Review Article

A Review of Deep Learning Approaches with CMR Images in the Diagnosis of Cardiovascular Diseases

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Abstract

Cardiovascular disease (CVD) is one of the leading causes of death worldwide, which has led to the recent intensification of Deep Learning (DL) studies in the field of cardiology. Patients usually experience symptoms such as rapid fatigue, edema below the knee and ankle, chest pain, shortness of breath, and palpitations. The most common types of CVD include coronary artery disease, arrhythmias, congenital heart defects, cardiomyopathy, valvular heart failure, and angina. Electrocardiography (ECG), blood tests, physical examination, and medical imaging are the most effective tools for diagnosing diseases. In recent years, cardiac magnetic resonance imaging (CMRI) has been increasingly used for the diagnosis, follow-up, treatment planning, and prognosis of CVDs. However, the large number of slices and low contrast of CMRI data make diagnosing CVD difficult. Deep learning techniques are being applied to diagnose CVD with CMRI data to overcome these difficulties, and intensive research continues to be conducted in this field. It is important to keep abreast of developments so that these studies can significantly impact clinical applications. This review aims to be a stepping stone for researchers in this process by comprehensively reviewing studies on CVD detection using DL methods on CMRI images.

Keywords: Artificial intelligence, deep learning, neural networks, classification, heart diseases,CMRI,CVD

1. Introduction

Artificial intelligence (AI) and its sub-branches machine learning (ML) and deep learning (DL) have become vital tools in the field of image recognition and analysis, especially in medical imaging [1]. These technologies offer several advantages over human capabilities when analyzing imaging such as magnetic resonance imaging (MRI), computed tomography (CT) and X-rays. These advantages include the ability of AI algorithms to process large amounts of data at speeds far beyond human capacity. Unlike humans, whose decisions can sometimes be influenced by emotions or biases, AI systems provide objective, consistent inferences based solely on data [2].

Cardiovascular diseases (CVD), which include disorders of the heart and blood vessels, can be caused by a range of conditions, including congenital, rheumatologic conditions, genetic factors, dietary habits, and high blood pressure, as well as a number of conditions known as atherosclerosis, which results from the deposition of various substances on the inner walls of blood vessels, leading to plaque formation. These heart-related conditions are among the leading causes of death worldwide, with mortality from CVD projected to increase from 17.5 million in 2012 to 22.2 million by 2030. Early detection and timely treatment are crucial to prevent the increasing number of heart disease cases and reduce the risk of death associated with heart disease [3]. Currently, the number of studies on cardiovascular diseases is increasing. Figure 1 presents the most common cardiovascular diseases [4].

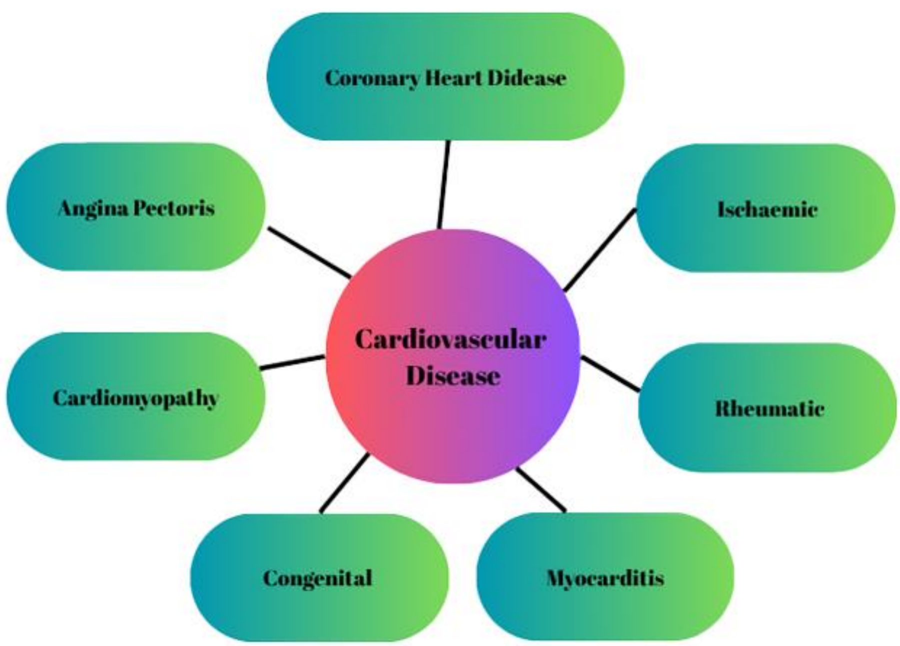

Figure 1: Major Types of Cardiovascular Diseases [4].

