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REVIEW ARTICLE

Advancements in artificial intelligence-driven techniques for interventional cardiology

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Abstract

This paper aims to thoroughly discuss the impact of artificial intelligence (AI) on clinical practice in interventional cardiology (IC) with special recognition of its most recent advancements. Thus, recent years have been exceptionally abundant in advancements in computational tools, including the development of AI. The application of AI development is currently in its early stages, nevertheless new technologies have proven to be a promising concept, particularly considering IC showing great impact on patient safety, risk stratification and outcomes during the whole therapeutic process. The primary goal is to achieve the integration of multiple cardiac imaging modalities, establish online decision support systems and platforms based on augmented and/or virtual realities, and finally to create automatic medical systems, providing electronic health data on patients. In a simplified way, two main areas of AI utilization in IC may be distinguished, namely, virtual and physical. Consequently, numerous studies have provided data regarding AI utilization in terms of automated interpretation and analysis from various cardiac modalities, including electrocardiogram, echocardiography, angiography, cardiac magnetic resonance imaging, and computed tomography as well as data collected during robotic-assisted percutaneous coronary intervention procedures. Thus, this paper aims to thoroughly discuss the impact of AI on clinical practice in IC with special recognition of its most recent advancements. (Cardiol J 2024; 31, 2: 321–341)

Keywords: artificial intelligence (AI), interventional cardiology (IC), cardiac modalities, augmented and/or virtual realities, automatic medical systems

Introduction

Artificial intelligence (AI), and in particular machine learning (ML), allows for the processing and analysis of huge amounts of medical data in real time, and will prove to be revolutionary for healthcare systems. AI is developing very fast particularly in the field of cardiology, ranging from electrocardiography (ECG) interpretation to clinical decision support systems for cardiac interventional procedures [1, 2]. According to recent updates of medical devices approved by the United States Food and Drug Administration (FDA) for general use, the majority of AI/ML-enabled devices are authorized in radiology, followed by the cardiovascular area. The latter is most prominently represented by interventional cardiology (IC), which is a subspecialty of cardiology that

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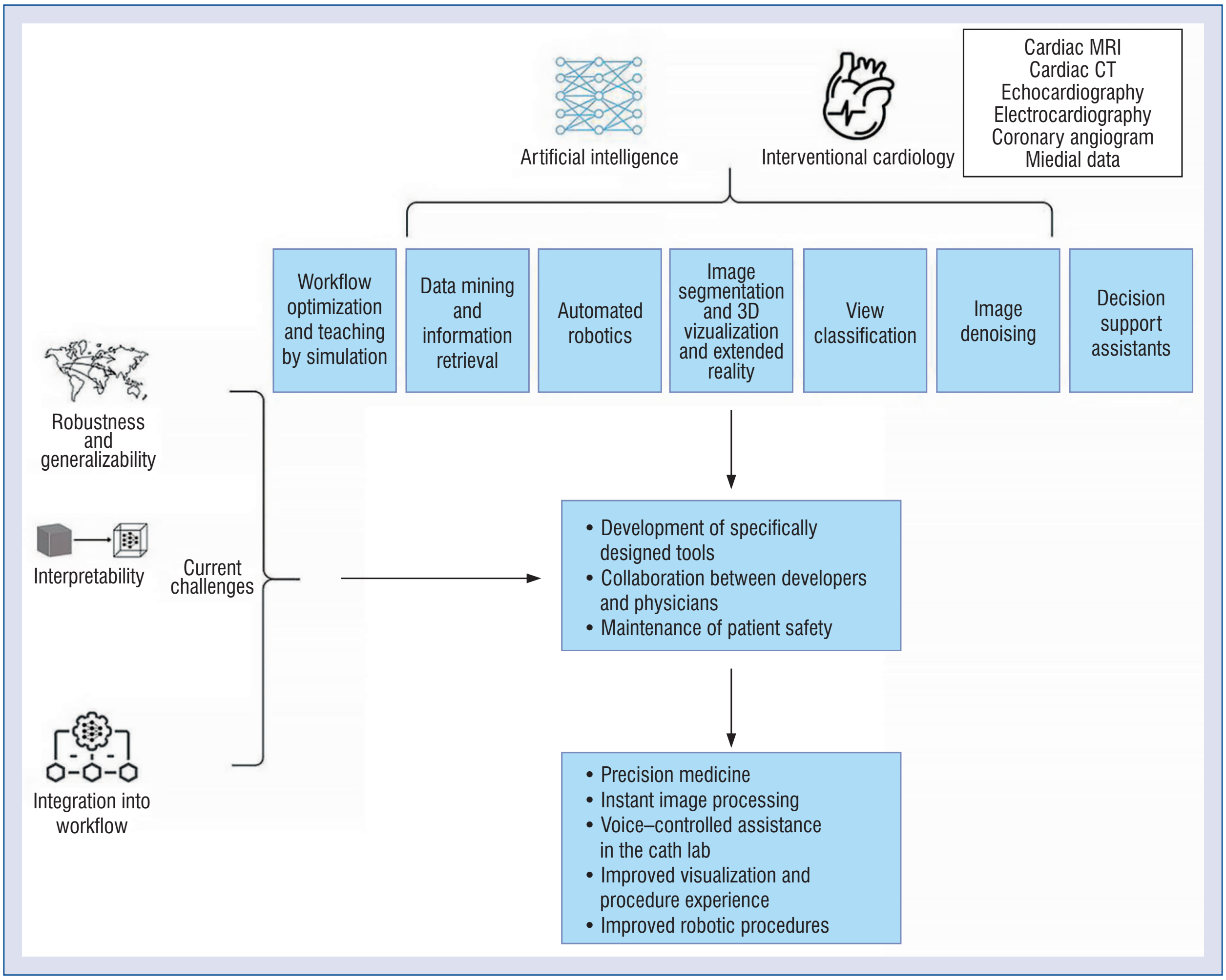
provides catheter-based treatment of structural heart diseases. The steady growth in the number of FDA-approved devices highlights the potential of embedding them into routine clinical practice. AI/ML-based devices empower cardiologists to implement a complex approach to heart diseases in numerous ways such as earlier establishment of diagnosis, patient risk stratification before targeted interventions, and general improvement in quality of care. The potential use of AI in IC may cover each step of the therapeutic process, including in-hospital first-line assessment of chest pain [3] and/ /or cardiogenic shock, periprocedural planning the intervention's strategy for better navigation and guidance as well as predicting periprocedural risks [4], and potential patient outcomes. The specific nature of IC provides clinicians with many imaging modalities, including both anatomic and functional assessment of structural heart diseases. Therefore, AI is considered a promising technological tool expected to have a significant impact on imaging reconstruction, analysis, and interpretation, leading to an increase in the availability and quality of healthcare data and further progress in analytic techniques in the future. The utilization of AI in clinical practice has been proven to be valuable, particularly regarding echocardiography examination [5], angiographic assessment of coronary artery stenoses [6], including lesion characteristics [7], assessment of cardiac perfusion via single photon emission computed tomography imaging [8], and in cardiac magnetic resonance (CMR) imaging [9]. The aforementioned studies suggest that in the future AI may be capable of providing both clinicians and patients with automated diagnosis based on the interpretation of imaging examination independent of an imaging specialist.

