IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 22 March 2024, accepted 30 April 2024, date of publication 3 June 2024, date of current version 3 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3408282

SURVEY

Automatic Classification of Cardiac Arrhythmias Using Deep Learning Techniques: A Systematic Review

FERNANDO VÁSQUEZ-ITURRALDE[1], (Member, IEEE), MARCO JAVIER FLORES-CALERO[2], FELIPE GRIJALVA[3], (Senior Member, IEEE), AND ANDRÉS ROSALES-ACOSTA[4,5], (Member, IEEE)

[1]Departamento de Electrónica, Telecomunicaciones y Redes de Información, Escuela Politécnica Nacional, Quito 170525, Ecuador
[2]Departamento de Eléctrica, Electrónica y Telecomunicaciones, Universidad de las Fuerzas Armadas, Sangolquí, Pichincha 171103, Ecuador
[3]Colegio de Ciencias e Ingenierías "El Politécnico," Universidad San Francisco de Quito (USFQ), Quito 170157, Ecuador
[4]Departamento de Automatización y Control Industrial, Escuela Politécnica Nacional, Quito 170517, Ecuador
[5]Escuela de Ciencias de la Tierra, Energía y Ambiente, Universidad de Investigación de Tecnología Experimental (Yachay Tech), Urcuquí 100115, Ecuador

Corresponding author: Marco Javier Flores-Calero (mjflores@espe.edu.ec)

This work was supported in part by the Universidad San Francisco de Quito through the Poli-Grants Program under Grant 24263, and in part by the Universidad de las Fuerzas Armadas through the Research Project under Grant 2020-PIC-001-CTE.

ABSTRACT Cardiac arrhythmias are one of the main causes of death worldwide; therefore, early detection is essential to save the lives of patients who suffer from them and to reduce the cost of medical treatment. The growth of electronic technology, combined with the great potential of Deep Learning (DL) techniques, has enabled the design of devices for early and accurate detection of cardiac arrhythmias. This article presents a Systematic Literature Review (SLR) using a Systematic Mapping study and Bibliometric Analysis, through a set of relevant research questions (RQs), in relation to DL techniques applied to the automatic detection and classification of cardiac arrhythmias using electrocardiogram (ECG) signals, during the period 2017-2023. The PRISMA 2020 methodology was employed to identify the most pertinent scholarly articles, by querying the following databases: Scopus, IEEE Xplore, and PhysioNet Challenges, resulting in 494 publications being retrieved. This study also included a bibliometric analysis aimed at tracing the evolution of the primary technologies utilized in the automatic detection and recognition of cardiac arrhythmias. Additionally, it evaluates the performance of each technology, offering insights crucial for guiding future research.

INDEX TERMS Cardiac arrhythmia, convolution neural network, deep learning, electrocardiogram, systematic literature review, classification.

I. INTRODUCTION

Cardiovascular diseases (CVDs), such as heart attacks and strokes, are among the leading types of non-communicable diseases that increase the risk of death and disability [1]. These diseases disproportionately affect low and middle-income countries, where more than 75% (32 million) of the deaths have been recorded [2]. In South America, a mortality rate of 17% has been reported compared to Europe and North America, which have mortality rates of 3%. In Ecuador, in 2018, cardiac arrhythmia was the primary cause of death in 4,430 patients with ischemic diseases and 1,368 with heart failure [3].

Experienced cardiologists can determine whether a heartbeat is healthy or abnormal by studying the ECG waveform. An abnormal heartbeat is known as an arrhythmia and can usually be recognized by its different waveform.

Arrhythmia leads to irregular electrical activity that manifests itself on the ECG. Some common types of arrhythmia are premature beats; supraventricular types, including atrial fibrillation, atrial flutter, paroxysmal supraventricular tachycardia, ventricular types including ventricular tachycardia, ventricular fibrillation; and heart blocks including right bundle branch block and left bundle branch block. Each of

The associate editor coordinating the review of this manuscript and approving it for publication was Gina Tourassi.

these conditions exhibits characteristic features that manifest and are identified in the electrocardiogram signal [4].

The interpretation of the ECG is the cornerstone of the diagnosis of arrhythmias [5], [6]. However, arrhythmias are usually paroxysmal, so they are difficult to detect.

Recent studies have shown that deep learning techniques are efficient in terms of precision and computational complexity, which are essential aspects of real-time applications [7], such as those for the detection of cardiac arrhythmia.

The objective of this study is to conduct an exhaustive review of the different methodologies used in the automatic detection and classification of cardiac arrhythmia (ACAD), focusing on deep learning methods [8].

Articles published between the period 2017-2023 were identified, considering several aspects, such as the deep learning technique, cardiac arrhythmia data set, performance evaluation metrics and optimization algorithms.

The remainder of this paper is organized as follows. Section I describes the general aspects of this study. Section II presents the methodology and steps used in this study. Section III presents the most relevant results. In Section IV, a discussion of the future of DL methods applied to the analysis of electrocardiograms is presented. Finally, in Section V, conclusions and recommendations are presented.

II. METHODOLOGY

This section describes the steps defined in the research protocol, for developing a SLR using the two methodologies.

- Systematic Mapping Study.
- Bibliometric Analysis.

A. SYSTEMATIC LITERATURE REVIEW THROUGH SYSTEMATIC MAPPING

1) RESEARCH METHODOLOGY

The search process and article filtering were performed according to the schemes for systematic reviews defined in the PRISMA protocol [9]. Figure 1 depicts this procedure. A Systematic Mapping Study (SMS) based research methodology was reviewed according to the guidelines indicated in [10], [11] and [12]. An SMS aims to structure the research area, by providing a general description of it, obtained through the classification and numbering of the contributions in its different topics. SMS was performed in five steps.

1) Establish the mapping questions.
2) Search for candidate publications.
3) Selection of candidate articles.
4) Summary writing.
5) Extraction of data and mapping of results.

2) LITERATURE RESOURCES

In this study, three bibliographic databases were used:

- Scopus
- IEEE Xplore
- PhysioNet Challenges

To search for publications, search strings were proposed to answer the research questions.

These strings are used in the search engines of digital libraries to find articles published between 2017 and 2023. The keywords used were as follows.

- Arrhythmia detection techniques.
- Techniques for 'automatic' detection of arrhythmias.
- Machine learning (ML) and electrocardiogram (ECG).
- Deep learning (DL) and electrocardiogram (ECG).
- Deep learning, electrocardiogram, arrhythmias.
- Deep neural network, electrocardiogram, arrhythmias.
- Convolutional neural network (CNN), electrocardiogram, arrhythmias.
- Pretrained networks, electrocardiogram, arrhythmias.
- Recurrent neural network (RNN), electrocardiogram, arrhythmias.
- Long-term short-term memory (LSTM) (BI-LSTM), electrocardiogram, arrhythmias.
- Transformers, electrocardiogram (ECG), arrhythmias.
- Quantum, electrocardiogram, arrhythmias.

The articles reviewed are categorized by the technique used and the result of its metrics, where the first includes detection classification, and the second includes analysis of the metrics used. The first task involved revising titles by executing search criteria in different digital libraries. Certain articles could be found in various libraries; therefore, it was necessary to use filters that guarantee title uniqueness: identifying 444 in Scopus, 150 in IEEE Xplore and 93 in PhysioNet Challenges, for a total of 687 publications. In addition, 140 publications that did not refer to the topics under study and 52 articles participating in Challenge 2020, which did not exceed the contest policies, were excluded. Therefore, due to this exclusion, 494 articles were obtained to be reviewed in detail. The process of inclusion and exclusion of publications is presented in Table 1.

3) DATA EXTRACTION FOR THE STUDY ANALYSIS

The procedure to accomplish the research objectives involved a systematic search for articles satisfying a predefined set of inclusion and exclusion criteria. Additionally, research questions were formulated based on the progression of cardiac arrhythmia detection and classification techniques.

4) RESEARCH QUESTIONS

This study aimed to identify evolution techniques for detecting and automatically classifying cardiac arrhythmias from 2017-2023. Table 2 presents the six research questions (RM) used for this purpose and their main motivations. The order of the questions is important because the trend of each question determines the focus of the next question.

- MQ1. It focuses on discovering the medical procedures frequently used to detect and classify cardiac arrhythmias.

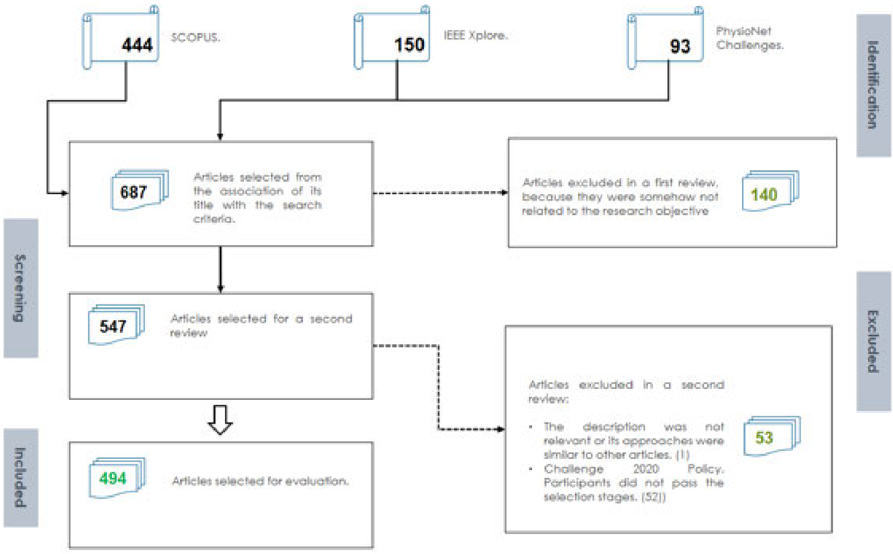

FIGURE 1. PRISMA flow diagram depicting the article selection process for this systematic review.

TABLE 1. Inclusion and Exclusion Criteria.

Inclusion Criteria	Exclusion Criteria
1. Articles using DCAAC methods using deep learning to address cardiovascular disease, even in conjunction with other diseases	1. Articles not written in English
2. Articles that compare with other classification techniques, but whose main purpose is the classification of arrhythmias	2. Articles that present a single classification technique and comparisons of the CAAD methods without providing a discussion.
3. In the case of duplicate documents that investigate the same topic, only the most recent and most complete ones were included.	
4. Articles that are within the study interval	

- MQ2. This study aimed to identify different methodologies for the "automatic" detection of cardiac arrhythmias.
- MQ3. It seeks to verify which artificial intelligence (AI) models are most frequently used for automatically detecting and classifying cardiac arrhythmias.
- MQ4. It identifies the different deep-learning methods used in automatically classifying cardiac arrhythmias using the electrocardiogram.
- MQ5. It identifies the hyperparameter optimization techniques used in training deep learning models and their contribution to published results.
- MQ6. The set of metrics used to evaluate the performance of the deep learning models was analyzed.
- MQ7. It aims to identify the impact and performance of quantum computing-based models compared with classical deep learning models.

5) SEARCH STRATEGY

The purpose of this study was to identify the primary studies that could potentially address the mapping questions. This involves two main steps: establishing a search and selecting bibliographic resources.

a: SEARCH STRING

Several steps are executed to establish search strings [11] and [10]. The keywords used are listed in Table 3.

6) TO IDENTIFY POTENTIAL AREAS OF RESEARCH

Table 4 shows each and every medical procedure used in the detection of cardiac arrhythmias. The aim is to identify potential procedures in which it may be possible to incorporate aspects based on artificial intelligence.

7) SELECTION OF STUDIES

Each document was categorized as either included, excluded, or marked as uncertain following the next rule, according to the following rule.

- Articles were classified as included if they met the first inclusion criterion and at least one of the remaining criteria.
- An article was classified as excluded if it met an exclusion criteria.
- An article was classified as uncertain if there were doubts about its classification.

Each article was examined based on its title, abstract, keywords, and full text, as deemed necessary. Table 1 lists the inclusion and exclusion criteria for selecting relevant articles.

TABLE 2. Research Questions and their motivation.