Blood tests, electrocardiography (ECG) and medical imaging are the most effective tools in the diagnosis of CVD. In particular, cardiac magnetic resonance imaging (CMR) is widely used to detect, monitor, adjust treatment and predict the prognosis of heart disease [5]. Cardiac magnetic resonance imaging provides an excellent quantitative analysis of the volume and function of the heart chambers as well as the extent of myocardial infarction and fibrosis. It is recommended as a guiding method for the diagnosis of various cardiovascular diseases such as ischemic heart disease, hereditary or acquired cardiomyopathy, myocarditis and congenital heart disease [6][7]. Accurate segmentation of endocardial (and epicardial for myocardial mass) boundaries is a mandatory step in standard cine CMR images for ventricular volume, function and mass measurements [8]. Usually these boundaries are determined by radiologists or cardiologists [9].

The purpose of segmentation, which is an analysis process that includes the classification of pixels to determine the shapes of objects, is to represent the image in a meaningful way to examine the anatomy and identify the region of interest [10][11]. In recent years, segmentation models that provide better performance with deep learning continue to stand out [12]. In the multilayer neural network structure, each layer extracts unique information from the incoming data, combines it with the previous one and gives it to the other layer, achieving the success of extracting complex features, and its use in the segmentation of anatomical structures in the field of cardiology is increasing [13]. These methods help to improve accuracy, minimize the time required for diagnosis and reduce the possibility of human error. Numerous studies in this field are available in the literature and emphasize the growing importance of these technologies in the early diagnosis and management of heart disease [4][14]. Table 1 shows some of the studies on image segmentation.

The main objective of this study is to assist researchers in the development of deep learning-based approaches for the evaluation of cardiac magnetic resonance (CMR) images. In this study, deep learning architectures used in the diagnosis of cardiovascular diseases are discussed with reference to publications in the literature. Important datasets, data augmentation and preprocessing techniques used in the study chapters are detailed to enlighten the researchers. In another section, DL-based classification of CMR images for CVD diagnosis is summarized in a tabular summary. In the final sections of the review, the challenges in developing DL models for diagnostic systems are addressed and the potential impact of DL models on current and near future applications are discussed.

Table 1: Use Cases of CMR Image Segmentation with Artificial Intelligence Tools

Year (Created)	Input	Methods	Segmentation	Work
2019	Cine CMR	Machine Learning Deep Learning	LV and RV myocardial borders	[15]
2019	Multi-modal	Deep Learning	Chamber and vessel borders, fibrosis	[11]
2022	LGE-CMR	Machine Learning Deep Learning	LA fibrosis	[16]
2020	3D cine CMR	Deep Learning	LV myocardial border	[17]
2021	LGE-CMR	Deep Learning	LV and LA fibrosis	[18]

2. Search Strategy

Articles were searched based on PRISMA guidelines. Using the general keywords "artificial intelligence", "deep learning", "neural networks", "classification", "heart diseases", "CMRI", "CVD", articles published between 2019-2025 in the field of artificial intelligence studies in cardiovascular diseases were searched. Keyword searches were performed in repositories such as Science Direct, Frontiers, MDPI, IEEE Xplore, Nature, SpringerArXiv databases and 65 articles were summarized by eliminating unrelated publications. General information on the field of cardiology is provided as additional references.

3. Overview of CVD Diagnostic Systems in Deep Learning Architecture

With the rapid and accurate analysis of CMR images, it is expected that the life expectancy and quality of life of people will increase as CVDs are diagnosed earlier [19]. Many papers have been published on analyzing images with artificial intelligence methods. ML and DL techniques are used in most of the studies that are expected to help clinicians in diagnostic systems [8][20].

Nancy et al [21] show how data preprocessing through a deep learning approach followed by a multilayer perceptron can improve data quality when calculating the probability of a person developing coronary heart disease. Besides being highly effective, the proposed approach resulted in a high accuracy of 96.50% [21].

