one of the main intravascular imaging methods for assessing coronary artery calcium, a predictor of adverse cardiovascular events and long-term mortality. (46) One of its limitations is the lack of an automated quantification system for coronary artery calcium. However, this limitation could be overcome by implementing AI systems that provide objective and reproducible automated quantification that correlates with validated coronary artery calcium scores. (47) In this context, a single-center retrospective cohort study evaluated the ability of an AI algorithm trained with IVUS imaging data to quantify coronary artery calcium and its association with adverse clinical events. (48) An IVUS calcium score (ICS) based on an AI model was shown to have a high predictive value for the development of adverse clinical events during follow-up. There was a 51% increased risk of adverse events in patients with an $ICS \geq 85$. This ICS represents the first validated coronary calcium score associated with adverse clinical events since the introduction of computed tomography-derived calcium scoring. (48,49) AI systems have the remarkable ability to distinguish between various coronary artery calcium patterns, such as calcium in the artery wall and calcified nodule. (Table 3)

Prediction of stent under-expansion using AI algorithms

Despite substantial improvements in interventional procedures, stent design, drugs and polymers, and the adoption of therapeutic strategies, acute stent thrombosis and in-stent restenosis remain critical issues. It can be difficult to fully expand a coronary artery stent in a heavily calcified coronary artery lesion. Careful evaluation of these risks of under-expansions before the intervention will aid treatment planning. AI-based systems play a crucial role in obtaining an automated and reproducible prediction since morphological characterization of atherosclerotic plaque and prediction of the risk of stent under-expansion are often challenging procedures.

IVUS is one of the most commonly intravascular procedures used to optimize stent implantation and

has been associated with a decrease in adverse clinical events during follow-up. (2-4) However, IVUS has certain limitations, as determining the minimum stent area (MSA) in a single cross-section does not fully reflect the stent status along the entire vessel length, and there are no guidelines to predict the postprocedural MSA and the degree of stent expansion. In this context, CNN-based AI algorithms can automatically and adaptively calculate the probability of under-expansion after implantation. One study has developed an IVUS-based AI algorithm to predict the post-stenting stent area and the probability of under-expansion. (58) A dataset of pre-procedural and post-stenting IVUS images was obtained and was subsequently divided into a training set and a validation set for the algorithm. A DL CNN-based system was used to create a regression model to predict post-stenting stent area. XGBoost models for binary classification were developed to predict post-stenting stent under-expansion (defined as an $MSA < 5.5 \text{ mm}^2$). MSA predicted by the pre-procedural IVUS-based regression model significantly correlated with those measured on post-stenting IVUS ($r = 0.802$; $p < 0.001$), and an accuracy of 94% was obtained to predict stent under-expansion ($AUC = 0.94$). (58) (Table 3)

Moderate to severe coronary artery calcification is a strong predictor of MACE after PCI. (64) This may be due to stent under-expansion caused by severely calcified plaque and inadequate lesion preparation prior to implantation. In this context, OCT-guided stent implantation provides a thorough assessment of coronary calcification and stent deployment characteristics, including aspects such as expansion, malapposition and stent edge dissection. (65) In addition, DL-based systems have been developed to optimize procedure duration and predict stent under-expansion using OCT. A retrospective single-center study analyzed OCT pullbacks with the goal of developing a DL algorithm to predict stent under-expansion before the procedure. (66) The DL algorithm exhibited remarkable discrimination ability to detect stent under-expansion, with an AUC of 0.853. This finding strongly supports the idea that AI systems may represent an extremely valuable addition to intravascular imaging methods, optimizing PCI. (66) In this context, we currently count with OCT imaging with AI-driven information (Ultreon™ 1.0 Software, Abbott). This software automatically detects the severity of coronary artery calcium, determines external elastic lamina and measures the vessel diameter, which not only increases the accuracy of real-time stenting, but also simplifies the interpretation of the acquired images, reducing inter-observer variability. (67)

Use of AI for segmentation and lumen area dimensions

In the assessment before PCI, it is crucial to accurately measure the vascular dimensions to select

Table 2. Studies using artificial intelligence as a strategy to optimize optical coherence tomography.