ID	Mapping Question	Motivation
MQ1	What medical procedures have been used to detect cardiac arrhythmias?	Identify the trends of the different articles, regarding the medical procedures used in the detection of arrhythmias
MQ2	What methods have been proposed to detect and classify cardiac arrhythmias using ECG automatically?	It is intended to identify the different technologies used to detect and classify cardiac arrhythmias.
MQ3	What AI models have been used to detect and classify cardiac arrhythmias using ECG automatically?	It is intended to identify which are the AI models, which are most frequently used in the detection and automatic recognition of cardiac arrhythmias on the ECG.
MQ4	What Deep Learning (DL) models have been used to detect and classify cardiac arrhythmias using ECG automatically?	It is intended to identify the different models of PA, used in detecting and recognizing cardiac arrhythmias using the ECG.
MQ5	What optimization techniques and hyperparameter configuration have been used to implement the DL models?	It is intended to identify the different optimization techniques and hyperparameter configurations used in the training and inference processes.
MQ6	What metrics have been used to assess the performance of DL models to detect and classify cardiac arrhythmias automatically. ?	It is intended to identify the performance metrics evaluation frameworks.
MQ7	What will be the impact and performance of quantum computing-based models compared to classical deep learning models. ?	it aims to identify the degree of impact and performance of quantum computing-based models compared to classical deep learning models.

TABLE 3. Terms used to establish the Search String.

Scope	Keywords
Population	Cardiology, cardiac pathologies, cardiac arrhythmias,
Intervention	Artificial intelligence, machine learning, deep learning
Comparison	Classification, prediction, regression

B. SYSTEMATIC LITERATURE REVIEW THROUGH BIBLIOMETRIC ANALYSIS

1) PERFORMANCE ANALYSIS

To evaluate the performance of scientific research on the topic of detection and automatic classification of arrhythmias, different bibliometric attributes have been used, such as the identification of authors, sources, citations, trends, networks and affiliations, considering individual contributions, groups and organizations. Scientific mapping identifies and visualizes the relationships and interconnections between authors, journals, etc., focusing on historical development, or research trends.

III. RESULTS OF THE RESEARCH

This section describes the main results related to the research questions.

A. SUMMARY OF THE SYSTEMATIC MAPPING STUDY

1) SUMMARY SELECTION PROCESS

Figure 1 shows the selection scheme of publications to be reviewed. The process began by searching three digital libraries, considering the inclusion and exclusion criteria. This initial collection yielded 687 articles. In the first review, 140 articles were excluded because the topics of their publications was not the objective of the study, leaving 547 for a new review. In the second review, 53 articles were excluded because similar approaches were found among the publications, as well as the PhysioNet Challenges. Articles that did not pass the contest rules were not considered, leaving a total of 494 publications, that served as a reference source to answer the mapping questions.

2) RESEARCH QUESTIONS

a: MQ1: WHAT MEDICAL PROCEDURES HAVE BEEN USED TO DETECT CARDIAC ARRHYTHMIAS?

In [13], [14] the different medical procedures for the detection of cardiac arrhythmias were explained, and are summarized in Table 5.

b: MQ2: WHAT MEDICAL TECHNOLOGICAL METHODS HAVE BEEN PROPOSED FOR THE AUTOMATIC DETECTION AND CLASSIFICATION OF CARDIAC ARRHYTHMIAS?

The objective of this study was to identify trends in the literature regarding medical procedures used to automatically detect arrhythmias. To do this, 120 of the latest publications were selected in Scopus, which responded to the search criteria: "automatic detection of arrhythmias." Figure 2, shows the tendency to use information from the ECG as the primary data source.

c: MQ3: WHAT AI MODELS HAVE BEEN USED FOR AUTOMATIC DETECTION AND CLASSIFICATION OF CARDIAC ARRHYTHMIAS USING ECG ?

Figure 3 shows the automatic learning models used to detect arrhythmias. It was observed that more deep-learning models were adopted. Likewise, classical machine learning models decreased throughout the study period. One explanation for this could be the results of the metrics described in Table 7.

TABLE 4. **Medical Procedures for the Detection of Cardiac Arrhythmias.**

	Methodology	Characteristics
1	Electrocardiogram	Non-invasive. Relatively simple. [15] [16] [17] [18]
2	Holter	Non-invasive. You can generate information of several days. [19] [20] [21] [22]
3	Event monitor	Non-invasive. It is of the patch type and can be used for long periods of time. [19] [23] [24] [25]
4	Treadmill test	Non-invasive. Physical exercise is ordered and heart rate and rhythm are monitored. [26] [27] [19] [28]
5	Tilting table test table test	Invasive. A catheter is placed in an artery to monitor blood pressure inside the blood vessel. An intravenous line (a small plastic tube in a vein) may also be placed before the test. [29] [30] [31]
6	Electrophysiological tests	Invasive. Temporary electrode catheters are introduced through the peripheral veins (or arteries) into the heart using a fluoroscope. [32] [33] [34] [35]
7	Invasive	Esophageal Electrophysiological Procedure. In this procedure, a thin, flexible catheter is inserted into the nostril and placed into the esophagus. The catheter wire performs an electrocardiogram (EKG). [36] [37] [38]
8	Echocardiogram	Painless procedure. Uses ultrasound waves to reveal the size, structure, and movement of your heart. [39] [40] [41] [42]
9	Cardiac CT Scan	CBT obtains images by passing thin beams of X-rays through the body at various angles to create a cross-sectional image. [43] [44] [45] [46]
10	Cardiac Magnetic Resonance	This technology is based on the images generated by hydrogen protons; this is an advantage given the abundance of water in the human body. [47] [48] [49] [50]

TABLE 5. **Distribution of Medical Procedures for the Detection of Cardiac Arrhythmias.**

Technique		Years	
	17-21	2022	2023
Ballistocardiogram Signal	1		
Cardiac computed tomography	5	2	
ECG	72	23	3
Echocardiography	4	1	
Molecular imaging	2		
MRI	6		
Multimodality imaging	3		1
Photoplethysmography	2		
Stereotactic body radiation therapy		1	
Cardioverter defibrillator	12	5	

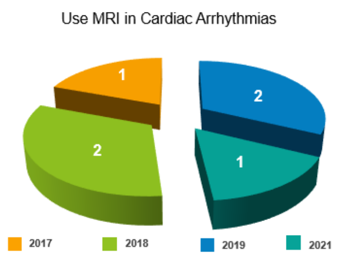

FIGURE 2. **Number of articles using MRI in Cardiac Arrhythmias.**

Similarly, Table 6 presents the values obtained using the deep learning models in their metrics.

d: MQ4: WHAT DL MODELS HAVE BEEN USED TO AUTOMATICALLY DETECT AND CLASSIFY CARDIAC ARRHYTHMIAS USING THE ECG?

Trends regarding the use of different DL models were identified during the period 2017-2023. From each of the digital libraries used in the study, the best articles are shown in descending order according to their accuracy; in the case of the Challenge 2020 articles, they are ordered according to the metric defined for the contest.

Figure 4 shows a boxplot of the precision metric used in the classification models to discriminate the various classes of cardiac arrhythmias. The mean values of the DNN and SVM models were closest. The CNN and LSTM models follow the behavior of close mean values, not DT (Decision Tree) or RNN, which present far mean values.

Considering the obtained accuracy, Table 6 and Figure 5 present the best publications from the Scopus Library, where articles with CNN models reaching 100% accuracy were observed, such as [8] and [52]. In [52], it is mentioned: "the dataset used was divided into three smaller subsets for training, validation, and testing." In [8] "we trained the model on 75% of the subjects, validated it with 5% of the subjects, and tested it on the remaining 20% of the subjects." A rigorous separation of the training and validation sets can lead to leakage problems, as achieving 100% accuracy certainly raises eyebrows, as there is the possibility that the model has memorized patterns rather than learned useful ones.

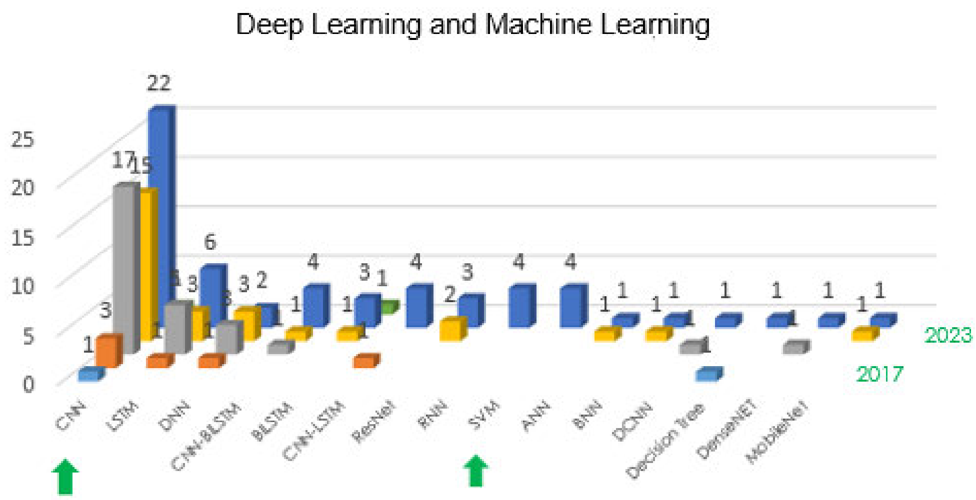

FIGURE 3. Number of articles with Deep Learning and Machine Learning models during the selected period of time.

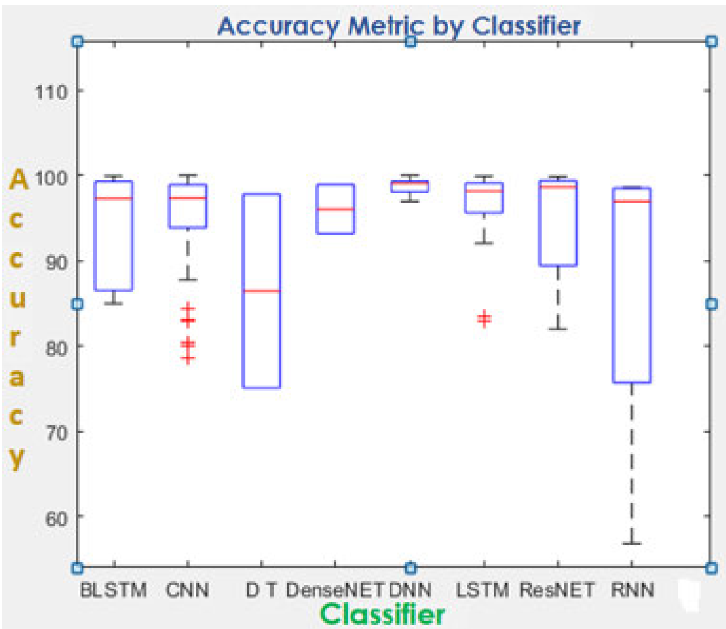

FIGURE 4. Box plots of accuracy metrics for each deep learning model.

Table 8 lists the best proposals for the "Challenge 2020" contest, which shows that the winning proposal used the transformer model. Table 9 presents the usage statistics for the different deep learning methodologies in the contest.

e: MQ5: WHAT OPTIMIZATION TECHNIQUES AND HYPERPARAMETER CONFIGURATION HAVE BEEN USED TO IMPLEMENT THE AP MODELS?

Building an effective deep learning model is a complex process that involves arriving at an appropriate algorithm with optimal architecture by tuning the hyperparameters. Hyperparameter settings should be adjusted according to the datasets [4], [85], and [86].

The first function to configure is the loss function, which is chosen primarily based on the type of problem (e.g., binary cross-entropy for binary classification problems; cross-entropy for multi-classification or multiclass problems, and RMSE for regression problems). In this case, crossed entropy has been observed in most publications because several arrhythmias must be classified [87], [88], and [89].

Another important hyperparameter is the activation function, which is chosen from among the following alternatives: softmax, rectified linear unit (ReLU), sigmoid, tanh, or softsign [87] [90] [91].

The optimizer type can be selected using Stochastic Gradient Descent (SGD), Adaptive Moment Estimation

TABLE 6. Summary of Deep Learning Scholary Publications in the period 2017-2023.