The potential of AI application in the IC field is presented in the Central illustration. For example, in the international research project CEREBRIA-1 (Machine Learning vs Expert Human Opinion to Determine Physiologically Optimized Coronary Revascularization Strategies) it was established that in the case of the treatment of patients with stable coronary artery disease, ML-based algorithms gave similar indications to those of an international team of medical doctors. Thus, when during specialized treatment the medical unit does not always have specialist knowledge that allows it to effectively interpret the ECG data, AI algorithms such as the AI-based triage algorithm (DELTAnet) [10] can be an effective support tool. In IC progress has also been made. Here, one can distinguish two main lines of research and potential applications of AI: virtual (medical image processing, decision making), and physical, such as robotic interventional procedures [11]. AI gives opportunities for improvements in the field of computer vision and image processing that can be applied to robotic interventions [12]. However, autonomous robotic vascular procedures remain a challenge [11]. On the other hand, in [13] an AI-supported approach in ultrasound-guided cardiac interventions to identify, localize and track the critical structures and lesions and validate the algorithm's performance was proposed. It turned out that the proposed model for identifying and locating heart structures successfully exceeded the abilities of experts (medical doctors).

The majority of imaging modalities in IC such as echocardiography, CMR, angiography, and computed tomography (CT) provide two-dimensional (2D) data that can be easily converted using various three-dimensional (3D) modeling techniques into physical objects with accurate representations of the heart and correct anatomical features [14]. Consequently, multi-modality image integration in cardiology contributes to a better understanding of structural cardiac anatomy, leading to a precise patient-tailored approach for interventional procedures. Indeed, here lies another promising potential combination of AI and other new technologies for example 3D modeling enhanced by immersive technologies. Immersive technologies, such as virtual reality, augmented reality, and mixed reality, have revolutionized the way we interact with digital environments. These technologies create highly engaging and interactive experiences by blending virtual components with the real world or by completely immersing the user in a virtual environment. AI plays a crucial role in enhancing these immersive experiences. By integrating AI, immersive technologies can become more interactive and responsive to user actions and behaviors immersive technologies and AI, the potential fusion of these technologies may contribute to a more thorough understanding of different aspects of cardiac anatomy during procedures [15]. They may also influence the selection of the appropriate device and procedural technique, due to better preprocedural planning and real-time intraprocedural visualization for complex anatomical and geometrical relations [16].

However, AI is a very general term. Also, the AI application field is wild. This paper concentrates on the algorithms taking into account the type of neural networks that have been applied in IC in particular. It presents and discusses the neural



Central illustration. Artificial intelligence workflow in interventional cardiology: a basic schema; CT — computed tomography; MRI — magnetic resonance imaging, 3D — three-dimensional.

networks and learning algorithms that have been used in the analysis of medical data and shows further directions of development of the AI-driven approach.

Review methodology

The methodology of this systematic review is based on the PRISMA Statement [17]. Recent publications, reports, protocols, and review papers from Scopus and Web of Science databases have been considered. The keywords ‘Artificial Intelligence, Machine Learning, Extended Reality, Mixed Reality, Virtual Reality, Metaverse, cardiology, interventional cardiology, segmentation, segmentation algorithms, classification algorithms, ethics, AI ethics’ and their variations were identified. In the first step, features of the material such as title and abstract were evaluated taking into account exclusion criteria (for example criterion 1, PhD thesis and materials not related to cardiology, was removed from the procedure whereas criterion 2, full-text papers in English, including electronic publications before printing, was considered). Subsequently, articles and technical reports meeting the criteria were retrieved and analyzed. The documents used in this study were selected based on the procedure presented in Figure 1. Finally, 100 documents were taken into account.

Application of artificial intelligence

Various neuronal networks have been used in the field of medicine. They differ not only in architecture but above all in the type of neuron model applied. And consequently, the number of parameters that need to be optimized. Also, depending on the type of neural network, different

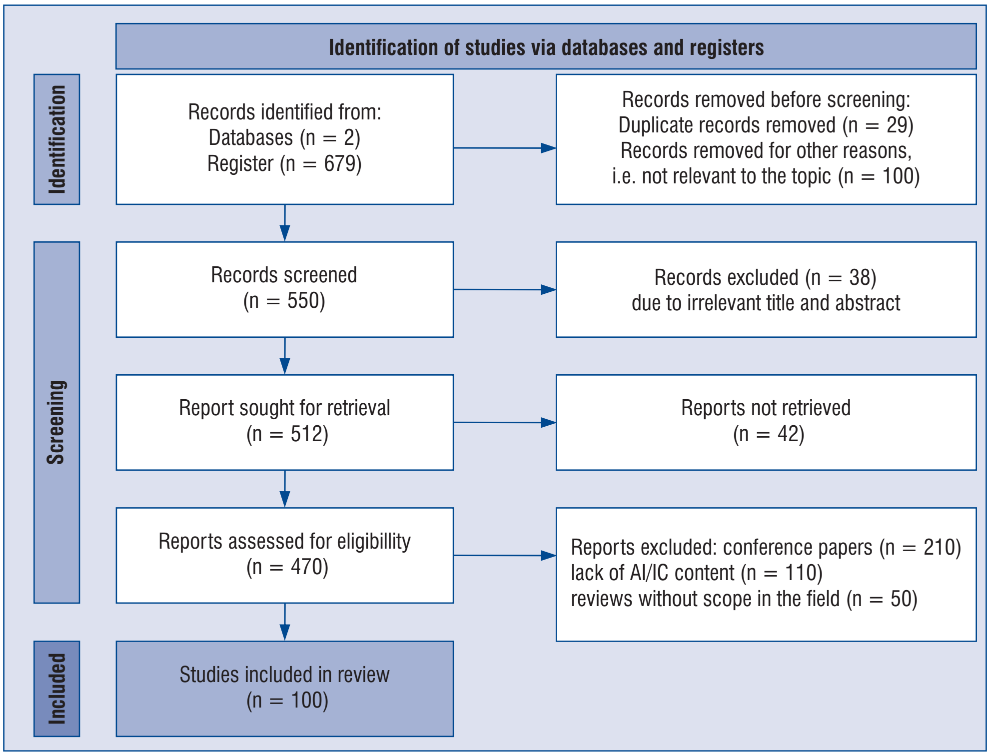


Figure 1. The scheme of the methodology of literature review; AI — artificial intelligence; IC — interventional cardiology.

training algorithms may provide obtaining higher accuracies of the predicted results.