Author	Year	Objective	Algorithm used	Results
Athanasiou LS, et al. (20)	2011	To extract a set of features from grayscale OCT images and employ them to classify the atherosclerotic plaque using an ML algorithm.	Random Forest	The ML algorithm associated with OCT accurately characterized the atherosclerotic plaques.
Wang Z, et al. (21)	2012	To propose and validate an OCT-based ML method to analyze fibrous cap volume to identify vulnerable atherosclerotic plaques.	Dynamic Programming	The proposed ML method is fast, accurate and robust, and can be used in future studies to further characterize atherosclerotic plaques.
Ughi GJ, et al. (22)	2013	To develop and validate an ML algorithm to optimize the characterization of atherosclerotic plaques by OCT.	Random Forest	The ML algorithm provided accurate characterization of atherosclerotic plaques.
Xu M, et al. (23)	2014	To propose a ML algorithm for automatic detection of atherosclerotic plaques using OCT.	Support Vector Machine	The proposed ML system is accurate and stable for the detection of atherosclerosis by OCT.
Wang Z, et al. (24)	2014	To examine the quantitative tissue properties that can differentiate plaque erosion from intact fibrous plaques and to develop a computer-aided classification model for in vivo diagnosis of plaque erosion.	Logistic regression	The quantitative logistic regression model can be used to improve the diagnostic accuracy for plaque erosion in vivo using OCT.
Shalev R, et al. (25)	2016	To develop an ML method automatic classification of calcium in OCT images.	Use of filters to select regions for extraction of sub-images (SI's)	The ML algorithm presents high accuracy for characterization of coronary artery calcium in OCT, images which could be used in 'real time'.
Rico-Jimenez JJ, et al. (26)	2016	To present a novel computational method for automated IV-OCT plaque characterization	A-line Modeling	The ML algorithm presents high accuracy for characterization of atherosclerotic plaques.
Xu M, et al. (27)	2017	To propose a DL model for the identification and characterization of fibroatheromas in OCT images.	AlexNet,GoogLeNet, VGG-16, VGG-19	The DL system provides a highly accurate characterization of fibroatheromas.
Shi P, et al. (28)	2018	To develop a DL-based model to identify vulnerable atherosclerotic plaques in OCT images.	Fully CNN, Deep CNN	The DL method presented high accuracy for characterizing vulnerable atherosclerotic plaques.
Guo X, et al. (29)	2018	To create a DL algorithm to characterize atherosclerotic plaque components and quantify fibrous cap thickness.	Least Squares Support Vector Machine (LS-SVM)	The segmentation method base on LS-SVM provided accurate characterization of fibrous cap thickness.
Kolluru C, et al. (30)	2018	To develop neural network-based methods for classifying plaque types in OCT images.	CNN, ANN	The DL model presented high accuracy for classifying atherosclerotic plaque subtypes.
He S, et al. (31)	2018	To analyze the performance of a DL model for characterization of atherosclerotic plaques in OCT images.	CNN	The DL algorithm demonstrated high accuracy to characterize atherosclerotic plaques.
Lee J, et al.(32)	2019	To develop a DL system for automatic segmentation of atherosclerotic plaques based on OCT images.	SegNet	The DL algorithm showed high accuracy for segmentation of atherosclerotic plaques.
Prabhu D, et al. (33)	2019	To develop ML methods to identify fibrolipidic and fibrocalfic A-lines in OCT images.	Support Vector Machine	The proposed classification algorithm is suitable for automated OCT plaque classification and segmentation.
Liu R, et al. (34)	2019	To improve the detection quality of vulnerable plaque using a DL algorithm associated with OCT.	Deep CNN	The proposed DL algorithm has high accuracy to detect vulnerable plaques in OCT images.
Johnson KW, et al. (35)	2019	To use a ML algorithm and transcriptomic data to estimate the predict if fibrous cap thickness will increase in response to statin therapy	Elastic net K top scoring pair	A ML algorithm using transcriptomic models could predict increase in fibrous cap thickness as a result of statin treatment.
Baruah V, et al. (36)	2020	To determine the feasibility of a histology-validated virtual OCT (VH-OCT) algorithm using AI.	CNN	"This note is the first report to classify automatically tissue components with AI based on histological validation and extension into in vivo patient images."