	Title	Year	Model	C	Accuracy	Sensib.	TrDS	TeDS	Optim	OS	AIR
1	Abnormal ECG Beat Detection Based on CNN [51]	2020	CNN	15	100.00	98.09	MIT-BIH	MIT-BIH/AHA	Relu	N/m	N/m
2	A deep neural network heartbeat classification approach for arrhythmia [52]	2020	DNN	8	100.00	96.20	MIT-BIH/BIDMC	N/m	Relu	N/m	N/m
3	Time adaptive ECG driven cardiovascular disease detector [8]	2021	CNN	4	100.00		MIT-BIH	MIT-BIH	Adam	N/m	N/m
4	Improved Arrhythmia Detection from Electrocardiogram [53]	2019	DAE	6	99.98	99.99	MIT-BIH	MIT-BIH	Adam	N/m	CSIR
5	Robust detection of atrial fibrillation from short-term electrocardiogram using.. [54]	2020	DWT-CNN	3	99.98	99.91	MIT-BIH	MIT-BIH/IHD	Adam	N/m	MRTE
6	A Novel Deep Arrhythmia-Diagnosis Network for Atrial Fibrillation Classi. [55]	2019	CNN-BLSTM	1	99.94	98.63	MIT-BIH AF	MIT-BIH NSR	Adam	N/m	FJHS
7	Inter- and Intra- Patient ECG Heartbeat Classification for Arrhythmia Detection. [56]	2019	LSTM	6	99.92	99.50	MIT-BIH	MIT-BIH	N/m	N/m	NSF
8	Classification of ECG heartbeats using deep neural networks [57]	2021	CNN-LSTM	6	99.90	98.60	MIT-BHI	MIT-BHI	Adam	N/m	N/m
9	A Two-level Attention-based Sequence-to-Sequence Model for Accurate Inter-patient. [58]	2020	LSTM	5	99.89	99.87	MIT-BHI	MIT-BHI	RMSProp	Y	DIRTP
10	Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection [59]	2021	CNN-LSTM	7	99.89	95.40	MIT-BIH PTBDB	N/m	Adam	N/m	N/m
11	ECG Signals Segmentation Using Deep Spatiotemporal Feature Fusion U-Net for QRS Complexes and R-peak Detection [60]	2023	ST-Res U-net	2	99.87	99.76	MIT-BHI	CPSC2019	Adam	N/m	N/m
12	An explainable attention-based TCN heartbeats classification model for arrhythmia detection [61]	2023	TCN	2	99.84	91.85	MIT-BIH-AD	MIT-BIH-AD	Adam	N/m	N/m
13	Computer Aided Diagnosis for atrial fibrillation based on new artificial adaptive systems [62]	2018	RNN	2	99.72	99.76	MIT-BIH	N/m	Adam	N/m	N/m
14	A Deep Learning-Based Model for Arrhythmia Detection Using Feature Selection and Machine Learning Methods [63]	2023	CNN	2	99.46		MIT-BIH	N/m	Adam	N/m	N/m
15	Classification of ECG Signal for Cardiac Arrhythmia Detection Using GAN Method [64]	2023	GAN	2	95.40	93	MIT-BIH	N/m	N/m	N/m	N/m
16	The continuous wavelet transform using for natural ECG signal arrhythmias detection by statistical parameters [65]	2023	CWT	3	87		MIT-BIH	MIT-BIH	N/m	N/m	DSR

(Adam), and Root Mean Square Propagation (RMSprop). An example of using the Adam optimizer can be found in [92]. The learning rate is another important hyperparameter that determines each iteration's step size, allowing the convergence speed to be calibrated. A large learning rate accelerates the learning process; however, the gradient may oscillate around a local minimum or may not even converge. However, with a low learning rate, the training time of the model is significantly increased by requiring more epochs [87] and [93].

Abandonment rate (drop-outs). Dropout is a standard regularization method for deep learning models and has been, proposed to reduce overfitting. At dropout, the proportion of neurons is randomly removed, and the percentage of neurons to be removed must be adjusted [92].

The number of epochs depends on the size of the training set and should be adjusted by slowly increasing its value until the validation accuracy decreases, indicating overfitting. However, deep learning models often converge within a few epochs, and subsequent epochs can result in unnecessary additional running time and overfitting, which can be avoided by the ''stop early'' method. Early stopping is a form of regularization whereby model training is stopped early when the accuracy does not increase after a certain number of consecutive epochs. The number of waiting epochs could also be adjusted to reduce the training time of the model.

Figure 6 shows the percentages of use of the different optimization algorithms. On the left are the percentages of optimizers used in the articles referenced in Table 6, which

TABLE 7. Summary of Scholary Publications on Machine Learning (period 2017-2023).

	Reference	Year	Model	C	Accur	Sensit	BDD
1	Human machine interfacing technique for diagnosis of ventricular arrhythmia using supervisory machine learning algorithms [66]	2018	SVM	2	100		MIT-BIH
2	Arrhythmia classification based on wavelet transformation and random forests [67]	2018	Random Forest	8	99.7	95.56	MIT-BIH
3	Classification of cardiac arrhythmia stages using hybrid features extraction with k-nearest neighbors [68]	2018	KNN	2	99.4		MIT-BIH
4	Neighborhood rough set based ecg signal classification for diagnosis of cardiac diseases [69]	2017	k-neighbors	5	99.32		MIT-BIH
5	Cardiac arrhythmia classification using boosted decision trees [70]	2017	Decision Tree	2	99		UCI
6	Automatic classification of cardiac arrhythmias based on hybrid features and decision tree algorithm [71]	2020	Decision Tree	5	98.88		MIT-BIH
7	An automated detection of heart arrhythmias using machine learning technique: Svm [72]	2021	SVM	3	95.92		MIT-BIH

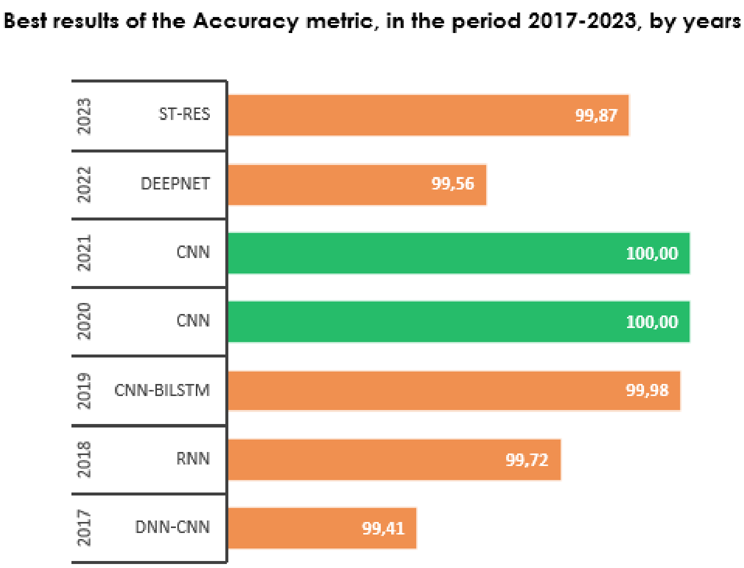

FIGURE 5. Best results of the Accuracy metric, in 2017-2023, by years.

are related to a summary of deep learning publications. On the right are the percentages of use of the optimizer algorithms in the articles participating in the 2020 challenge. The two graphs show that the Adam optimizer was the most used, with values of 58 and 59%, respectively.

f: MQ6: WHAT METRICS HAVE BEEN USED TO ASSESS THE PERFORMANCE OF PA MODELS IN THE AUTOMATIC DETECTION AND CLASSIFICATION OF CARDIAC ARRHYTHMIAS?

The Accuracy(Accur), Specificity(Specif), Sensitivity (Recall) and Score-F1 (S-F1), etc. [94] have been some metrics used to validate the classification models.

- Accuracy: measures the proportion of all correct predictions of the classifier in relation to the total predictions.

$$\text{Accur} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- Specificity: measures the proportion of all positive predictions in the positive class.

$$\text{Specif} = \frac{TP}{TP + FP} \tag{2}$$

- Sensitivity: Sensitivity or recall measures the ratio of the total number of elements belonging to the positive class to the number of positive predictions belonging to the

TABLE 8. Summary of Scholarly Publications on the PhysioNet Challenge.

	Title	Model	C	Score	Optim.
1	A Wide and Deep Transformer Neural Network for 12-Lead ECG Classification [73]	TNN	27	0.533	Noam
2	Adaptive lead weighted ResNet trained with different duration signals for classifying 12-lead ECGs [74]	ResNet	27	0.52	Adam
3	Classification of Cardiac Abnormalities From ECG Signals Using SE-ResNet [75]	SE-Resnet	27	0.514	Adam
4	Combining Scatter Transform and Deep Neural Networks for Multilabel ECG Signal Classification [76]	ResNet	27	0.485	Adam
5	Classification of 12-lead ECG Signals with Adversarial Multi-Source Domain Generalization [77]	CNN-LSTM	27	0.437	Adam
6	Bag of Tricks for Electrocardiogram Classification with Deep Neural Networks [78]	DNN	27	0.42	Adam
7	Automated Comprehensive Interpretation of 12-lead Electrocardiograms Using Pre-trained Exponentially Dilated Causal Convolutional Neural Networks [79]	CNN	24	0.417	Adam
8	SE-ECGNet: Multi-scale SE-Net for Multi-lead ECG Data [80]	SE-Net	27	0.411	N/m
9	Impact of Neural Architecture Design on Cardiac Abnormality Classification Using 12-lead ECG Signals [81]	CNN-BILSTM	27	0.382	N/m
10	Arrhythmia Detection and Classification of 12-lead ECGs Using a Deep Neural Network [82]	ResNet34	27	0.359	Adam
11	Cardiac Pathologies Detection and Classification in 12-lead ECG [83]	Decision Tree	27	0.354	N/m
12	Rule-Based methods and Deep Learning Networks for Automatic Classification of ECG [84]	CNN	24	0.298	N/m

TABLE 9. Model utilization frequency in the PhysioNet Challenge.

	Trend of Models in the Physionet Challenge			
	Model	No Artic.	Prom Fb	Prom Gb
1	Convolucional Neural Network (CNN)	30	82.1	56.7
2	Artificial Neural Networks (ANN)	3	55.4	33.7
3	Autoencoder CNN	1	88.2	87.6
4	CNN BI-LSTM	4	92.19	93.44
5	CNN FNN	1	81.3	82.2
6	CNN BI GRU	1	77.1	57.1
7	Resnet	5	68.4	69.4
8	RNN GRU	1	81.8	60.2
9	RNN LSTM	2	77.1	57.1
10	U Net	1	88.2	87.1
11	XGBoost	1	73.1	47

positive class.

$$\text{Sensit} = \frac{TP}{TP + FN} \tag{3}$$

- Score-F1: It is the harmonic mean of specificity and recall.

$$\text{S-F1} = 2\frac{Specif \times Recall}{Specif + Recall} \tag{4}$$

- Macro-F1: This metric was evaluated over C classes, in a multi-classification problem.

$$\text{mF1} = \frac{1}{C}\sum_{n=1}^{C}\frac{TP}{TP + 1/2(FP + FN)} \tag{5}$$

In all the equations, TP is a true positive, TN is a true negative, FP is a false positive, FN is a false negative, and C is the number of classes.

In [95] and [96], the metric (score column of Table 8) developed for the "PhysioNet/Computing in Cardiology Challenge 2020" is described, which grants partial credit to erroneous diagnoses that result in values similar to the true diagnoses, in the opinion of cardiologists. This is based on the fact that some misdiagnoses are more harmful than others, and [82] should be scored accordingly. Furthermore, it reflects the fact that confusing some classes is much less harmful than confusing others because of the nature of their pathology.

g: MQ7: WHAT WILL BE THE IMPACT AND PERFORMANCE OF QUANTUM COMPUTING-BASED MODELS COMPARED TO CLASSICAL DEEP LEARNING MODELS. ?

The emerging role of deep learning (DL) in automatic arrhythmia detection has been highlighted. This role is driven by large amounts of data and its ability to address challenges more efficiently.

In [97], an introduction to quantum computing (QC) and its symbiotic relationship with quantum machine learning was provided based on the principles of quantum theory. This approach has experienced significant growth, particularly in the healthcare sector. The intersection of machine learning and quantum computing has gained relevance in artificial intelligence (AI), with research successfully applying quantum algorithms to real medical datasets, emphasizing Quantum Machine Learning (QML). In the healthcare domain, applying QML to analyze complex data, such as electronic health records, medical imaging, genomic and sensor data, can potentially enhance disease diagnosis and prognosis.

In the field of automatic detection of cardiac arrhythmias, QML has been presented as a promising tool to accelerate processing and analysis. It enables the identification of patterns in ECG signals faster and more accurately than traditional methods. This enhances predictions of certain diseases and their progression, providing new possibilities for future research.

Table 10 shows some of the performances observed in publications in which the model was based on a quantum-based machine learning algorithm.

B. SUMMARY OF THE BIBLIOMETRIC ANALYSIS

In the Bibliometric Analysis, use will be made from the Scopus database, using the computer tools Biblioshiny [106] and VOSviewer [107], to present important information such as annual scientific production, best publications by number of citations, most productive authors, most productive countries, total citations by country, and most relevant sources (journals) [108].