Artificial Neural Networks (ANNs)

The first type of AI solution in cardiology is based on Artificial Neural Networks (ANNs). These are an interconnected group of nodes (artificial neurons) that model connections of biological neurons as weights between nodes. ANNs find applications in IC, including echocardiography and cardiac CT, contributing to the automation and improvement of the assessment of cardiovascular diseases as well as significantly enhancing the diagnosis and treatment of cardiovascular diseases [18]. These neural networks provide a computational tool that can automate the analysis of echocardiography and cardiac CT images, increase accuracy, and reduce the detection time of heart conditions such as vessel constrictions or congenital defects [19]. ANNs also aid in the identification of important cardiac structures in medical images, making the work of doctors and radiologists easier [20]. One of the key advantages of ANNs is their ability to learn from vast amounts of data, predicting outcomes based on patterns. Another advantage is automation. They can automatically extract features and process data, which is extremely valuable in medical image analysis, imaging studies, and ECG data analysis. This automation can significantly expedite and simplify diagnostic and research work. Neural networks adjust weights and model parameters to minimize prediction errors based on training data. This allows the model to extrapolate its capabilities and is also known for its ability to detect subtle patterns and relationships in data. This can help identify the risk of heart diseases and other conditions at an earlier stage, improving healthcare quality and reducing diagnosis time. However, it's important to note that ANNs also have limitations. Their complex architecture and operation require a large amount of training data to achieve high accuracy. There is also a risk of overfitting, where the model may learn irrelevant noise in the data (a model learns the training data too well, including its noise and random fluctuations, this issue leads to a model that performs exceptionally on the training data but poorly on new, unseen data). Additionally, interpreting results obtained through neural networks can be challenging due to their intricate structure [21]. ANNs have been successfully applied for the automatic measurement of ejection fraction and left ventricular longitudinal strain based on biplanar images of the left ventricle with high accuracy, as much as 98% [22]. ANNs have also been used to automatically differentiate hypertrophic cardiomyopathy from physiological cardiac hypertrophy in athletes [23]. In addition to echocardiography, ANNs have played a role in analyzing ECG data for the detection of electrolyte imbalances. Notably, ANNs have been effective in identifying moderate to severe hypokalemia and hyperkalemia based on ECG patterns. These AI-based systems can contribute to the early diagnosis of electrolyte disturbances, which can lead to various cardiac complications.

Recurrent Neural Networks (RNNs)

The second type of neural network that can be applied in cardiology includes Recurrent Neural Networks (RNNs). These allow for the managing and interpreting of data that have a naturally sequential character, such as natural language or time series. Their structure enables the "remembering" and integration of information from previous stages of the sequence, making them especially useful in analyzing complex medical data such as ECG recordings, echocardiogram data, or continuous monitoring of a patient's health condition [5]. In IC, RNNs can be applied to analysis of the patterns and trends in the patient's medical data. As a consequence, RNNs can predict potential outcomes of interventions, assisting in planning more effective treatment plans, for example, predicting the prognosis of patients with adult congenital heart disease, and pulmonary hypertension [24]. One interesting solution based on RNNs is that of DeepHeart [25]. This employs semi-supervised sequence learning based on data from popular wearable devices (Fitbit, Apple Watch, or Android Wear) to predict cardiovascular risk more effectively than traditional biomarkers. RNNs also play an important role in the automatic selection of myocardial inversion time, a key factor in assessing heart conditions. This automation streamlines the diagnostic process, making it more efficient and accurate [26]. Moreover, the adaptability of RNNs allows them to process data from various sensors to predict conditions such as diabetes, high cholesterol, high blood pressure, and sleep apnea [27].

Convolutional Neural Networks (CNNs)

Another solution that has emerged as a transformative force in the field of IC, a branch of medicine focused on the catheter-based treatment of heart diseases regards Convolutional Neural Networks (CNNs). These enable the processing and interpreting of complex cardiovascular images, significantly enhancing the accuracy of diagnoses and the effectiveness of treatments [28]. Convolutional Layers, serving as the foundation of CNNs, are instrumental in extracting features from input images, such as angiograms or echocardiograms. By utilizing a diverse array of filters, these layers efficiently identify patterns and features that are key indicators of heart diseases. This identification and analysis process is crucial in diagnosing and understanding various cardiac conditions. Pooling Layers also play a vital role in reducing the complexity of the data processed by convolutional layers. This process involves retaining only the most essential features, thereby streamlining the data while preserving the critical diagnostic information. The ability to simplify image data without losing important details is a significant advantage in the precise analysis of cardiac images. Fully Connected Layers are responsible for the critical tasks of classification or regression, based on the features extracted by the convolutional and pooling layers. In the context of IC, this means accurately identifying specific cardiac conditions, predicting patient outcomes, and providing valuable insights for procedural planning. Thus, CNNs improve both diagnostic accuracy and the effectiveness of treatment strategies [29]. As CNNs continue to evolve, their impact on IC is expected to grow, paving the way for more sophisticated and personalized patient care [30]. For example, CNNs can be successfully applied to the analysis of aortic valves during transcatheter aortic valve implantation procedures [1]. It has been found that the proposed approach ensured a higher degree of accuracy, thereby increasing the likelihood of successful outcomes. In this paper [31] employed CNNs to classify views in transthoracic echocardiograms. This AI-based solution ensured a more precise interpretation of cardiac imaging, which is essential for administering the correct treatment to patients. A significant advancement has also been made in the segmentation of heart chambers [32]. Moreover, an important element in interventional surgery also comprises the education of future medical staff. Indeed, Akinyemi et al. [33] describes the application of CNNs to a system enabling the identification of operators' activities.

Spiking Neural Networks (SNNs)

Recently, more complex, brain-inspired neural networks such as Spiking Neural Networks (SNNs) are beginning to be used in medicine [34], his approach provides a good computational tool to analyze dynamic data and time-dependent information and offers a highly useful solution for applications such as temporal sequences or patterns. In IC, SNNs have found an application that could expand in the future in the analysis of ECG signals. ECG signals are inherently temporal and contain complex patterns that describe various cardiac conditions. SNNs are a good choice for this task because they can analyze these signals with a high degree of precision, identifying subtle anomalies that might be overlooked by more traditional methods. This capability is crucial for the early detection and classification of arrhythmias, which can assist in rapid intervention and better outcomes for patients [35]. In turn, [36] applied SNNs to the classification of various cardiac arrhythmias. This solution allows for more targeted and effective treatment strategies for different types of arrhythmias. Similarly, [37] emphasizes the precision of SNNs in cardiac analysis, particularly in their ability to classify heartbeats with high accuracy. Their work is especially significant in identifying conditions such as Ventricular Ectopic Beats, a type of arrhythmia that can be challenging to detect. This highlights the adaptability of SNNs to a wide range of cardiac data, proving their versatility and effectiveness in various clinical contexts. Moreover, the building and training of a deep spiking neural network, as outlined in research [38], expanded this scope by classifying ECG signals for a broad range of heart-related conditions.