In [22], Dutta et al. introduced a neural network model with convolutional layers aimed at addressing the challenges of class imbalance in datasets. The research highlighted the success of the 2D-CNN architecture in predicting cases using data from the National Health and Nutrition Examination Survey (NHANES) to predict the occurrence of coronary artery castration (CAD). The use of different DL architectures in cardiovascular disease diagnostics has paved the way for medical professionals to develop cost-efficient, intelligent diagnostic systems that can support them in delivering improved treatments [23][24].

Segmentation of CMR images plays an important role in quantitative CMRI assessments, such as the calculation of heart chamber volumes and function, and the identification of abnormal myocardial tissues (e.g., myocardial infarction, fibrosis, etc.). CMR data are affected by different artifacts and are sometimes known to have low contrast [13]. To increase the success of diagnostic systems, the images are preprocessed to remove artifacts and increase contrast, and then DL modes are fed with CMR images [14]. Although the diagnosis of CVD is mostly based on the subjective judgment of physicians, DL-based systems provide results that will help physicians. Furthermore, a block diagram for cardiovascular disease detection using DL methods is presented in Figure 2.

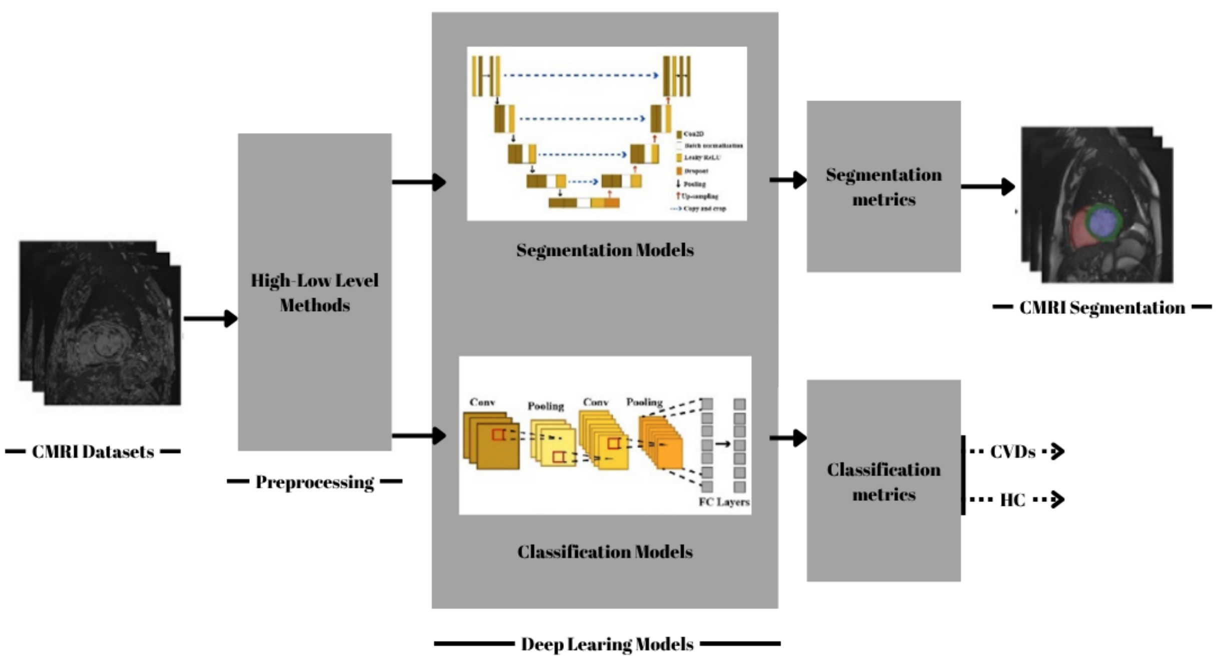

Figure 2. Detection Schematic of CVDs with DL Methods [22].

4.1. Data Sets

The success of deep learning models in the diagnosis of CVDs is directly influenced by the scope and quality of the datasets. Several datasets including ECG, echocardiography and CMRI are presented for researchers to use in their studies. Some of the CMRI datasets are also listed in Table 2.