1) MOST PRODUCTIVE SOURCES, AUTHORS, MOST PRODUCTIVE COUNTRIES

a: SOURCES

Most Relevant Sources:

The most relevant sources are essential for evaluating the performance of a journal regarding the target topic of study. In the article [108] the following is mentioned: "The journal "Computer in Biology and Medicine" has reached first position with 11 publications. The second prolific source is the journal "Physiological Measurement" which focuses on research and clinical practices. The next three journals are "Biomedical Signal Processing and Control.", "Expert System with Applications.", and "IEEE Access." have equaled positions by publishing nine articles." In our 2023 review Figure 7, the first position goes to "Biomedical Signal Processing and Control." with 26 publications, leaving "Computer in Biology and Medicine" in second place with 19 publications.

Most Local Cited Sources: Figure 8 shows the article [109] by Professor Acharya U R (PhD University of Southern Queensland School of Mathematics, Physics and Computing) as the most cited local sources with 263.

Sources' Production over Time: Figure 9 shows the constant performance that BIOMEDICAL SIGNAL PROCESSING AND CONTROL has maintained, clearly positioning itself in first place in terms of production. It was also observed that COMPUTERS IN BIOLOGY AND MEDICINE has remained the leader since its inception in 2017, until mid-2021 when it was surpassed by BIOMEDICAL SIGNAL PROCESSING AND CONTROL.

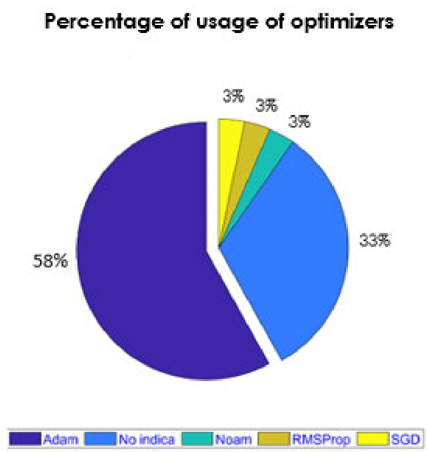

FIGURE 6. Percentage of optimizer usage in the publications under study.

b: AUTHORS

Most Relevant Authors:

Figure 10 shows the top 10 authors with the highest number of published articles on the classification of arrhythmias. Tuncer et al. [110] appears in it, leading the group with 13 contributions and Zhang et al. [111] with a record of 11 contributions.

Authors' Production over Time:

Figure 11 details the production of the authors by periods, highlighting 2021 as one of the most fruitful stages.

c: AFFILIATIONS

Most Relevant Affiliations:

The term "relevant affiliation" refers to organizations in which related research is conducted. The order of information presented was based on the number of investigations and publications. Article [108] describes the following: "in Figure 3, which shows that the USA is one of the most productive countries, based on the number of published papers. The analysis of the most relevant affiliations (Figure 5) revealed that the University of Pennsylvania, located in the USA, is the most relevant affiliation with 12 published articles. Johns Hopkins University in the USA is the second most relevant institution with 11 publications.". In the present study Figure 12 shows that the top affiliations correspond to Universities in China, displacing US Universities.

TABLE 10. Summary Scholary Publications whose models are based on Quantum Machine learning.(period 2017-2023).

	Reference	Year	Model	C	Accur	Sensit	BDD
1	An IOT framework for detecting cardiac arrhythmias in real-time using deep learning Resnet model [98]	2023	MCHResNet	5	98.2		MIT-BIH
2	Real-Time Patient-Specific ECG Arrhythmia Detection by Quantum Genetic Algorithm of Least Squares Twin SVM [99]	2020	QAG	3	98		MIT-BIH
3	Quanvolution Neural Network to Recognize arrhythmia from 2D scaleogram features of ECG signals [100]	2022	QNN	5	98		MIT-BIH
4	QuCardio: application of quantum machine learning for detection of cardiovascular diseases [101]	2023	QNN	5	97.31		MedMNIST
5	Detection of Cardiac Arrhythmia Using Multi-Perspective Convolutional Neutral Network for ECG Heartbeat Classification [102]	2022	QNN	5	91.7		MIT-BIH
6	ECG-based heartbeat classification using exponential-political optimizer trained deep learning for arrhythmia detection [103]	2023	QNN		91.4	92	MIT-BIH
7	A classification and prediction hybrid model construction with the iqpso-svm algorithm for atrial fibrillation arrhythmia [104]	2021	IQPSO-SVM	2	91		MIT-BIH
8	Performance Evaluation of Quantum-Based Machine Learning Algorithms for Cardiac Arrhythmia Classification [105]	2023	QSVM	4	85		Chapman

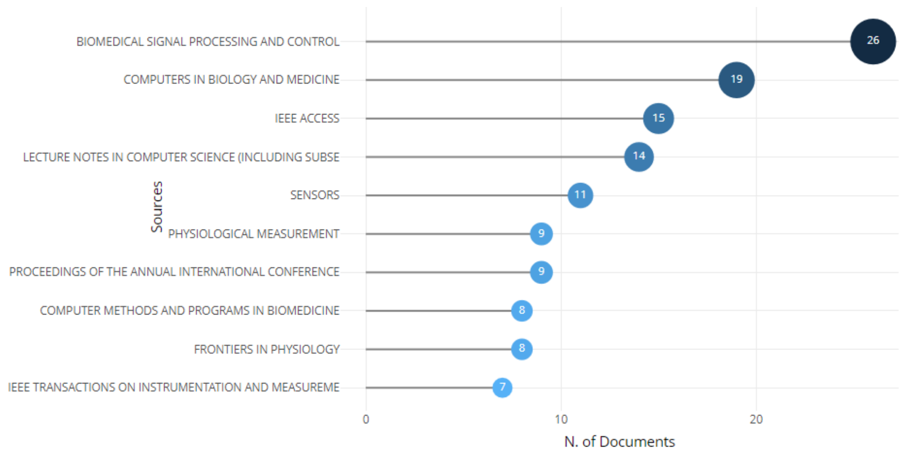

FIGURE 7. Most Relevant Sources.

Affiliation Production over Time:

Figure 13 clearly shows the great production of Asian Universities, in which Shanghai Jiao Tong University stands out with notable leadership.

d: COUNTRIES

Most Productive Countries: Figure 14 shows the 20 most productive countries in publishing articles from 2017 to 2023, for the detection and classification of arrhythmias using Deep Learning models. The section marked in blue ''Scientific Collaboration Production'' (SCP) reports the number of publications in which the authors are all from the same country, whereas the orange box ''Multi-Country Collaboration Production'' (MCP) indicates production in which at least one co-author is from a different country. China and India have a significantly higher number of publications than the rest of the countries, including the USA.

Most Cited Countries: It necessary to determine the degree of importance that an article would have in the general context of research on the topic. We quantify this by the number of citations that other publications make about the article. Figure 15 shows the ten most cited countries worldwide. We highlight China's leadership.

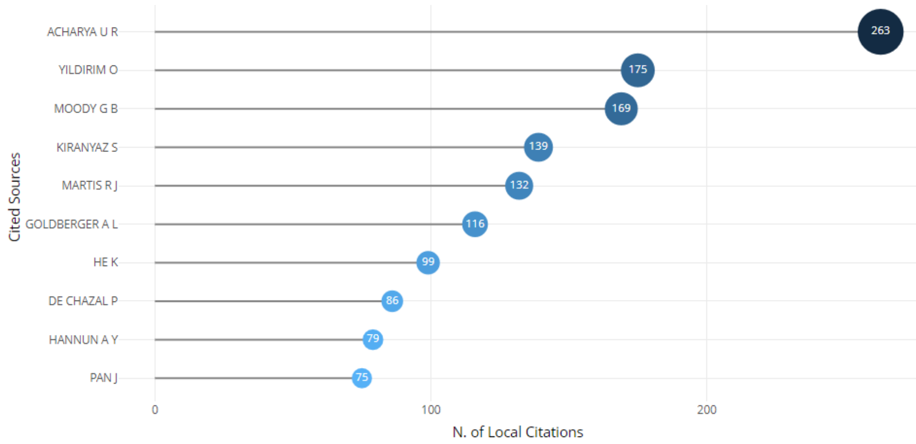

FIGURE 8. **Most Local Cited Sources.**

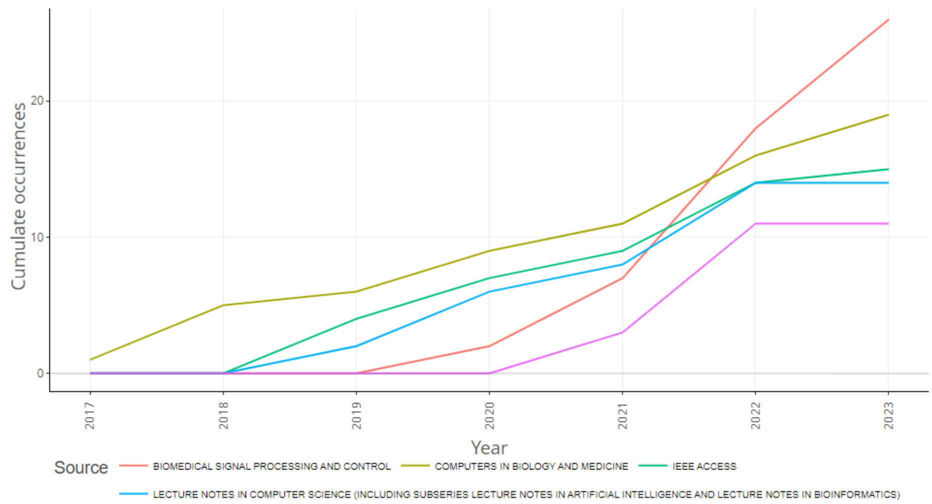

FIGURE 9. **Trends in digital library production over the period.**

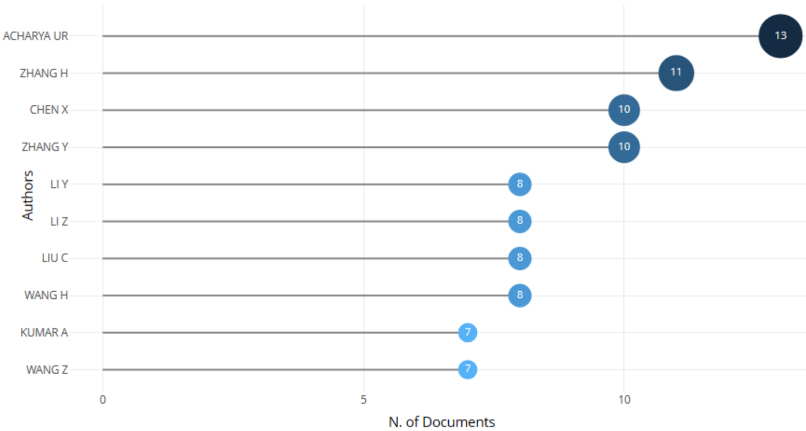

FIGURE 10. **List of most relevant authors over the period.**

Countries Production over time: Figure 16 shows that China and India led research on detecting cardiac arrhythmias during the study period. The growing trend in the leading countries is also notable, while in the

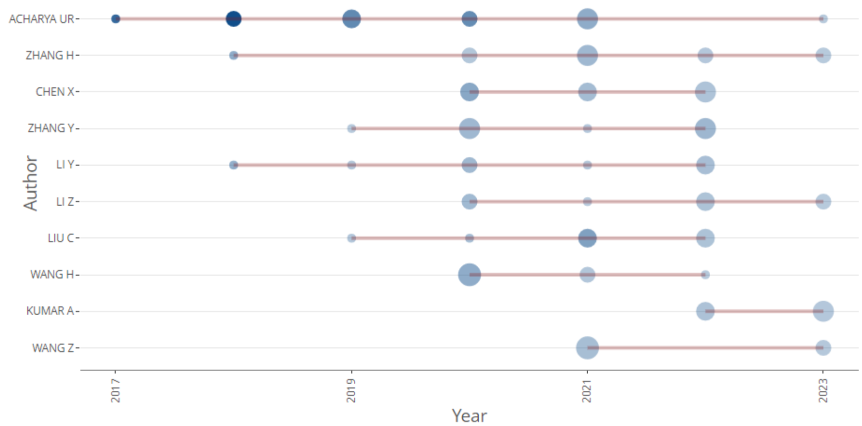

FIGURE 11. Academic production of authors over the period.