Deep Neural Networks (DNNs)

All these networks can be considered as Deep Neural Networks (DNNs), namely networks that have multiple layers between input and output layers. They are exceptionally effective in deciphering complicated patterns contained in extensive data sets, making them indispensable tools in modern medical analysis and decision-making processes [39]. By processing vast amounts of medical data, including diagnostic images and patient records, DNNs can uncover subtle patterns and indicators that might be missed by traditional analysis methods [40]. The most significant advantages of DNNs include their ability to model complex relationships thanks to their structural depth, enabling efficient pattern and feature recognition in data. The flexibility of DNNs allows for their application in a wide range of uses, from computer vision and image analysis to natural language processing, and even robotics and automation. Automatic feature extraction from data is another notable advantage, eliminating the need for manual feature determination and selection, particularly beneficial in complex or multi-dimensional data sets. Another DNN type that is applied in dimensionality reduction and unsupervised learning is the autoencoder, which can effectively encode input data into a smaller dimension form, aiding in data compression or multidimensional data visualization. For example, based on DNNs, (Fully Connected Neural Networks [FNN]), a comprehensive method for representing entire raw Electronic Health Records (EHR) of patients using the Fast Healthcare Interoperability Resources (FHIR) format has been developed [41]. This approach enables accurate prediction of multiple medical events across various centers without the need for site-specific data harmonization. In the field of IC, FNNs have been applied to assess the severity of coronary artery stenoses [42]. Then, [43] showed how a DNN model successfully reclassified hemodynamically insignificant stenosis, showing performance comparable to computational fluid dynamics-based CT-fractional flow reserve methods. Additionally, the combination of Fuzzy C-Means Clustering with DNN has been applied to the diagnosis of coronary artery disease using CMR imaging data [44]. Other important and interesting DNN applications in IC include the development of autoencoder for effectively reconstructing output data from input datasets, thus creating a 3D segmentation of the heart, which serves as a data source for a supervised noise-reducing autoencoder [45]. On the other hand, Generative Adversarial Networks (GANs) find applications in generating new data similar to training data. They consist of a generator (learning part) and a discriminator (the part that learns how to distinguish the generator's fake data from real data). GANs are particularly valued for generating realistic images, applicable in computer graphics, augmented reality, and other fields requiring synthetic yet realistically appearing data [46]. GANs were utilized to transform low-dose cardiac CT images into standard-dose images, contributing to improved diagnostic quality [47]. Moreover, GANs have been applied to reduce noise in coronary CT angiography images, showcasing the multifunctionality of DNNs in enhancing cardiac imaging techniques and diagnostic efficiency in IC [48].

Summary

Table 1 summarizes a comparison of the neural networks that are applied in IC [24, 28, 31, 36–38, 42–44, 49–78]. Thus, all types of neural networks suffer from the overfitting issue that appears when the network loses its generalization. In this context, it is extremely important to prepare a good quality and appropriate quantity of data sets.