Table 2 (Cont.)

Author E3:I3	Year	Objective	Algorithm used	Results
Lee J, et al. (37)	2020	To develop an ML algorithm for characterization of atherosclerotic plaques using a hybrid learning approach.	Deep CNN	The proposed algorithm could accurately characterize the atherosclerotic plaques.
Lee J, et al. (38)	2020	To develop an automated, two-step DL approach for characterizing coronary calcified plaque	CNN, SegNet	Compared to the standard approach, the two-step DL system is highly accurate for characterization of atherosclerotic plaques in OCT images.
Cha JJ, et al. (39)	2020	To evaluate the usefulness of ML FFR based on OCT and compare it with wire-based FFR.	Random Forest	OCT-based ML-FFR has good correlation with wire-guided FFR.
Chu M, et al. (18)	2021	To develop and validate a DL algorithm for characterization of atherosclerotic plaques in OCT images.	CNN	The DL algorithm for automatic characterization of atherosclerotic plaques in OCT images offers provides excellent diagnostic accuracy in both internal and external validation.
Balaji A, et al. (40)	2021	To develop a DL algorithm for automatic coronary artery segmentation in OCT images.	DeepCap	The AI system linked to OCT demonstrated high accuracy for automatic segmentation of coronary arteries.
Yin Y, et al. (41)	2021	To develop DL algorithm for characterization of atherosclerotic plaques in OCT images.	TwopathCNN	A proposed DL algorithm presented higher accuracy for the characterization of atherosclerotic plaques, compared with conventional DL algorithms.
Li C, et al. (42)	2021	To develop a DL algorithm for automatic quantification of coronary artery calcium in OCT images.	DenseNet, CNN	The proposed DL model presents high accuracy for discriminating coronary artery calcium in OCT images.
Yang G, et al. (43)	2021	To develop a DL model to automatically analyze stents with both thin (≤ 0.3 mm) and very thick (> 0.3 mm) tissue coverage, and an algorithm to accurately analyze stent area for vessels with multiple stents.	CNN	The proposed model can accurately detect stent struts with very thick tissue coverage and analyze stent areas in vessels implanted with multiple stents.
Hong H, et al. (19)	2022	To analyze the role of AI for predicting major adverse cardiovascular events by determining the plaque morphology and coronary artery physiology in OCT images.	Deep CNN	The study identified a novel DL algorithm to characterize the morphology and physiology of atherosclerotic plaques, which can predict the risk of adverse cardiovascular events.
Sun H, et al. (44)	2022	To develop a DL-based AI method for fully automated detection of atherosclerotic plaque erosion.	Mask RCNN with convexity and curvature (RCNN-CK), SVM	The developed DL algorithm presented good ability to discriminate atherosclerotic plaque erosion in OCT images.
Wu P, et al. (45)	2023	To analyze whether OCT and IVUS images can assist each other in stent 3D reconstruction	F1-score	Using AI systems, intravascular images of OCT and IVUS can provide reciprocal assistance to each other in stent 3D reconstruction.

AI: artificial intelligence; ANN: artificial neural network; CNN: convolutional neural network; DL: deep learning; FFR: fractional flow reserve; IVUS: intravascular ultrasound; ML: machine learning; OCT: optical coherence tomography

the adequate stent. Determining the length of the atherosclerotic plaque is crucial to avoid geographic miss during implantation. Additionally, knowing the lumen and vessel diameter is crucial in selecting the appropriate stent for implantation. One of the most arduous tasks when analyzing IVUS datasets is the segmentation of the lumen boundary and external elastic lamina, for which an expert has to manually outline them. This process is performed in the transversal axis and longitudinal view and usually results in large intra and interobserver variability. Additionally, artifacts are often present in IVUS images throughout the longitudinal view, and can lead to errors in lumen segmentation. To

correct these errors, electrocardiogram-gating is necessary. Since this process is crucial for accurate data interpretation, AI algorithms are presented as an accurate and consistent alternative for selecting the correct frames. One study proposed an automated workflow to segment lumen boundaries in IVUS datasets using a DL approach and multi-frame (MF) CNN. The dataset consisted of IVUS pullbacks. After an automated gating, AI identified end-diastolic frames to avoid longitudinal artifacts and performed automated lumen segmentation using the MF-CNN algorithm. The correlation between the actual lumen and that obtained by the DL algorithm was high ($r = 0.99$). (55) (Table 3).