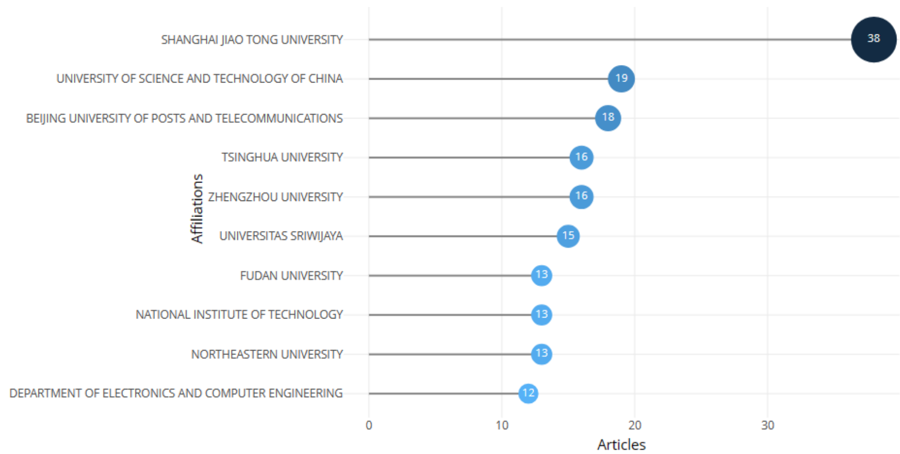

FIGURE 12. List of most relevant university o research center affiliations.

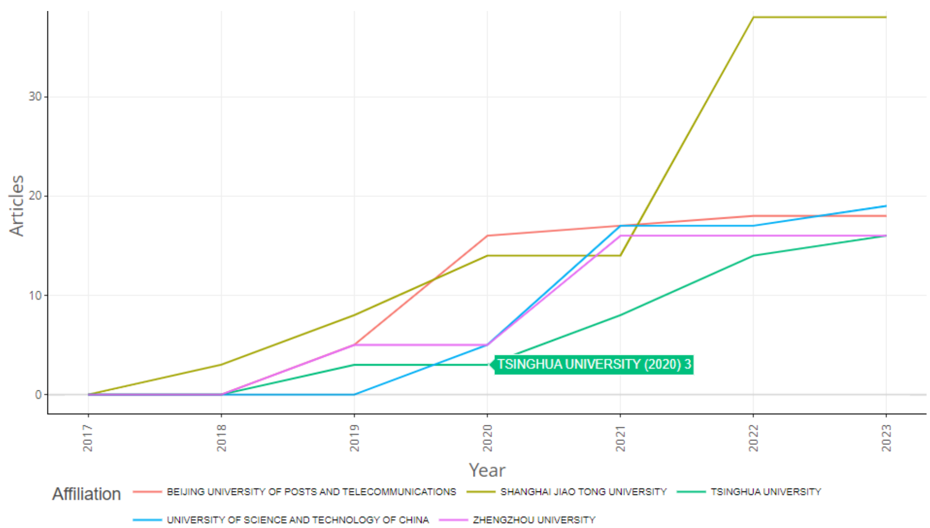

FIGURE 13. List of most relevant universities o research centers production over the period.

rest of them (including the US), scientific production since 2021 tends to stabilize at less representative values.

e: DOCUMENTS

Most global cited documents: Global citations represent the total number of citations a document receives from

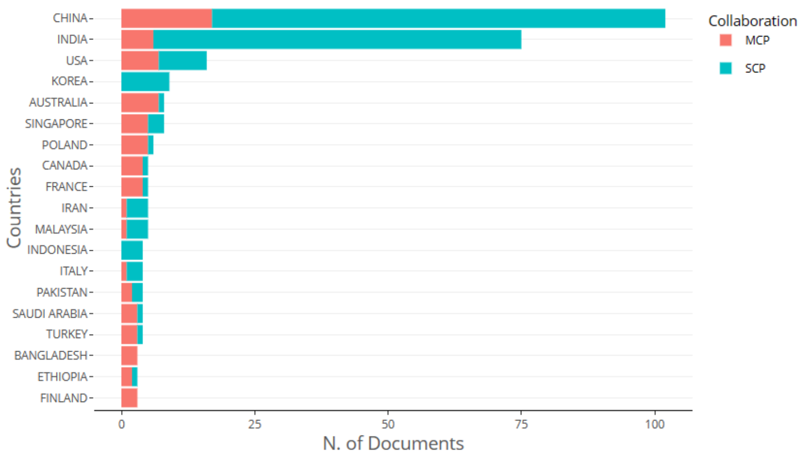

FIGURE 14. Scientific production by countries considering: (SCP) those publications in which the nationality of their authors is all from the same country, and (MCP) those conducted in collaboration with multiple countries.

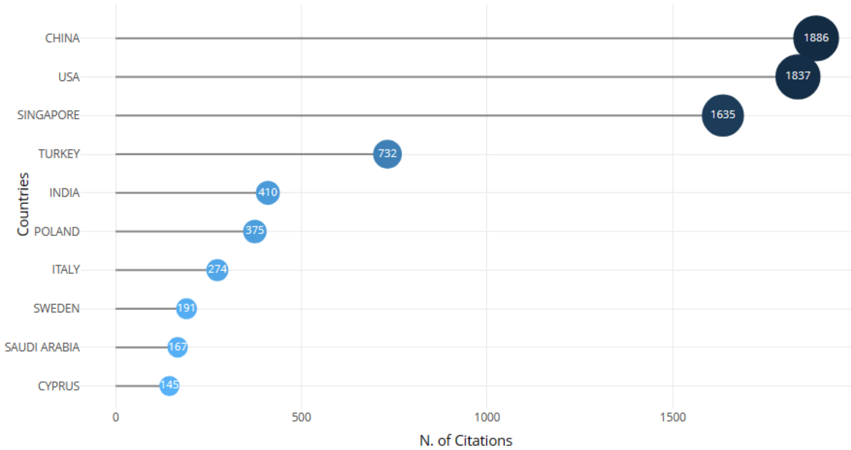

FIGURE 15. List of most cited countries over the period.

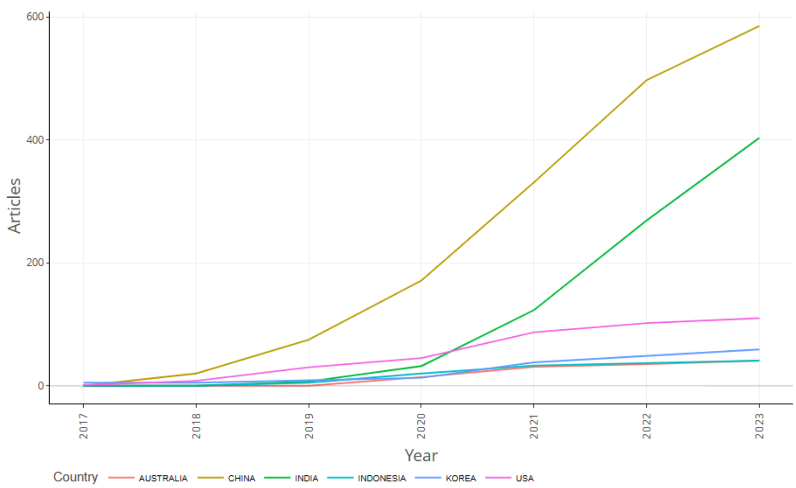

FIGURE 16. Scholarly Publications Production by Country Over Time.

all publications indexed in a source (Scopus, WOS, Google Scholar, etc.) [112]. Figure 17 shows Hannun AY (Department of Computer Science, Stanford University, Stanford, CA, USA) as the most referenced author with

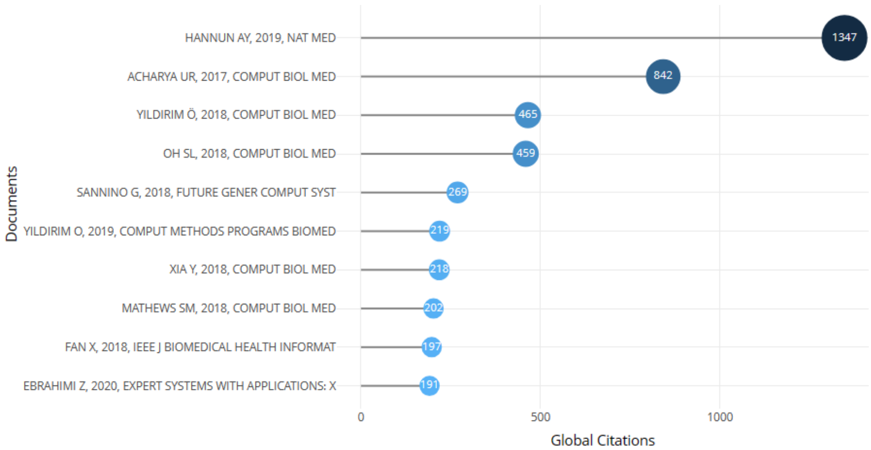

FIGURE 17. List of highly cited scholarly publications worldwide.

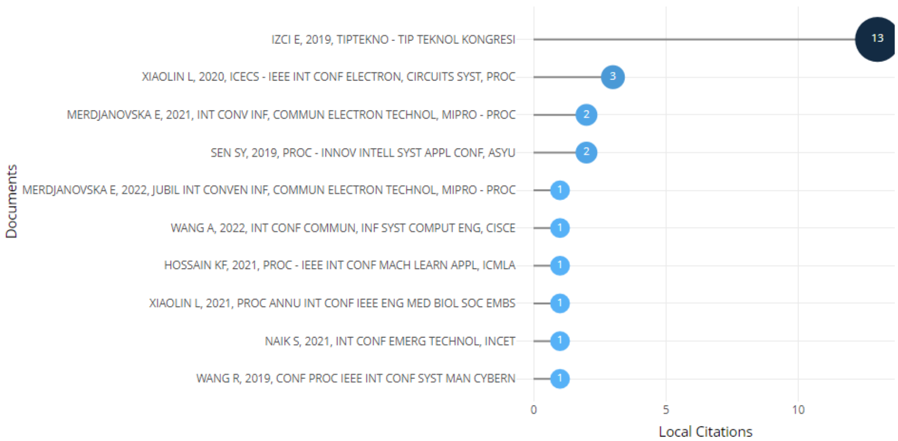

FIGURE 18. List of highly cited scholarly publications locally.

1347 citations, the curious thing is that said author does not have many publications (in fact he appears with an article [113], similar to the case of Acharia UR, who follows him in terms of the number of citations but leads in the number of publications.

Most Local Cited Documents: Local Citation refers to the number of citations a document received from other documents in the specific search performed (that is, in the sample of highly specialized papers under review) [112]. Figure 18 shows the document IZCI E, 2019, TIPTEKNO - TIP TEKNOL KONGRES as the most cited with 13.

f: WORDS

Word Cloud of Keywords: A comparison was made to determine the variation in the most used terms throughout the study period of 2017-2023. In Figure 19, the most used term is ELECTROCARDIOGRAPHY and, Figure 20 shows that the trend in the use of artificial intelligence is increasingly evident, with the most used term being DEEP LEARNING.

Words' Frequency over Time: The Figure 21 shows that although the volume of occurrence of the themes increased, the trends between them remained constant throughout the study period.

2) NETWORK ANALYSIS

One of researchers' concerns is to identify colleagues who carry out studies in similar lines of research and could suddenly carry out collaborative work. Therefore, having a method to analyze the relationships between journals, affiliations, etc., from several countries may be useful.

a: CO-AUTHORSHIP

Organizations: The list of organizations referred to in the citations is led by the Department of Electronics and Computer Engineering of Singapore, with 2355 citations. The second highest is occupied by the Department of Biomedical Engineering, School of Science and Technology, Singapore University with 1480 citations. The five organizations in Figure 22 are located in Singapore. The Department of Electronics and Computer Engineering maintained research relationships with the four organizations indicated.

Countries: Figure 23 illustrates the relationships among the research-oriented countries. Countries such as China and the United States stand out and their contact with other countries is evident. Figure 24 shows the United States, which

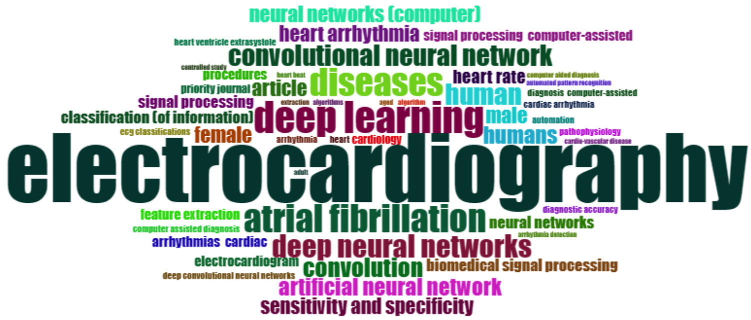

FIGURE 19. Keyword Word Cloud for the Year 2017.