Table 1. A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
ANN	Accuracy 92.00%	Automatic detection of arrhythmia on ECG	MIT-BIH arrhythmia database, ECG recording *50/50*	ECG records	Classification of three different cardiac conditions (normal, RBBB, and paced beats)	Isin, Ozdalili, 2017 [49]
RNN	Diagnosis, accuracy 97.00% Patient presentation at a MDT 90.20%	Estimating prognosis and guiding therapy in ACHD and pulmonary hypertension	Dataset, which consists of 10,019 adult patients under follow-up at the Royal Brompton Hospital London, from 2000 to 2018 *The division of data into training, testing, or validation sets is not specified*	Clinical and demographic data, ECG parameters, cardiopulmonary exercise testing, and selected laboratory markers	Categorization of diagnostic group, disease complexity, NYHA class, need for discussion at MDT meetings	Diller at al., 2019 [24]
RNN	Accuracy 91.00%	Classification of arrhythmia-based ECG records	The heart disease dataset collected from Kaggle consists of 303 records *The division of data into training, testing, or validation sets is not specified*	ECG signals	Classification of heart arrhythmias	Bavani, 2021 [50]
RNN	Accuracy 85.40%	Classification of arrhythmia based on ECG recordings	MIT-BIH arrhythmia database, ECG recordings *The division of data into training, testing, or validation sets is not specified*	ECG signals	Classification of ECG arrhythmia	Singh et al., 2018 [51]
RNN	Accuracy 95.00%	Real-time detection of AF from short--time single lead ECG traces	MIT-BIH AFDB and MIT-BIH NSRDB *The division of data into training, testing, or validation sets is not specified*	ECG signals	Classification of ECG traces NSR and AF	Sujadevi et al., 2018 [52]
CNN	Accuracy 91.70%	Recognition of different standard echocardiographic views	A total of 834,267 images from 15 views *80/10/10*	Echocardiographic images from various echocardiographic views, including parasternal long axis, RV inflow, basal short axis, etc.	Multi-category classification of 15 echocardiographic views	Madani et al., 2018 [31]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
CNN	Accuracy AlexNet: 78.90% GoogLeNet: 79.50% ResNet-152: 82.10%	Detection and classification of MDE patterns on MRI	1995 MDE images from 200 patients *The division of data into training, testing, or validation sets is not specified*	MDE images classified into 7 categories	Classification of MDE patterns	Ohta et al., 2019 [53]
CNN	Accuracy 85.70%	Identifying asymptomatic LV systolic dysfunction using ECG recordings	Patients at the Mayo Clinic 625,326 patients screened *40/10/50*	12-lead ECG data paired with TTE data	Classification of EF as ≤ 35% or > 35%	Attia et al., 2019 [54]
CCNN	Accuracy 99.01%	Automatic detection of STEMI using ECG recordings	Dataset of 667 STEMI ECGs and 7571 control ECGs training set (5697 ECGs) *70/30*	12-lead ECG data with preprocessing and data-expanding techniques	STEMI detection and classification	Zhao et al., 2020 [55]
CNN combined with GAN	Accuracy 98.30%	Classification of arrhythmia using ECG recordings	ECG recordings from the MIT-BIH arrhythmia dataset *The division of data into training, testing, or validation sets is not specified*	Single lead ECG recordings	Classification of ECG heartbeats into 15 different arrhythmia classes	Shaker et al., 2020 [56]
CNN	Accuracy 91.33%	Detection of cardiac arrhythmias based on ECG signal analysis	1,000 ECG signal from the MIT-BIH arrhythmia database *The division of data into training, testing, or validation sets is not specified*	Long-duration raw ECG signals, specifically 10-second signal fragments, without QRS detection and segmentation	Classification of the ECG signals into 17 different cardiac arrhythmia disorders	Yıldırım et al., 2018 [57]
CNN	Accuracy 94.03%	Classification of heartbeats in different categories in ECG signals	The study used 109,449 single lead/ /beat ECG signals from 47 subjects. The signals are from the PhysioBank MIT-BIH arrhythmia database *The division of data into training, testing, or validation sets is not specified*	Single lead ECG signals	Classification of heartbeats into 5 AAMI classes: non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown beats	Acharya, 2017 [58]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
CNN-attention-LSTM	Accuracy 93.75%	Reduction of false arrhythmia alarms in ICUs using single-lead ECG segments	The study used a training set of 750 recordings from the PhysioNet computing in cardiology challenge 2015 *The division of data into training, testing, or validation sets is not specified*	Single-lead ECG segments, along with other biosignals like photoplethysmogram and arterial blood pressure waveform	Classification of ICU alarms into 'true' or 'false' categories, specifically targeting 5 types of life-threatening arrhythmia alarms	Mousavi et al., 2020 [59]
CNN-LSTM	Accuracy 98.10%	Automated diagnosis of arrhythmia using ECG signals	The study used 16,499 ECG segments from the MIT-BIH arrhythmia database *The division of data into training, testing, or validation sets is not specified*	Modified limb lead II ECG signals, segmented with 99 samples to the left of the first R peak and 160 samples to the right of the last identified uninterrupted R peak	Classification of ECG segments into 5 arrhythmia classes (normal, LBBB, RBBB, APB, PVC)	Oh et al., 2018 [60]
CNN	Accuracy 96.00%	MI detection via ECGs	The study used actual ECG datasets from the PTB diagnostic database, with a focus on generalized anterior MI *The division of data into training, testing, or validation sets is not specified*	Multilead ECG data, with preprocessing involving fuzzy information granulation and beat segmentation	Detection of MI	Liu et al., 2018 [61]
CNN	Accuracy Class-based MI detection: 99.95% Patient-specific MI detection: 98.79%	MI detection and localization using 12-lead ECG	The study used 12-lead ECG signals from the PTB diagnostic ECG database, from 290 subjects *The division of data into training, testing, or validation sets is not specified*	12-lead ECG signals, including 5 types of MI and healthy controls, sampled at 1 kHz with 16-bit resolution	Automated detection and localization of MI using ECG data	Liu et al., 2018 [61]
CNN	Accuracy 95.11%	Automated detection of CAD using ECG signals	ECG signals from the Fantasia database (for normal) and St.-Petersburg Institute of Cardiology Technics 12-lead arrhythmia database (for CAD), sampled at 257 Hz *The division of data into training, testing, or validation sets is not specified*	Two and five-second durations of ECG signal segments, preprocessed using discrete wavelet transform and Z score normalization	Diagnosis of CAD using ECG signal	Acharya et al., 2017 [62]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
CNN	Sensitivity of 91.24% Specificity of 95.37% PPV of 90.5% Pearson coefficient of 0.983	Automatic quantification of calcium score in ECG-triggered non-contrast enhanced cardiac CT images	The study included 152 exams from a screening study *40/15/45*	Non-contrast enhanced CT images with slice thickness of 3.0 mm, acquired with various in-plane resolutions	Segmentation and classification of candidate lesions as coronary or non-coronary, and quantification of calcium score	Santini et al., 2017 [63]
CNN	Sensitivity of 97.2% for coronary calcification detection, and an accuracy of 84.4% for risk category assignment	Automatic detection and quantification of CAC in low-dose chest CT scans of heavy smokers	The study included 1028 heavy smokers aged between 50 and 75, scanned between 2004 and 2006 at 3 medical centers *The division of data into training, testing, or validation sets is not specified*	Low-dose chest CT scans without contrast enhancement, acquired using different CT scanners	Identification of CAC and subsequent cardiovascular risk categorization based on Agatston scores	Zreik et al. [64]
CNN	AUC of 0.74 ± 0.02 Specificity at sensitivity levels of 0.60, 0.70, and 0.80 was 0.77, 0.71, and 0.59, respectively	Identification of patients with functionally significant coronary artery stenosis using deep learning analysis of the LV myocardium in CCTA scans	Retrospectively collected CCTA scans of 166 patients (59.2 ± 9.5 years, 128 males) from 2012 to 2016 *20 images were used to train the LV myocardium encoder, and classification was evaluated in the remaining 126 CCTA scans with 50 10-fold cross--validation experiments*	CCTA scans, segmented LV myocardium, divided into spatially connected clusters	Classification of patients according to the presence of functionally significant coronary artery stenosis	Zreik et al., 2018 [64]
CNN	Frame-wise AUC: 0.971 Frame-wise accuracy: 0.934 Clip-wise accuracy: 0.965 External validation frame-wise AUC: 0.925 (single model), 0.956 (ensemble model)	Lesion detection, localization, and classification in coronary angiography	452 right coronary artery angiography movie clips *The division of data into training, testing, or validation sets is not specified*	Key frames extracted from coronary angiography movie clips	Classification of areas narrowed by over 50%, visualization of stenotic locations	Moon et al., 2021 [65]
CNN	Cardiac phase detection accuracy 98.80%, sensitivity was 99.30%, and specificity was 97.60% End-diastolic frame prediction had a precision of 98.40% and a recall of 97.90%	End-diastolic frame detection in coronary angiographies	The networks were trained on 56,655 coronary angiographies from 6820 patients and evaluated on 20,780 coronary angiographies from 6261 patients *The division of data into training, testing, or validation sets is not specified*	Coronary angiography images	Cardiac phase labels for each frame and detection of end--diastolic frames	Ciusdel et al., 2020 [66]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
CNN	Accuracy 95.00%	Lesion detection in X-ray coronary angiography	The study used a synthetic dataset of 10,000 images *80/20*	X-ray coronary angiography images	Detection and classification of coronary artery stenosis	Ovalle-Magallanes et al., 2020 [67]
CNN	Recall of CTO detection: 89.3% Sensitivity and specificity of CTO classification: 94.5% and 89.1%, respectively F1 Score: 0.89 Area under the curve: 0.98	Lesion detection, localization, and classification in coronary angiography images	A total of 2059 cases (326 cases in blunt and 1732 cases in tapered morphology), with data augmentation techniques applied *The division of data into training, testing, or validation sets is not specified*	Coronary angiography images	Detection and classification of CTO lesions	Liu et al., 2019 [68]
CNN	F1 Score: 0.96 Mean average precision: 0.95 (Faster-RCNN Inception ResNet V2), 0.83 (SSD MobileNet V2), 0.94 (RFCN ResNet-101 V2)	Detection and localization of coronary artery	The study used clinical angiography data of 100 patients *The division of data into training, testing, or validation sets is not specified*	Stenoses Coronary angiography images	Detection and localization of coronary artery stenoses	Danilov et al., 2021 [69]
CNN	For segment prediction, the recognition accuracy 98.40%, and the recognition sensitivity 85.20% For detecting lesion morphologies, the F1-scores ranged from 0.80 to 0.85	Lesion detection, localization, and classification in coronary angiography images	The study used 20,612 angiograms from 10,073 patients *65/35*	Angiograms in DICOM format with various angiographic views	Identification of coronary artery segments and recognition of lesion morphology including stenotic lesion, total occlusion, calcification, thrombosis, and dissection	Du et al., 2020 [28]
CNN	Accuracy 97.42%	ECG signal processing and arrhythmia classification	ECG signals from MIT-BIH arrhythmia database *50/50*	Two-dimensional grayscale images of segmented ECG heartbeats	Classification of 5 different arrhythmia types	Izci et al., 2019 [70]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
CNN	Accuracy 93.75%	ECG signal classification for heart conditions	ECG signals from MITDB (47 subjects), NSRDB (18 subjects), BIDMC congestive HF database (15 subjects) 162 recordings used from PhysioNet databases *The division of data into training, testing, or validation sets is not specified*	ECG signals	Classification of ECG signals into 3 categories: congestive HF, arrhythmia, normal heartbeats	Kaouter et al., 2019 [71]
CNN	Accuracy 96.67%	ECG arrhythmia classification	ECG signals from MITDB (54 subjects) Total 1000 non-overlapping frames representing various cardiac issues and normal conditions, from 45 subjects (19 women, 26 men) *The division of data into training, testing, or validation sets is not specified*	Images of ECG signals	Diagnosis of 17 types of arrhythmia	Al-Huseiny et al., 2020 [72]
CNN	Accuracy 93.40%	Heartbeat and MI classification	MITDB (47 subjects), PTBDB (290 subjects) *The division of data into training, testing, or validation sets is not specified*	ECG signals	Classification of heartbeats and MI	Kachuee et al., 2018 [73]
CNN	Accuracy 85.99%	Heartbeat diseases classification, AF detection	PhysioNet/CinC Challenge 2017 (8,528 ECG records) *Division of data into training, testing, or validation sets is not specified*	Single lead ECG recordings of variable length	Classification of normal sinus rhythm, AF, other abnormal rhythms, and noise	Kamaleswaran et al., 2018 [74]
CNN	Accuracy 99.78%	Classification of MI	Physiobank (PTB) ECG database: 52 normal subjects, 148 MI patients *Division of data into training, testing, or validation sets is not specified*	12-lead ECG signals	Diagnosis of MI	Baloglu et al., 2019 [75]
SNN	Accuracy 95.60 ± 0.5 [%]	ECG signal processing and arrhythmia classification	MIT-BIH dataset ECG signals encoded into spike trains using delta modulators *Division of data into training, testing, or validation sets is not specified*	ECG signals that are encoded into spike trains using delta modulators	Classification of ECG signals into different arrhythmia classes	Corradi et al., 2019 [36]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
SNN	Accuracy 97.16 [%]	ECG signal processing and classification, specifically for arrhythmia detection	PhysioNet MIT-BIH arrhythmia database *60/40*	Input encoding of ECG signals into spike trains using delta modulators	Classification of heartbeats into various categories, focusing on the detection of VEBs and normal heartbeats	Kovács, Samiee, 2022 [37]
SNN	Accuracy 97.90%	ECG signal processing for cardiac arrhythmia detection	The MIT-BIH ECG arrhythmia database *The division of data into training, testing, or validation sets is not specified*	ECG signal	Classification of ECG signals for arrhythmia detection	Amirshahi, Hashemi, 2019 [76]
SNN	Accuracy 84.80%	ECG classification that is used for diagnosing arrhythmias and other heart-related conditions	2017 PhysioNet/CinC Challenge 8,528 single-lead ECG records with varying lengths from 9 to 60 seconds *90/10*	The ECG signals are subjected to zero padding to standardize signal length	Classification results of the ECG signal into the 4 categories (normal, AF, other, noise)	Feng et al., 2022 [38]
SNN	Accuracy 95.60 ± 0.5 [%]	ECG signal processing and arrhythmia classification	MIT-BIH dataset ECG signals encoded into spike trains using delta modulators *Division of data into training, testing, or validation sets is not specified*	ECG signals that are encoded into spike trains using delta modulators	Classification of ECG signals into different arrhythmia classes	Corradi et al., 2019 [36]
DNN	Accuracy 83.20%	Determination of the severity of coronary artery stenoses	Data from 125 lesions in 87 patient-specific anatomical models from CT data *The division of data into training, testing, or validation sets is not specified*	Patient-specific anatomical models from CT data	Prediction of FFR values	Itu et al., 2016 [42]
DNN	Accuracy 74.60%	Improvement in the performance of CCTA by correctly reclassifying hemodynamically nonsignificant stenosis	122 consecutive patients were initially included, with exclusions leading to a final sample *The division of data into training, testing, or validation sets is not specified*	CCTA data	Detection of functionally important CAD	Coenen et al., 2015 [43]