Table 2: Datasets Used in the Diagnosis of CVD

Dataset Name	Year (Created)	Case#	Study
ACDC	2017	100	[7]
Kaggle	2015	1140	[25]
SCD	2009	45	[4]
LVSC	2011	200	[9]
LASC STACOM 2018	2018	100	[26]
STACOM	2017	100	[6]
York University	2008	33	[3]

4.1.1. ACDC (2017)

ACDC is an open access dataset containing CMR images of 100 patients in NIfTI format. Contour images of end-systolic and end-diastolic phases were provided for each patient [7]. Experts manually drew the contours of the left ventricle (LV), right ventricle (RV) and myocardium in end-diastolic (ED) and end-systolic (ES) slices to measure the 3D volumes of the endocardial and myocardial cavities [7]. Cine CMR images were acquired using SSFP sequence in the short axis plane with retrospective or prospective triggering during breath-hold [7]. Detailed information about the data set is given in the references [7].

4.1.2. Kaggle Data Science Bowl Cardiac Competition

The Kaggle dataset contains 700 records for the training and validation phases and 440 records for the testing phase [25]. This dataset does not provide gold standard LV (left ventricular) contours [25]. The target and evaluation criteria are based on the estimated

LV volume at end-diastole (ED) and end-systole (ES) [25]. Detailed information about the dataset is given in the references [25].

4.1.3. SCD

The SCD dataset includes cine-CMR images of 45 people with four different disease states; healthy, hypertrophic, heart failure with infarction and heart failure without infarction. The images were recorded during 20 phases of the cardiac cycle, with patients holding their breath for 10-15 seconds. Data are in DICOM format and contain metadata including patient and image information **[**4**]**. For each patient, contours were manually drawn on end-diastolic (ED) and end-systolic (ES) slices [4]. These drawings were made by Perry Radau from Sunnybrook Health Science Center [4]. Data were submitted by physicians without any preprocessing for analysis [4]. Currently, the entire dataset is available through the Cardiac Atlas Project (CAP) [4]. Detailed information about the dataset is given in the references [4].

4.1.4. LVSC

The LVSC dataset was presented to researchers at MICCAI in 2011 and consists of 200 cardiac MR images with coronary artery disease and myocardial infarction [9]. The images were acquired from different scanners with resolutions ranging from 0.7-2.1 mm/pixel and matrix sizes ranging from 156x192 to 512x512 [9]. The dataset is divided into a training/test group of 100 anodized samples and a validation group of 100 unanodized samples [9]. The gold standard anotations show the LV myocardium in all cardiac phases with expert-drawn binary masks [9]. Detailed information about the dataset is given in the references [9].

4.1.5. LASC STACOM 2018

This dataset was used for left atrial segmentation in the STACOM 2018 competition and includes 100 3D LGE-CMR images diagnosed with atrial fibrillation [26]. Most of the images were provided by the University of Utah and the rest were provided by various institutions [26]. The binary mask labels indicating the left atrial cavity in the images were prepared by experts [26]**.** Detailed information about the dataset is given in the references [26].

4.1.6. STACOM

This dataset consists of cardiac MR images of 100 patients with coronary artery disease and myocardial infarction [6]. The patients were randomly divided into two groups, 66 were used for training and 34 for testing, and a total of 12,720 training and 6,972 test images were obtained [6]. The images recorded with different CMR devices ranged in size from 138×192 to 512×512 pixels [6]. Each image has ground truth annotations for the blood cavity and myocardium [6]. Detailed information about the dataset is given in the references [6].

4.1.7. York University-CMR Data Set

Cardiac MR images in DICOM format, including segmentations of the LV endocardium and epicardium, were obtained from 33 individuals totaling 7980 frames [3]. The segmentations included 5011 images and 10022 contours covering the endocardium and epicardium of the left ventricle [3]. Metadata information such as pixel pitch, distance between slices, patient age and disease status are also available [3]. Detailed information about the dataset is given in the references [3].

4.2. Data Augmentation Preprocessing Technique

The success of deep learning networks is directly affected by the amount of data [27]. Therefore, some methods have been developed to overcome problems related to small data sets such as overfitting. While data augmentation procedures offer improvements on the existing data, generative adversarial network (GAN) networks allow to generate completely new synthetic data sets by learning the intrinsic distributions of the data [20][22][28]. Another method, known as transfer learning, allows to train a previously trained algorithm by using it with a new data set [29]. One of the biggest problems with the dataset is the variation of images obtained from devices with different technical specifications. To overcome this and ensure uniformity in the data, preprocessing techniques such as normalization/histogram equalization and intensity/dimension-based filtering are used [30].