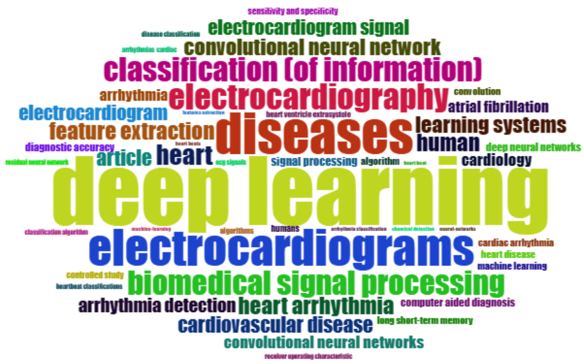

FIGURE 20. Keyword Word Cloud for the Year 2023.

despite having fewer publications than China, has garnered more citations for its documents, reaching 3475 citations.

b: CO-OCURRENCE

Author keywords: Figure 25 shows how ''Deep Learning'' is the word most repeated in research, followed by ''arrhythmia'' and ''ECG.''. This result is important because it determines which areas of the research line have been the ones on which most studies were conducted during the study period.

c: CITATIONS

Documents: Figure 26, Figure 27 highlights the documents by Hannun et al. [113] and Acharya et al. [114] as the most cited articles, published in 2017 and 2020 respectively.

d: BIBLIOGRAPHIC COUPLING

Documents: Figure 28 details which articles have been most referenced in Bibliographic Coupling mode, highlighting '' Hannun a.y.; Rajpurkar P.; haghpanahi m.; tison g.h.; bourn c.; turakhia m.p.; ng a.y. (2019)'' followed by Acharya with his article ''acharya u.r.; oh s.l.; hagiwara and.; tan j.h.; Adam M.; Gertych A.; so r.s. (2017)''. It is worth mentioning that Acharya presented other publications that are referenced in a relevant manner. Bibliographic coupling occurs when two studies refer to a third common work in their literature.

IV. DISCUSSION

Next, it is crucial to carefully examine the potential limitations inherent in the SLR methodology when applied to detect and classify cardiac arrhythmias from ECG signals using DL.

A. LIMITATION AND OPPORTUNITIES

The classification of cardiac arrhythmias using DL could have certain limitations, one of which is data imbalance, because certain types of heartbeats are more challenging to detect than others. The number of normal cases is typically much larger than the number of abnormal cases. This can affect the efficiency of the DL models [115]. Classes trained with fewer samples may show obvious inaccuracy compared to other [115] and [116] classes. Aspects such as noise and unbalanced categories can influence the effectiveness of DL models. Likewise, the complexity of these models can be a handicap when implemented.

Table 6, Table 7 and Table 10 shows that 85% of the publications used the MIT-BIH database (Arrhythmia Database v1.0.0 PhysioNet) of high quality, but with short-term ECG records. These led to poor classification performance, especially when using DL methods [115]. Therefore, creating high-quality information sources in the long term could stimulate studies based on ECG signals. There is no standard methodology for collecting and organizing data, making comparing different databases difficult. In [115], it was recommended to use the MWM-HIT and PTB-XL databases, or to build new large ECG data sets.

A common feature of all DL methods is their ability to preserve the temporal variation of the signal, which is considered necessary for the classification of cardiac arrhythmias. It is important to note that variations can occur within and over beats. This requires learning both in the short and long term for efficient classification [117].

Through many experimental results, DL techniques have been found to have an advantage over machine learning algorithms, which require preprocessing in tasks such as noise removal, data cleansing, and feature selection. DL methods can work well even without preprocessing steps from the input; that is, raw ECG signals can be fed directly to the classifier [4].

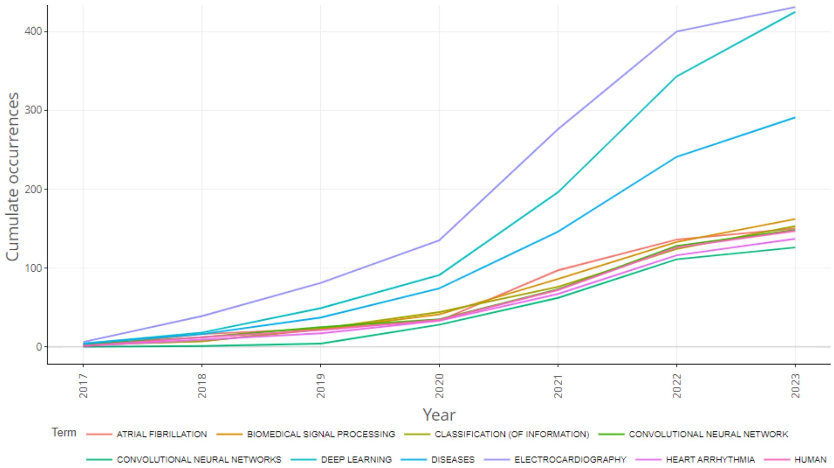

FIGURE 21. Trends of the most relevant keywords over the period.

FIGURE 22. Map of co-authorship among universities or research centers.

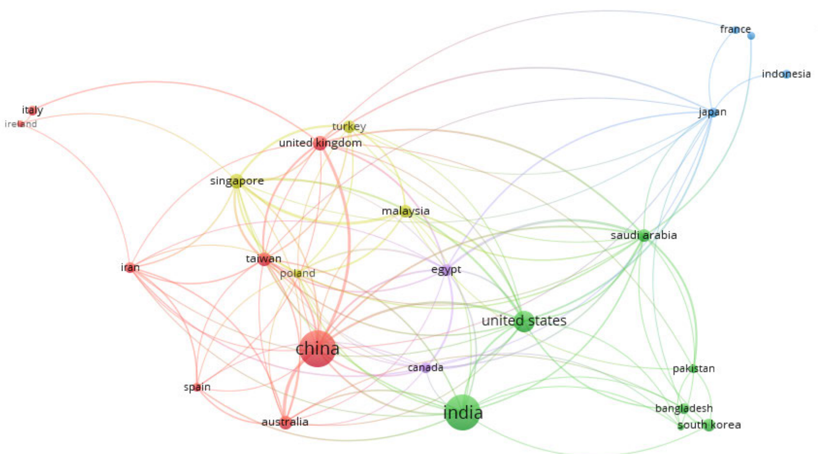

FIGURE 23. Map of co-authorship among countries.

B. LIMITED PROSPECTIVE VALIDATION OF MACHINE LEARNING MODELS FOR MEDICAL DIAGNOSIS

In the review of engineering-oriented machine learning papers for medical diagnosis, it is observed that there are few models validated prospectively using independent data from different medical settings. Prospective validation using independent data from diverse medical settings is crucial for assessing these models' generalization and real-world applicability. The following are some key points to consider:

1) DIFFICULTY OF GENERALIZABILITY

Without prospective validation in diverse medical settings, there is a risk that the performance of machine learning models may be overly optimistic and not reflective of their true generalizability. In Table 6, Table 7 and Table 10, it is shown that the majority of publications used the MIT-BIH arrhythmia database as the training dataset (TrDS), but they did not describe the name of the test dataset (TeDS). Models trained on specific datasets may not perform well when applied to different populations or clinical environments.

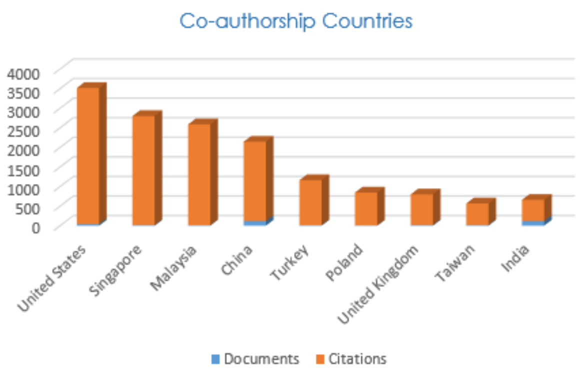

FIGURE 24. Relation between No of documents and citations.

Although encouraged, validation on more datasets than the original development dataset is not always feasible, as there may be ethical, technical, or financial challenges in sharing clinical data [118] and [119]. Thus, to make ML healthcare models more accessible across different hospital settings, different model customization approaches are needed to translate specific, locally trained models to new settings [118].

2) BIAS AND OVERFITTING CONCERNS

Models that were not prospectively validated with independent data were more susceptible to overfitting due to the peculiarities of the training dataset. This can result in biased predictions that may not accurately reflect the complexities of real-world clinical scenarios. It is imperative to meticulously consider each developmental stage to construct a robust pipeline to identify and mitigate various biases. None of the articles described in Table 6 and Table 7, successfully developed a comprehensive process for the detection and management of multiple types of biases. Future studies should address all possible types of bias during model development for healthcare. Future studies should address all possible types of bias during model development for healthcare [120].

3) REAL-WORLD VARIABILITY

Medical settings vary significantly regarding patient demographics, data collection practices, equipment, and protocols. Prospective validation in diverse settings helps the model handle this variability and maintain a robust performance. Real-world clinical testing demonstrates substantial variability within a single manufacturer between two separate methods and demonstrates an impact on patient follow-up and implications in decisions regarding follow-up intervals and treatment [121].

4) CLINICAL IMPACT

Inaccurate or poorly generalizable models can have serious consequences in clinical settings, potentially leading to misdiagnosis or inappropriate treatment decisions. Prospective validation helps build confidence in these models' reliability and safety. In [122], the prospective validation of a clinical decision rule allowed us to identify patients who presented to the emergency department with chest pain and could be safely removed from cardiac monitoring.

5) REGULATORY COMPLIANCE

Regulatory bodies may require rigorous validation in many regions before approving machine learning models for clinical use. Prospective validation is necessary to meet these regulatory standards. Validation helps ensure products meet standard quality, safety, efficacy, purity, and effectiveness [123].

6) ETHICAL CONSIDERATIONS

From an ethical standpoint, deploying models without thorough validation may expose patients to unnecessary risk. It is essential to prioritize patient safety and well-being through a comprehensive validation process. Currently, no well-defined regulations are in place to address the legal and ethical issues that may arise due to the use of artificial intelligence in healthcare settings [124].

7) COLLABORATION AND DATA SHARING

Prospective validation in different medical settings promotes collaboration and data sharing among researchers, clinicians, and institutions. This collaborative approach can lead to more robust models better suited to widespread adoption. Learning from COVID-19-induced developments in data-driven collaboration between hospitals and other healthcare organizations is important to address systemic barriers, sustain resilience, and build transformative capacity to help build better-integrated healthcare systems [125].

In conclusion, emphasizing the importance of prospective validation using independent data from diverse medical settings is crucial to ensure the reliability, generalizability, and ethical use of machine learning models in medical diagnosis. As the clinical adoption of deep learning algorithms progresses, concerns have arisen regarding the impact of AI biases and discrimination on patient health [126]. Researchers and practitioners should actively seek opportunities for such validation to bridge the gap between theoretical advancements and real-world applications in healthcare.

C. DATA LEAKAGE

Data leakage is a critical issue in deep learning and most machine learning methods. It occurs when information from the validation or test set leaks into the training set, leading to an unrealistically optimistic assessment of model performance.

In Table 6, it can be observed that the same dataset origin predominates in the articles for both training and testing, although they could come from different areas, such as MIT-BIH AF and MIT-BIH NSR.

The lack of clarity in the rigorous separation of the training and validation sets can result in leakage problems.