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Table 1 (cont.). A comparison of the neural networks that are applied in interventional cardiology.

Network type	Type of evaluation metrics	Application field	Data sets — training/testing/validation sets [%] or training/testing sets [%]	Input parameters	Out parameters	References
DNN	Accuracy 99.91% with 10 clusters (5 clusters for healthy subjects, 5 clusters for sick subjects)	Diagnosing CAD using CMRI dataset	CMRI dataset with labeled and unlabeled data *The division of data into training, testing, or validation sets is not specified*	CMRI data	Diagnosis of CAD	Joloudari et al., 2022 [44]
DNN	Accuracy Inter-patient: 93.10% For reduced rhythm classes: 92.24% For merged rhythm classes: 96.13%	Detection of different rhythm classes from an ECG database	New ECG database with 50,977 single lead beats, classified into 5 AAMI classes *Division of data into training, testing, or validation sets is not specified*	ECG data from all 12 leads	Detection of cardiac arrhythmias	Xu et al., 2018 [77]
DNN	The AUROCs for DEHF were 0.843 (internal validation) and 0.889 (external validation) for HFrEF; and 0.821 (internal validation) and 0.850 (external validation) for HF with mid-range to reduced EF	HF identification using ECG	55,163 ECGs from 22,765 patients at 2 hospitals *Division of data into training, testing, or validation sets is not specified*	ECG records	Identification of HFrEF (EF $\leq$ 40%), and HF with mid-range to reduced EF ($\leq$ 50%)	Kwon et al., 2018 [78]