Table 3. Studies using artificial intelligence as a strategy to optimize intravascular ultrasound.

Author	Year	Objective	Algorithm used	Results
Sheet D, et al. (50)	2014	To develop an innovative ML-based technique (SDH) to automatically characterize morphology in IVUS images.	Random Forest	SDH is highly consistent with traditional histology in characterizing calcification, fibrotic tissues and lipids.
Kim GY, et al. (51)	2018	To develop a classification model based on virtual histology to characterize atherosclerotic plaque components in fibrous tissue, fibro-fatty tissue, necrotic core, and dense calcium.	Multi-level classification model consisting of three different nets	The proposed method showed high accuracy for classifying all types of plaques.
Bae Y, et al. (52)	2019	To develop ML models to predict optical coherence tomography (OCT) thin-cap fibroatheroma (TCFA).	ANN, Support Vector Machine, Naïve Bayes	The presence of OCT-TCFA was predicted with high accuracy by ML algorithms.
Jun TJ, et al. (53)	2019	To identify the most accurate method to classify TCFA using various ML classifiers.	Feed-forward neural network (FNN), K-nearest neighbor (KNN), Random Forest, CNN	The CNN classifier performed best, while FNN, KNN and Random Forest classifiers were found to be similar to the physician's TCFA diagnostic criteria.
Wang L, et al. (54)	2020	To identify the most accurate ML classifier to predict atherosclerotic plaque vulnerability change as determined by IVMP.	Generalized linear mixed regression model (GLMM), Support Vector Machine, Random Forest	MPVI was the best single risk factor using both GLMM and Random Forest while plaque area was the best using SVM.
Ziemer PG, et al.(55)	2020	To evaluate the utility of a novel, automated ML system to segment the lumen boundary in IVUS datasets.	Multi-frame convolutional neural network	The proposed ML algorithm is suitable to effectively segment the lumen boundary in IVUS scans, reducing time required and need for manual delineation.
Lee JG, et al. (56)	2020	To determine the usefulness of AI algorithms for identifying functionally significant coronary stenoses (FFR \leq 0.80).	L2 penalized logistic regression, ANN, Random Forest, AdaBoost, CatBoost, Support Vector Machine	IVUS-based ML algorithms showed good diagnostic performance for identifying ischemia-producing lesions.
Cho H, et al. (57)	2021	To develop IVUS-based ML algorithms for classifying attenuation and calcified plaques.	EfficientNet	The ML algorithm for plaque characterization accurately identifies high-risk coronary artery lesions.
Neleman T, et al. (48)	2021	To develop and validate an ML algorithm to automatically quantify coronary calcifications in IVUS images.	Support Vector Machine	The IVUS calcium score calculated by an ML algorithm was strongly associated with the long-term risk of major adverse cardiac events.
Min HS, et al. (58)	2021	To develop pre-procedural IVUS-based DL models for predicting the occurrence of stent underexpansion.	CNN, EXtreme Gradient Boosting' (XGBoost)	The algorithms accurately predicted (94%) incomplete stent expansion.
Bass RD, et al. (59)	2022	To compare the performance of human readers to the ML algorithm and against the readings from a Core Laboratory for coronary vessel segmentation.	Multi-frame convolutional neural network	Similar assessment of segmentation performed by humans, ML algorithm and core lab, with machines being more time efficient.
Bajaj R, et al. (60)	2022	To train and assess the efficacy of a ML classifier for plaque component classification that relies on IVUS echogenicity and NIRS-signal.	Algorithm J48	The combination of echogenicity with NIRS-signal appears capable of overcoming limitations of echogenicity.
Wissel T, et al.(61)	2022	To propose a fully data-driven strategy to longitudinally detect and subsequently segment stent struts in IVUS frames.	Deep cascade learning	Using the DL algorithm, a reduced risk of ambiguities and false-positive predictions was observed for segmenting stents.
Blanco PJ, et al. (62)	2022	To determine the accuracy of a DL algorithm for automatic segmentation in IVUS images.	Multi-frame convolutional neural network, Gaussian process	The proposed DL approach provides accurate segmentations, which facilitates its implementation in clinical routine by mitigating the costs involved in the manual management of IVUS datasets.
Arora P, et al. (63)	2023	To use a DL algorithm to identify the extent of vascular calcification in IVUS images.	AlexNet, GoogLeNet, SqueezeNet	DL algorithm identify the extension of vascular calcification with high accuracy.