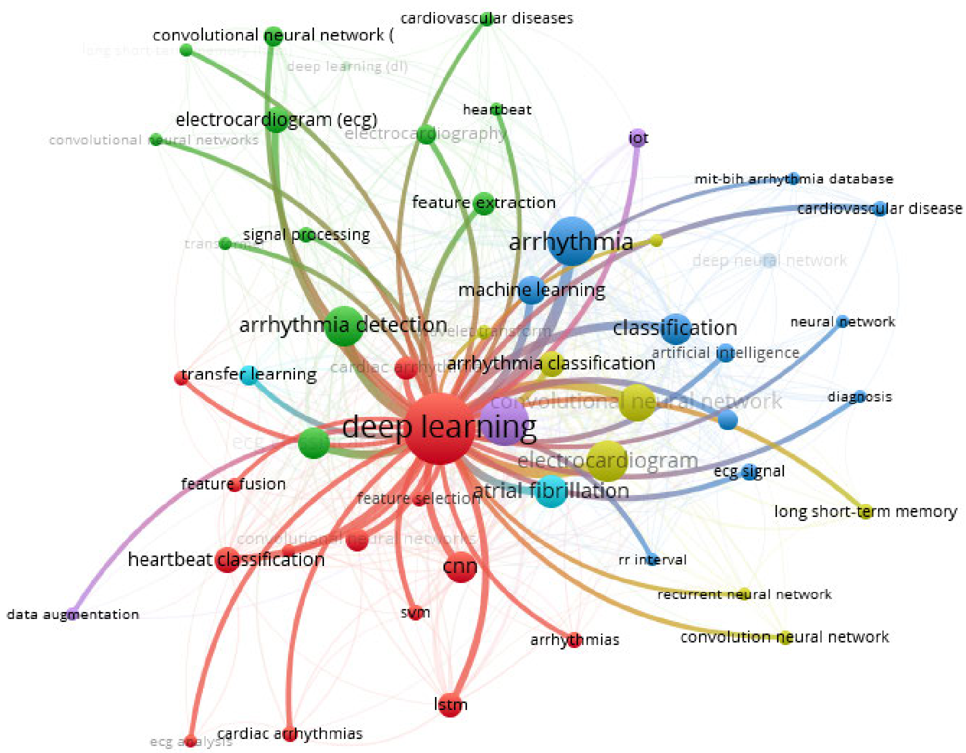

FIGURE 25. Map of keyword Co-occurrence over the period.

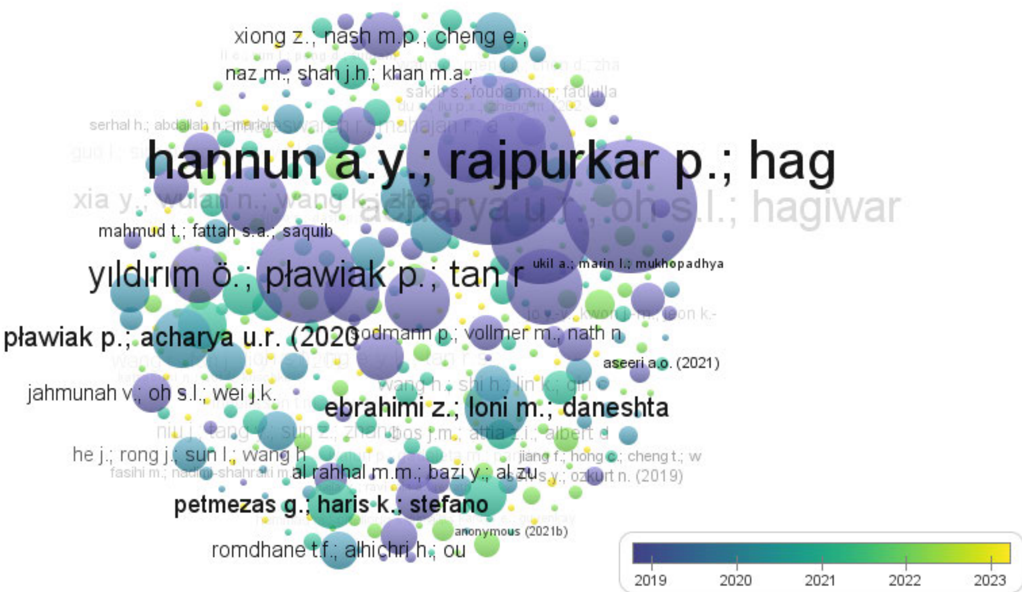

FIGURE 26. Map of citations documents.

If some documents do not adequately address this issue and achieve 100% accuracy, it is a cause for concern, as it may indicate that the model has memorized patterns rather than learned useful ones. When data augmentation is employed, the performance of deep learning models can be enhanced; however, the classifier's performance might be significantly inflated when incorrect cross-validation is applied owing to data leakage [127].

Establishing proper separation between training, validation, and test sets is essential to assess the model's ability

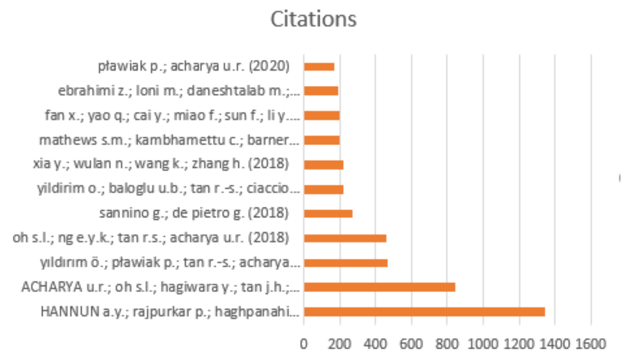

FIGURE 27. Number of citations per scholarly document over the period.

to generalize unseen data fairly. Deep learning researchers and practitioners should be aware of this issue and apply robust set separation and cross-validation practices to prevent leaks and ensure model robustness. Transparency in the methodology used to split the data and train the model is fundamental for reproducibility and confidence in the results.

D. THE PRACTICAL UTILITY OF DEEP LEARNING MODELS

The lack of reproducibility and the difficulty of implementing trained models in real-world environments are legitimate concerns. The following are some considerations.

1) REPRODUCIBILITY AND TRANSPARENCY

Reproducibility is fundamental to science and research. Deep learning models should be transparent, and details of the training process must be available for others to replicate the results. The lack of transparency and excessive complexity of algorithms can make models inaccessible to most researchers, limiting their practical utility. The lack of detailed methods and algorithm codes undermines its scientific value [128].

2) APPLICABILITY IN REAL-WORLD SCENARIOS

The true utility of a model is its ability to address real-world problems and provide practical solutions. Researchers should strive to present models that achieve high performance on specific datasets and are adaptable and applicable to practical, real-world situations.

In Table 6 column "AIR" (Academy Industry Relationship), articles supported by various research institutions are detailed, including the Council for Scientific and Industrial Research, India (CSIR), the Ministry of Research, Technology, and Higher Education, Indonesia (MRTE), the Foundation of Jiading Health Science (FJHS), the National Science Foundation (NSF), and the Dongguan Innovative Research Team Program (DIRTP).

Therefore, tools and techniques for data management are urgently needed to generate useful insights from data in a timely and intelligent manner, upon which real-world applications are based [129].

3) SIMPLICITY VS. COMPLEXITY

Algorithmic complexity does not always translate into better practical results. In many cases, simpler and easily interpretable models can be more effective and useful in real-world applications. It is important to determine a balance between the complexity of the model and its practical utility. The objective is to maintain a certain level of comprehensibility and control in response to the complexity of the model resulting from the proliferation of machine learning techniques [130].

4) OPEN SOURCE AND SHARED RESOURCES

Encouraging the adoption of open-source practices and sharing resources, such as source code, datasets, and pre-trained models, can improve the utility and applicability of research results. Knowledge of existing open source frameworks can be utilized to implement difficult and complex models of Deep Learning more efficiently and quickly by reducing the time and effort required for duplicate development [131].

Table 6 column "OS" (Open Source) describes that only one of the articles makes reference to including links to the source code and data used in its research.

In summary, deep learning researchers must prioritize transparency, reproducibility, and practical applicability of their models. This will strengthen confidence in research results and contribute to the genuine advancement of the discipline in real-world settings.

E. PROSPECTIVE OF TRADITIONAL DEEP LEARNING MODELS REGARDING THE NEW EMERGING MODELS BASED ON QUANTUM COMPUTING

It is necessary to analyze the past and future behavior of emerging models, such as quantum computing, in relation to traditional machine learning models. These models and their performance in the classification and automatic detection of cardiac arrhythmias will be compared. The following aspects were emphasized.

1) LITERATURE REVIEW

As shown in Figure 6, based on the accuracy metrics, the best outcomes were achieved using traditional deep learning models. Figure 10 shows the best results using quantum computing-based models. It is observed that traditional models exhibit better performance; however, it is confirmed that quantum computing-based models have a much faster execution speed than traditional machine learning methods [99].

2) MODEL CHARACTERISTICS

a: INFORMATION REPRESENTATION

Traditional models use binary bits to represent information. Quantum models use qubits that can exist in superposition, representing multiple states simultaneously, allowing

FIGURE 28. Bibliographic Coupling Documents.

for information manipulation that differs from traditional bits [132].

b: PARALLELISM

Traditional models sequentially perform operations by processing data at a time. Quantum models leverage quantum parallelism to perform calculations in multiple states simultaneously, providing significant advantages for solving certain types of problems [133] and [134].

c: QUANTUM ENTANGLEMENT

Traditional models do not harness quantum entanglement because the classical bits are independent. Quantum models can be entangled, meaning that the state of one qubit is linked to that of another [132].

d: ALGORITHM COMPLEXITY

Quantum models can leverage specific quantum algorithms that may outperform traditional models in certain problems [101].

e: MODEL SIZE

The classical processing capacity and available memory generally limit traditional models. In quantum models, the number of qubits and their coherence directly affect the size and complexity of quantum models [135].

f: ERROR CORRECTION

In traditional models, errors are handled using optimization techniques and parameter adjustments. In quantum models, quantum error correction is essential due to the sensitivity of qubits to environmental interferences and errors [135] and [136].

3) PERFORMANCE AND RESULTS

Classical deep learning models, executed on conventional hardware, have proven to be more effective and practical for various applications than quantum models. Quantum computing still has limitations regarding quantum stability, error correction, and scalability [105] and [135].

4) SCALABILITY AND EFFICIENCY

a: SCALABILITY

Traditional models can leverage parallelism in conventional hardware, such as GPUs, to accelerate training and use the trained model for predictions or decision-making on new input data. Quantum bits (qubits) can simultaneously represent multiple states, allowing for massive parallel processing, referred to as quantum superposition and entanglement [133] and [135].

b: EFFICIENCY

The training times can vary depending on the complexity of the model and the size of the dataset. Some models may be efficient regarding the training process, whereas others may require more resources. Quantum algorithms have the potential to solve certain problems efficiently [137].

5) FUTURE PERSPECTIVES

The future of traditional machine learning and quantum computing-based models will depend on advancements in hardware, algorithm development, hybrid integration, identification of practical applications, and overcoming technical and ethical challenges [138]. These technologies have the potential to coexist and complement each other in the future computing landscape.

V. CONCLUSION

This document presents the results of a systematic review of scientific articles developed between 2017 and 2023 on the systematic detection and classification of cardiac arrhythmias from ECG signals using DL techniques. This study reveals the superiority of DL over traditional machine learning methods. Unfortunately, computational cost remains one of the main limitations of DL methods. The study showed a growing interest in DL over the last decade for ECG signal medical applications. This growth is sustained as DL architectures have become more popular.

The creation of large long-term public databases, together with the choice of a suitable DL deep learning method, will improve the classification results. In the meantime, researchers and clinicians will be empowered to understand DL appropriately, allowing them to interpret the results of such methods as they continue to be adopted into modern use. In summary, this study aimed to consolidate the fundamental information on all aspects of ECG signal classification using DL techniques and present it as a reference material for new researchers to improve their modeling performance.

This analysis allowed us to answer the seven RQs raised in the study. The main findings related to each question are detailed below.

- MQ1: Bibliography describes the procedures used by the medical community for the detection/classification of cardiac arrhythmias. Their knowledge could allow the discovery of new opportunities to improve medical diagnoses.
- MQ2: A retrospective study of the study period was carried out to determine which techniques have been used in the automatic detection/classification of cardiac arrhythmias, emphasizing the use of electrocardiograms; however, we observed other techniques such as echocardiography, cardiac computed tomography, and cardiac magnetic resonance. These could constitute an opportunity for future research using techniques such as DL.
- MQ3: DL models revealed in new publications owing to the excellent performance of its metrics [139], [140], [141], and [142].
- MQ4: Table 6, Figure 4 and Figure 5 shows the DL models, with the best performance based on the accuracy metric, with CNN being the best performer, with participation of 49% of the best publications found in the study.
- MQ5: The main optimization technique is Adam, which has the highest participation (58-59%) among the best publications of the study Figure 6.
- MQ6: In the "PhysioNet/Computing in Cardiology Challenge 2020, a new scoring metric was described to assess the performance of DL architectures. This scoring metric reflects reality evidence that some misdiagnoses are more harmful than others and should be scored accordingly and reflects the fact that it is less serious about confusing some classes than others [95].
- MQ7: Quantum computing has a highly valuable potential through qubits [100], allowing be more effective, especially in solving complex problems, leveraging the capabilities of quantum gates [99]. As quantum computing becomes more consolidated, quantum algorithms are expected to become significantly more powerful. Therefore, the future prospects in this field are promising. Advancements in this field include integrating quantum machine learning models with quantum hardware and incorporating them into existing medical systems to help improve diagnostics [101].