AAMI — Association for the Advancement of Medical Instrumentation; ABP — arterial blood pressure; ACHD — adult congenital heart disease; AF — atrial fibrillation; AFDB — Atrial Fibrillation Database; ANN — Artificial Neural Networks; APB — Atrial Premature Beat; AUC — area under the receiver operating characteristic curve; BIDMC — Beth Israel Deaconess Medical Center; CAC — coronary artery calcifications; CAD — coronary artery disease; CCTA — coronary computed tomography angiography; CMRI — cardiac magnetic resonance imaging; CNN — Convolutional Neural Networks; CT — computed tomography; CTO — chronic total occlusion; DEHF — deep-learning algorithm for ECG-based HF identification; DNN — Deep Neural Networks; ECG — electrocardiogram; EF — ejection fraction; FFR — fractional flow reserve; GAN — Generative Adversarial Networks; HF — heart failure; HFrEF — heart failure with reduced ejection fraction; ICUs — intensive care units; LBBB — left bundle branch block; LSTM — long short-term memory; LV — left ventricle; MDE — myocardial delayed enhancement; MDT — multidisciplinary team; MI — myocardial infarction; MIT-BIH — MIT-BIH Massachusetts Institute of Technology - Beth Israel Hospital; MITDB — MIT-BIH Arrhythmia Database; MRI — magnetic resonance images; NSR — normal sinus rhythm; NSRDB — Normal Sinus Rhythm Database; NYHA — New York Heart Association; PPV — positive predictive value; PTB — Physikalisch-Technische Bundesanstalt; PTBDB — Physikalisch-Technische Bundesanstalt Diagnostic ECG Database; PVC — Premature Ventricular Contraction; RBBB — right bundle branch block; RNN — Recurrent Neural Networks; RV — right ventricle; SNN — Spiking Neural Networks; STEMI — ST-segment elevated myocardial infarction; TTE — transthoracic echocardiogram; VEBs — ventricular ectopic beats

Ethical implications of ai in interventional cardiology

It is trivially true that all human systems are important for well-being, but the heart and circulatory function are clearly of prime significance. Any use of AI in cardiac interventions must thus be subjected to rigorous ethical scrutiny to ensure that it is in conformity with correct practice on at least two levels. The first is the set of institutional ethical norms established on the central level by international bodies and national government and on the local level by clinical institutions such as hospitals. The second concerns the detailed sets of ethical practices that need to be taken into account when AI is being implemented, such as ethical risk points [79]. Naturally, many aspects of ethical challenges, norms, and practices will be common across all areas of medicine. On the level of practical ethics, these include the collection and categorization of data, the data journey (as data are transferred, interpreted, and potentially adapted between systems and departments [80] and the ownership of and access to data.

However, there are certain specific characteristics of cardiological intervention that set it apart when it comes to the application of artificial technology, and each has its own ethical dimension. Notably, cardiological interventions are often made when the patient is at serious risk of dying. In that case, ethical decisions may have to be made concerning when or whether to attempt resuscitation. Legal implications need to be taken into account as well as the views of relatives, especially if they are holders of powers of attorney. It has already been pointed out that physicians may be reluctant to take certain actions because of this background [81]. AI now adds another layer of complication especially where the system makes recommendations as to courses of action: questions arise such as where the liability lies [82]. Indeed, just as a cardiac event may occur quickly, so too should treatment be given immediately. Emerging digital twin technology based on AI promises to be able to analyze complex datasets quickly, build cardiac models, and suggest treatment pathways. As described by Coorey et al. [83] a digital twin in cardiology is a digital representation of the physical system that is updated in real-time as the system changes. The ambition would be to create a perfect model with two interfaces: the first between the physical and its digital model, and the second between the nexus and the social plane (including, at least, physicians, the patient, caregivers, and others). Indeed, AI is increasingly being deployed in cardiology in terms of real-time data exchange, detection of conditions, severity assessment, and disease prognosis [84]. Then, Monzelum et al. (2022) [85] developed a cardiac arrest risk prediction score in an innovative clinical predictive model called The Cardiac Arrest Cardio-Oncology Score (CACOS), with the intention of providing early predictions and improving resource allocation and health outcomes. Aqel et al. [86] has also pointed out that AI will be particularly useful in predicting and managing sudden cardiac arrest, thus leading to better patient outcomes. The question next arises as to the relationship between a person and their digital twin: many issues of ownership, control, and decision-making arise [87]. For example, will the individual (now a patient) own the digital twin and be able to make decisions in advance as to its use? Will those decisions be linked to covenants in a life insurance policy? Whereas these can be discussed over a long time period with some diseases, at a moment of cardiac arrest it is difficult to see how these can be considered fully on the spot without specific easily accessible ethical protocols previously put in place to cater to the interaction with AI.

In addition, good regulation of AI is clearly needed regarding health care, with special reference to significant practices such as IC. However, the regulatory landscape is in its infancy at present. All stakeholders need to be able to interpret and explain AI and trust it: Explainable AI (XAI) and Trustworthy AI (TAI) are needed [88]. Regulation is being developed on the national and international level, although it is partial in extent and overlap [89]. The European Union has formulated a tool called the Assessment List for Trustworthy Artificial Intelligence (ALTAI) [90] and is working on extensive legislation [91]. Further suggestions have been made for rules and an assessment list for TAI by Floridi [92]. However, the general challenge for regulators in AI is to keep up with developments in a technological field that is developing extremely rapidly [93].

Future approach: Application of extended reality and 3D visualization supported by AI

Integrating AI into immersive technologies is crucial for handling the complexity of medical data, especially when combining multiple data modalities and if its possible 3D representation of these data. AI's ability to process and analyze complex, multi-layered data efficiently makes it essential for real-time processing in digital immersive environments, ensuring seamless user experiences. With increasing quality and resolution in medical imaging, 3D reconstruction of organs comes within clinical reach [94]. Medical imaging provides many 1D (ECG) and 2D views of the 3D heart (CT/MRI/ECHO DICOM), leaving the 3D interpretation to medical experts. Recent developments enable the 3D reconstruction of organs with many available segmentation tools [95]. Although segmentation software provides such capabilities, for clinical practice and education these are too complex to be used [96]. To train medical students and staff to deal with these advanced medical imaging-based reconstructions, an easy-to-use tool accompanied by educational material needs to be developed and tied to the clinical educational field of IC [97].

Complex cardiac procedures, such as implantation of the aortic valve (transcatheter aortic valve implantation procedures), complex ablation cases, patent foramen ovale, and surgical procedures on hearts with genetic defects, require advanced (functional) imaging and combination with anatomical and electrical behavior. 3D visualization in these anatomical complex examples is very difficult, whereas present research results create the opportunity to obtain a digital 3D view.

Recent developments enable the 3D reconstruction of organs with many available segmentation tools. Although segmentation software provides these capabilities, for clinical practice and education such tools are too complex to be used. An easy-to-use tool and educational material need to be developed to educate medical students and staff to effectively use these advanced medical imaging-based reconstructions. These 3D reconstructions provide many advantages in clinical evaluation, diagnosis, and preprocedural planning [15]. However, there are no standard clinical tools available to provide 3D segmentation alongside medical imaging. Such an approach brings 3D segmentation a step closer to the clinical workflow and thus improves clinical diagnostic, prognostic, and procedural planning.