DL: deep learning; FFR: fractional flow reserve; IVUS: intravascular ultrasound; ML: machine learning; MPVI: morphological plaque vulnerability index; NIRS: near infrared spectroscopy; OCT: optical coherence tomography; SDH: stochastic driven histology; TCFA: thin-cap fibroatheroma; VH: virtual histology

This DL algorithm has been extended for lumen and external elastic lamina segmentation with excellent results. (62) In turn, these results were replicated in other studies, such as a post-hoc, cross-sectional analysis of the IBIS-4 study, (68) which evaluated the performance of a DL algorithm based on a MF-CNN for automated lumen and vessel contour segmentation. (59) This study showed that, compared to the determination of vessel structures by human readers, the DL algorithm showed a strong correlation with those of the Core Lab. This offers the advantage of eliminating human inter and intraobserver variability, improving accuracy in lumen contour segmentation, and significantly reducing the time required to complete the analysis (average human time spent per pullback = 47 minutes vs. ML = 1 minute). (59)

Utility of AI to optimize stent implantation

After PCI, it is essential to optimize stent placement to reduce the likelihood of adverse clinical events during follow-up. Intravascular imaging guidance using IVUS or OCT provides clear advantages over conventional angiographic guidance in terms of optimization. However, determining the parameters to be corrected in complex PCI procedures can be a challenging task. In this context, three-dimensional (3D) reconstruction of implanted stents using intravascular imaging methods is useful for addressing implantation issues. Of note, as manual reconstruction is a complicated process, AI algorithms can be a valuable tool. The introduction of DL algorithms has revolutionized automatic stent 3D reconstruction visualized by intravascular imaging methods, enabling reliable and real-time analysis during the intervention. (61) OCT and IVUS have different image styles, share the same anatomic structures, and can be aligned by cross-modal translation. In this context, a study explored the feasibility of using OCT and IVUS to assist each other in DL-based automatic 3D reconstruction of the stents implanted during PCI. The study found that the DL algorithm performs exceptionally well in generating 3D reconstructions of implanted stents, regardless of whether conventional IVUS or high-definition IVUS were used for optimization. This information can be valuable when analyzing potential improvements and optimizations in the implantation procedure. (45) (Table 2).

CHALLENGES AND FUTURE PERSPECTIVES

Considering that AI is a data-driven science, the lack of standardization in collecting and storing medical data may negatively influence the interoperability of AI systems in the medical field. Data heterogeneity hinders the effective integration of AI algorithms in different clinical settings and the communication of information between healthcare systems.

Furthermore, the performance of AI algorithms in clinical practice depends heavily on the representativeness of the training data compared to the

data encountered in daily practice. In some cases, the data collected for developing AI algorithms may not be representative of the population it serves, leading to poor performance. In this sense, external validation and field testing are essential to determine the level of confidence of AI algorithms.

As artificial AI is already being integrated into clinical workflows, it is essential to demonstrate its value in patient care, support investment in these new algorithms, and encourage the adoption of new reimbursement or payment models. To achieve this on a large scale, it is essential to conduct cost-effectiveness studies of these emerging technologies.

CONCLUSIONS

When combined with intravascular imaging methods such as IVUS or OCT, AI systems significantly optimize stent implantation through a fully automated framework that identifies vascular structures and guides correct stent positioning. This facilitates the accurate selection of the stent to be implanted and the need for stent correction techniques. Additionally, it reduces both the total procedure time and interobserver variability. This could promote greater adoption of intravascular imaging techniques and ultimately reduce the incidence of adverse clinical events during follow-up.

Conflicts of interest

None declared.

(See conflicts of interest forms on the website).

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