4.3. Deep Learning Models

In this section, the most important DL models that work with CMR images for CVD detection are discussed. CNN-based classification and segmentation networks (2D-CNN [31], 3D-CNN [31] U-Net [32], FCN [33]), RNN models [34] and an important class of data augmentation methods (GAN [28]). Details of the methods are given in the chapters. AEs and CNN-AEs models for heart disease diagnosis [16][35] are also mentioned. Based on the existing studies, the commonly used models and their details for cardiovascular disease classification using deep learning models are presented in Table 3.

4.3.1. Convolutional neural network (CNN)

The basic components of CNN structures, which have produced successful models in the analysis of medical images and in many other fields, are convolutional, pooling and fully contextualized layers [31]. There are also different types of CNN architecture for classification and parsing, which use supervised learning in the learning phase [42][47]. With the development of CNN models, hardware resources continue to evolve as computational costs increase significantly [22]. Some of the most important models are 2D-CNNs, 3D-CNNs and pre-trained structures [3].

Table 3: Summary of CVD Diagnosis Classification Studies with CMR Images

CVD	Dataset Name	Preprocessing Type	DL Method	Classifier Type	Results#	Study
LV	ADSB	Gabor F.	2D-CNN	FC	Vary considerably	[36]
LV	Clinical	ROI Extraction	AE	NA	Acc = 97.50% Sen = 84.20% Spec = 98.60%	[37]
LV	DSBCCD	ROI Extraction DA	2D-CNN	FC	-	[38]
LV	DSBCCD	ROI Extraction	CNN	FC	EDV R2 = 97.40 ESV R2 = 97.60 EF R2 = 82.80	[39]
LV-SV	Clinical York University	DA	NF-RCNN	Softmax	AUC = 98.00% Rec = 96.0	[40]
Myocardial Ischemia	MICCAI 2009	ROI Extraction	CNN	NA	Acc = 86.39% You = 90.00%	[41]
Dense Thickness Estimation	MICCAI 2017 Synthetic MICCAI 2019	-	U-Net	NA	MSE = 14.30 MAE= 28.50	[23]
Cardiac view	Clinical	-	AE	Softmax	Acc = 96.70%	[42]
Multitype cardiac indices estimation	Clinical	ROI Extraction	DCAE	NA	NA	[43]
Myocardial	Clinical	-	CNNEC	FC	Acc = 95.30%	[44]
LV	Sunnybrook, Kaggle	LBP, DA	HFCN	Softmax	RMSE = 13.20 ESV RMSE = 9.31	[45]
ED-ES	Clinical	DA	TempReg-Net	FC layer	ADF ED = 0.38 ADF ES = 0.44	[46]
Detection	Clinical	Visualization	2D-CNN	NA	AUC= 89.10%	[48]
ED-ES	STACOM	DA	2D-CNN	NA	Acc = 76.50%	[24]
Detection	Clinical	ROI Extraction	2D-CNN	Softmax	Acc = 94.84%	[49]

					Sen = 92.73%	
Classification	MICCAI 2017	Feature Extraction	Modified 2D and 3D UNets	Ensemble L.	Acc = 92.00%	[50]
Classification of Myocardial	Clinical	-	Pretrained Models	Softmax	Acc = 82.10%	[51]
Classification Prediction	Clinical	-	DeeplabV3 InceptionResnetV2	LSTM	Vary considerably	[52]

4.3.2. Generative Adversarial Networks (GAN)

Generative models proposed for image synthesis, i.e. the generation of new images, are very popular for their ability to model data distribution [32]. In training, there are 2 competing networks, one is the generative network and the other is the discriminative network. The generative network tries to deceive the discriminative network while the discriminative network tries to find the truth [48][53]. After training, the generative part of the GAN (the second network) usually generates realistic data [32]. It is noteworthy that generative adversarial networks are widely used in cardiovascular disease diagnosis studies [32].

4.3.3. Fully Convolutional Neural Network (FCN)

Muthulakshmi et al. described the FCN deep learning architecture used as the basis for image¨ symbolization [41]. The architecture uses an encoder-decoder¨ structure, where the encoder first transforms the input into a high-level feature representation, while the decoder simultaneously interprets the feature maps and then produces output of the same size [41]. It appears to be a powerful type that takes the image as input and estimates an image-sized segmentation [41].