The teaching of the latest technological development in cardiac treatment combining imaging data with 3D segmentation needs to be improved. The 3D educational medical imaging tool aims to provide a 3-D viewing tool that is easy to use by many students and professionals to promote the teaching of complex cardiac patient treatment. To ensure the embedding of the software in the clinical curriculum, the project will also build up educational clinical cases in which this educational tool will play an important role.

One of the primary benefits of using computer-generated 3D models extended by immersive technologies in cardiac anatomy is the ability to provide educators with a highly realistic and interactive learning experience. In particular, the visualization of something you cannot see, the electrical processes of the heart, is educationally powerful and challenging. Incorporating the outcomes of the spatial relationship of cardiac structures with educational content will provide a new dimension in the future of clinical cardiac education.

All strategy connecting with multimodality cardiac imaging refers to non-invasive imaging of the heart using ultrasound, magnetic resonance imaging, CT, or other imaging methods as well as ECGs. These cardiac techniques are referred to for everyday practice in preprocedural planning and educational approaches [98]. The teaching of these applications is brought to a higher level through the use of 3D visualization with the incorporation of non-invasive imaging of ECG output enhanced by immersive technologies in terms of a new digital educational tool with a multimodality approach and can be enriched with the use of artificial intelligence for the segmentation process.

Artificial intelligence facilitates personalization by analyzing user behavior, enhancing engagement in various applications. It plays a key role in integrating diverse data streams like visual, sensor, and user input data, ensuring a coherent and functional environment. AI also enables more intuitive interactions through technologies like natural language processing and gesture recognition. As digital applications expand, AI ensures scalability and adaptability to new data types and volumes. Additionally, AI contributes to error reduction and quality assurance, critical in precision-dependent applications. In summary, AI's role in immersive technologies is not just beneficial but fundamental to the development and enhancement of them.

Discussion and conclusions

Artificial intelligence application in medicine, in particular in IC represents a significant advancement in the field, offering potential improvements in patient care, diagnosis, treatment, and procedural outcomes [99]. AI has to be taken into account in the process of integration into everyday practice regarding key ways and approaches such as enhanced diagnostic accuracy [100]. AI can analyze raw medical data and images with high precision, aiding in the detection and assessment of cardiovascular diseases. It can provide an alternavtive to identifying patternes and anomalies that might be missed by the human eye. AI can process large datasets to predict the outcome of cardiac interventions, such as the likelihood of complications or success of a procedure. Moreover, one of the big developments for use in IC concerns AI-driven robotic systems that can aid in performing precise movements during procedures such as coronary angioplasty, potentially improving outcomes and reducing physician fatigue. Indeed, such systems can give decision support, offering recommendations based on patient data, which may help in choosing the most appropriate interventional strategies. Based on patient datasets and clinical information, AI can assist in remote patient monitoring, analyzing data from wearable devices to detect signs of heart failure and arrhythmias. It can also improve post-procedural care, ensuring patients adhere to medications and lifestyle changes. AI gives a wide spectrum of opportunities, but its limitations also need to be considered, especially data dependency. AI systems require large amounts of data for training. The quality and quantity of this data are crucial. Poor or biased data can lead to inaccurate or biased outcomes. Another very important issue is lack of transparency, which can be a significant issue. AI, especially with its deep learning models, often operates as a "black box", making it difficult for non-specialists to understand how it arrives at certain conclusions or decisions in fields that require trust and explain ability.

To summarize, the combination of AI and IC has great promise to increase the efficiency and accuracy of cardiovascular imaging technologies combined with reducing costs of the whole process. However, their full integration and clinical application is still a challenge. In Table 1 the comparison of the neural networks that are applied in IC is shown. It turns out that the most commonly used neural networks in IC are CNNs that enable the processing of ECG output to classify heart diseases with high accuracy. However, calculations using traditional neural networks, including CNNs, are very time and energy-consuming. Yet AI, inspired by the structure of the brain, in its deployment of particular SNNs, is becoming a promising, energy-saving alternative to traditional ANNs. Furthermore, the difference in the performance of ANNs compared to SNNs translates into the application potential of SNNs. To fully exploit the potential of SNNs, including the ability to detect abnormalities in biomedical signals and design more specialized neural networks, their learning mechanisms need to be improved. Another important issue is connected with the fact that the majority of researchers have so far used ready-made AI solutions in the field of medicine, without going into the principles of their operation. In other words, they have treated them as the contents of a black box, whereas, in order to be better understood and used, the application of AI-based methods requires clarification of their structures and principles of operations. AI-based algorithms can be adapted to fit data, in the hope that the used data is a good representation of the population it is meant for and, that the resulting algorithm can classify new data correctly. A major problem is still how the algorithm came to its conclusion, at best it can identify the parts of the input data that were used to come to that conclusion, but it will not be able to explain underlying mechanisms. Considering that AI is applied in such an important field as human health and life, it is necessary to ensure that operators who are using AI know the principles on which the results are obtained. Additionally, this knowledge will help in their correct interpretation, which is especially of huge importance in the context of efficient disease treatment. Another issue is connected with the quality and availability of datasets, namely, access to electronic health records (EHRs). This is also connected with the risk of biases in medical data. Also, the internet segmentation of medical data may include errors. On the other hand, taking into account ethical considerations and the regulatory landscape, AI raises numerous ethical concerns, including the inextricable connection of ethical risk points to technical risk points. Indeed, any future AI-based system must meet the ethical, technical, and legislative issues raised. Thus, the first condition in this field has been done by formulating guidelines for AI-based systems. Additionally, in some countries, patients must give informed consent to sharing their medical data with AI algorithms and the AI-assisted diagnosis process, which is good practice.

In the future, AI-driven simulations will be utilized for training interventional cardiologists, providing them with a safe environment to practice complex procedures and enhance their skills. These simulations will allow cardiologists to engage in intricate medical procedures in a controlled setting. This scientific advancement will highlight the role of AI in augmenting the education and training of medical professionals, focusing on skill enhancement and proficiency in complex cardiac interventions. Integrating AI into immersive technologies is crucial for transforming cardiology, simplifying complex 3D medical data analysis, and enhancing education and clinical practice with personalized, interactive, and efficient solutions. Additionally, novel approaches will involve the use of immersive technologies such as mixed reality or virtual reality, integrated with AI, for conducting remote multidisciplinary heart team meetings. AI will play a crucial role in facilitating these remote consultations and diagnostics, effectively bridging geographical obstacles. This will enable advanced IC care and expert consultations to be accessible remotely. The integration of AI and these cutting-edge technologies will be transformative, significantly improving healthcare delivery by gathering interdisciplinary teams from various locations, thereby expanding the reach and quality of cardiac care.

Artificial intelligence's transformative role in IC, enhances diagnostic accuracy, procedural outcomes, remote monitoring, and education, while acknowledging the need for ethical considerations and a deeper understanding of AI mechanisms in healthcare is evidence-based on presented PRISMA Statement methodology.

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