4.3.4. U NET

Image¨ segmentation is an important step in disease localization [33]. Since traditional CNNs cannot give the output of the network the same size as the input image, FCN and U-net are two famous¨ networks proposed [33]. In U-Net, shortcuts are added between the encoder and decoder¨ , allowing the networks to converge faster and increase information sharing [33]. There are also many studies in which they are used as architectures developed for the diagnosis of cardiovascular diseases. [33].

4.3.5. Autoencoder Models (AE)

It is one of the oldest neural networks and is still used for many tasks. As a working logic, they can help in dimension reduction and decoding in high data space [42]. In order to minimize the reconstruction loss , two networks placed back-to-back work by encoding the data into a smaller latent space while the other network transmits the data from the latent space back to the original space [16][31]. Optimally trained AEs try to find the most important information from the data. Among the different types of AEs such as denoising AEs, Sparse AEs and Stacked AEs, convolutional autoencoders (CNN-AEs), which exploit convolutional capabilities, are widely used in medical diagnostics [21][42].

4.3.6. Recurrent Neural Network (RNN)

Recurrent neural network RNN models have been developed due to the detection of temporal patterns and the concern that the variable length of these patterns cannot be captured by classical deep learning methods [31][54]. In particular, models such as long short-term memory (LSTM) and gated linear unit (GRU) are widely used in areas such as signal processing [47] [31][47][55][56]. In addition, these RNNs are often combined with convolutional neural networks (CNNs), and the combined model CNN-RNN, which enables the extraction of both spatial and temporal features, has also taken its place in studies [31][57].

5. Challenges

In this chapter, we discuss the challenges in cardiovascular disease diagnosis using CMR images and deep learning techniques. Researchers face continuous and multiple challenges in various areas such as datasets, deep learning models, explainable artificial intelligence, and hardware infrastructure while developing new methods for CVD diagnosis [58].

Datasets are a key component of deep learning-based diagnostic systems for CVD detection [59][60]. However, the scarcity of publicly available CMRI datasets and the limited number of subjects makes it difficult for researchers to utilize the latest deep learning models. The lack of disease type-specific CMRI datasets of different CVD types poses another challenge [45]. Due to these challenges and for more accurate diagnostic systems, researchers have resorted to multimodality imaging methods, a procedure in which CMR images are combined with other imaging techniques such as ECHO, tomography [24][61].

Due to the current challenges in this field, researchers have not yet been able to fully integrate advanced deep learning methods using multimodal imaging in the diagnosis of cardiovascular diseases. Therefore, datasets based on CMR images with a large number of subjects can facilitate important research in the field of CVD diagnosis.

Although researchers have made significant progress in the development of deep learning (DL) models, there are still many challenges in building tools suitable for real-world applications in cardiovascular disease (CVD) diagnosis [62][63]. As mentioned in the previous sections, there have been numerous studies on CVD diagnosis with DL techniques from CMR images. However, DL models based on CMR images need to be further enhanced for the development of real diagnostic software. One of the biggest challenges faced by researchers is the limited access to comprehensive CMRI datasets. To overcome these challenges, some studies have used pre-trained models or data augmentation (DA) techniques [64]. While pre-trained models have their advantages, they also have some limitations; for example, they are usually trained on natural images such as ImageNet [38]. Researchers have obtained satisfactory results by applying these architectures on medical images, especially CMRI. To increase the effectiveness of the pre-trained models, it is more appropriate to train them on grayscale medical images and then use them for CVD diagnosis [38]. Furthermore, DA methods play a critical role in the generation of synthetic medical data; in particular, GAN models are widely preferred for synthetic data generation on data such as CMRI [30][65]. While these models have had great success in training DL systems and preventing overfitting, further development is needed to fully adapt them to real-world applications in CVD diagnosis.

6. Conclusion and Discussion

In this study, the datasets used, dataset augmentation methods, image classification and segmentation methods of CMR images using DL models were comprehensively reviewed. The classification and diagnosis studies developed with deep learning techniques are summarized in Tables 2-3. The application is presented together with the dataset, preprocessing methods, implementation methods and evaluation parameters.

In order to overcome the difficulties experienced in deep learning architectures developed for the diagnosis of cardiovascular diseases, future studies may include the creation of hybrid DL structures with multimodal data sets and different preprocessing techniques. The systems to be developed for CVD diagnosis may lead to the development of high-performance real software for medical professionals at many stages from diagnosis to prognosis of cardiovascular diseases.

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