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

ACKNOWLEDGMENT

This work was partially supported by the Universidad San Francisco de Quito through the Poli-Grants Program under Grant 24263. The authors also gratefully acknowledge the support of the 2020-PIC-001-CTE research project from the Universidad de las Fuerzas Armadas. Additionally, they extend their sincere appreciation to the editor and reviewers for their invaluable suggestions.

AUTHOR CONTRIBUTIONS

Marco Javier Flores-Calero is credited with the research methodology, design, and supervision. Fernando Vásquez-Iturralde developed the research implementation, writing, and information validation. Felipe Grijalva contributed to the analysis of results and actively participated in writing the paper. Andrés Rosales-Acosta has reviewed the manuscript.

FUNDING

This research received no external funding, and the authors' institutions funded the APC.

REFERENCES

[1] A. Rosiek and K. Leksowski, "The risk factors and prevention of cardiovascular disease: The importance of electrocardiogram in the diagnosis and treatment of acute coronary syndrome," *Therapeutics Clin. Risk Manage.*, vol. 2, pp. 1223–1229, Aug. 2016.

[2] (2021). *Noncommunicable Diseases*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases

[3] A. Gudiño and R. Buitrón, "Prevalencia de la fibrilación auricular en población mestiza ecuatoriana con diabetes mellitus tipo 2 inadecuadamente controlada," *Cardiocore*, vol. 1, pp. 16–44, Jan. 2018.

[4] S. Naik, S. Debnath, and V. Justin, "A review of arrhythmia classification with artificial intelligence techniques: Deep vs machine learning," in *Proc. 2nd Int. Conf. Emerg. Technol. (INCET)*, May 2021, pp. 1–14.

[5] A. Raza, K. P. Tran, L. Koehl, and S. Li, "Designing ECG monitoring healthcare system with federated transfer learning and explainable AI," *Knowl.-Based Syst.*, vol. 236, Jan. 2022, Art. no. 107763. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950705121009862

[6] K. F. Hossain, S. A. Kamran, A. Tavakkoli, L. Pan, X. Ma, S. Rajasegarar, and C. Karmaker, "ECG-adv-GAN: Detecting ECG adversarial examples with conditional generative adversarial networks," in *Proc. 20th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2021, pp. 50–56, doi: 10.1109/ICMLA52953.2021.00016.

[7] S. Sahoo, M. Dash, S. Behera, and S. Sabut, "Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey," *IRBM*, vol. 41, no. 4, pp. 185–194, Aug. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1959031819301654

[8] M. S. Haleem, R. Castaldo, S. M. Pagliara, M. Petretta, M. Salvatore, M. Franzese, and L. Pecchia, "Time adaptive ECG driven cardiovascular disease detector," *Biomed. Signal Process. Control*, vol. 70, Sep. 2021, Art. no. 102968. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809421005656

[9] M. J. Page, J. E. McKenzie, P. M. Bossuyt, and D. Boutron, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, p. n71, Mar. 2020. [Online]. Available: https://www.bmj.com/content/372/bmj.n71

[10] K. Petersen, S. Vakkalanka, and L. Kuzniarz, "Guidelines for conducting systematic mapping studies in software engineering: An update," *Inf. Softw. Technol.*, vol. 64, pp. 1–18, Aug. 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950584915000646

[11] M. Hosni, J. M. Carrillo de Gea, A. Idri, M. El Bajta, J. L. Fernández Alemán, G. García-Mateos, and I. Abnane, "A systematic mapping study for ensemble classification methods in cardiovascular disease," *Artif. Intell. Rev.*, vol. 54, no. 4, pp. 2827–2861, Apr. 2021.

[12] B. Kitchenham, "Guidelines for performing systematic literature reviews in software engineering," in *Proc. EBSE Tech.*, 2007.

[13] AH Association. (2022). *Heart Attack and Stroke Symptoms*. [Online]. Available: https://www.heart.org

[14] UD Surgery. (2022). *Arrhythmias*. [Online]. Available: https://surgery.ucsf.edu/conditions–procedures/arrhythmias.aspx

[15] EBV. (2021). *Scopus*. [Online]. Available: https://www.scopus.com/sources.uri

[16] C. K. Jha and M. H. Kolekar, "Electrocardiogram data compression techniques for cardiac healthcare systems: A methodological review," *IRBM*, vol. 43, no. 3, pp. 217–228, Jun. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1959031821000750

[17] T.-M. Chen, C.-H. Huang, E. S. C. Shih, Y.-F. Hu, and M.-J. Hwang, "Detection and classification of cardiac arrhythmias by a challenge-best deep learning neural network model," *iScience*, vol. 23, no. 3, Mar. 2020, Art. no. 100886. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2589004220300705

[18] B. Singh, A. Kaur, and J. Singh, "A review of ECG data compression techniques," *Int. J. Comput. Appl.*, vol. 116, no. 11, pp. 39–44, Apr. 2015.

[19] (2020). *Heart Attack and Stroke Symptoms*. [Online]. Available: https://www.heart.org/en/health-topics/arrhythmia/symptoms-diagnosis–monitoring-of-arrhythmia/common-tests-for-arrhythmia

[20] C Clinic. (2024). *Cleveland Clinic*. [Online]. Available: https://my.clevelandclinic.org/health/diagnostics/21491-holter-monitor

[21] S. K. Chua, L.-C. Chen, L.-M. Lien, H.-M. Lo, Z.-Y. Liao, S.-P. Chao, C.-Y. Chuang, and C.-Z. Chiu, "Comparison of arrhythmia detection by 24-hour Holter and 14-day continuous electrocardiography patch monitoring," *Acta Cardiologica Sinica*, vol. 36, pp. 251–259, May 2020.

[22] S. Kwon, S.-R. Lee, E.-K. Choi, H.-J. Ahn, H.-S. Song, Y.-S. Lee, S. Oh, and G. Y. H. Lip, "Comparison between the 24-hour Holter test and 72-hour single-lead electrocardiogram monitoring with an adhesive patch-type device for atrial fibrillation detection: Prospective cohort study," *J. Med. Internet Res.*, vol. 24, no. 5, May 2022, Art. no. e37970. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/35532989

[23] H Medicine. (2024). *Hopkins Medicine*. [Online]. Available: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/event-monitor

[24] V Link. (2024). *Viva Link*. [Online]. Available: https://www.vivalink.com/arrhythmia

[25] UH Oxford. (2024). *United Healthcare Oxford*. [Online]. Available: https://www.uhcprovider.com/content/dam/provider/docs/public/policies/oxford/outpatient-cardiovascular-telemetry-ohp.pdf

[26] (2020). *University of Ottawa Heart Institute*. [Online]. Available: https://www.ottawaheart.ca/test-procedure/treadmill-exercise-stress-test

[27] (2020). *Mayo Clinic*. [Online]. Available: https://www.mayoclinic.org/tests-procedures/stress-test/about/pac-20385234

[28] L. Frick, C. C. Schwarzwald, and K. J. Mitchell, "The use of heart rate variability analysis to detect arrhythmias in horses undergoing a standard treadmill exercise test," *J. Veterinary Internal Med.*, vol. 33, no. 1, pp. 212–224, Jan. 2019.

[29] (2020). *Mayo Clinic Tilt Table Test*. [Online]. Available: https://www.mayoclinic.org/tests-procedures/tilt-table-test/about/pac-20395124

[30] (2020). *Tilt Table Test*. [Online]. Available: https://www.sciencedirect.com/topics/medicine-and-dentistry/tilt-table-test

[31] (2020). *Tilt Table Test*. [Online]. Available: https://www.heart.org/en/health-topics/heart-attack/diagnosing-a-heart-attack/tilt-table-test

[32] (2020). *Electrophysiological Tests*. [Online]. Available: https://www.heart.org/en/health-topics/heart-attack/diagnosing-a-heart-attack/tilt-table-test

[33] (2020). *Electrophysiology-studies-eps*. [Online]. Available: https://www.heart.org/en/health-topics/arrhythmia/symptoms-diagnosis–monitoring-of-arrhythmia/electrophysiology-studies-eps

[34] W. Piwowarska, D. Mroczek-Czernecka, A. Pietrucha, M. Węgrzynowska, and B. Stobierska-Dzierżek, "The value of electrophysiological testing in diagnosis of syncope in post-infarction patients, without complex ventricular arrhythmias detected in 24-hour ECG," in *Cardiac Arrhythmias, Pacing & Electrophysiology: The Expert View*. Dordrecht, The Netherlands: Springer, 1998, pp. 109–112, doi: 10.1007/978-94-011-5254-9_15.

[35] D. G. Katritsis, T. Zografos, and G. Hindricks, "Electrophysiology testing for risk stratification of patients with ischaemic cardiomyopathy: A call for action," *EP Europace*, vol. 20, no. FI2, pp. f148–f152, Sep. 2018, doi: 10.1093/europace/eux305.

[36] (2020). *Esophageal-Studies-EPS*. [Online]. Available: https://www.heart.org/en/health-topics/arrhythmia/symptoms-diagnosis–monitoring-of-arrhythmia/electrophysiology-studies-eps

[37] R. Wildhaber, S. Mortier, A. Haeberlin, R. Sweda, D. Bruegger, T. Niederhauser, M. Jacomet, J. Goette, and H. Tanner, "A novel 2D spatial temporal ECG representation using multipolar esophageal catheters: A pilot study," *JACC, Clin. Electrophysiology*, vol. 3, no. 10, p. S2, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405500X17307806

[38] R. A. Wildhaber, D. Bruegger, N. Zalmai, H. Malmberg, J. Goette, M. Jacomet, H. Tanner, A. Haeberlin, and H.-A. Loeliger, "Estimation of the cardiac field in the esophagus using a multipolar esophageal catheter," *IEEE Trans. Biomed. Circuits Syst.*, vol. 12, no. 4, pp. 791–800, Aug. 2018.

[39] C. H. Papadopoulos, D. Oikonomidis, E. Lazaris, and P. Nihoyannopoulos, "Echocardiography and cardiac arrhythmias," *Hellenic J. Cardiol.*, vol. 59, no. 3, pp. 140–149, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1109966617304104

[40] (2020). *Echocardiogram*. [Online]. Available: https://www.mayoclinic.org/diseases-conditions/heart-arrhythmia/diagnosis-treatment/drc-20350674

[41] (2022). *SH Care*. [Online]. Available: https://stanfordhealthcare.org/medical-conditions/blood-heart-circulation/arrhythmia/diagnosis.html

[42] (2022). *HealthinAging*. [Online]. Available: https://www.healthinaging.org/a-z-topic/arrhythmias/tests

[43] (2020). *Cardiac-Computed-Tomography*. [Online]. Available: https://www.sciencedirect.com/topics/medicine-and-dentistry/cardiac-computed-tomography

[44] S. Oda, M. Kidoh, S. Takashio, M. Nishi, H. Kanazawa, Y. Nagayama, T. Nakaura, K. Tsujita, and O. Ikeda, "Identification of wild-type transthyretin cardiac amyloidosis by quantifying myocardial extracellular volume using cardiac computed tomography in atrial arrhythmias," *Circulation, Cardiovascular Imag.*, vol. 13, no. 6, Jun. 2020, Art. no. e010261. [Online]. Available: https://www.ahajournals.org/doi/abs/10.1161/CIRCIMAGING.119.010261

[45] N. Courtial, A. Simon, E. Donal, M. Lederlin, and M. Garreau, "Cardiac cine-MRI/CT registration for interventions planning," in *Proc. IEEE 16th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2019, pp. 776–779.

[46] X.-N. Li, J.-X. Wang, Q. Wei, X.-B. Yu, Y.-T. Zhou, X.-Y. Ma, N. Zhao, and B. Lu, "Diagnostic value of delayed contrast-enhanced cardiac computed tomography for detecting left atrial appendage thrombus in patients with atrial fibrillation," *Frontiers Cardiovascular Med.*, vol. 9, Apr. 2022. [Online]. Available: https://www.frontiersin.org/article/10.3389/fcvm.2022.847163

[47] K. Laubrock, T. von Loesch, M. Steinmetz, J. Lotz, J. Frahm, M. Uecker, and C. Unterberg-Buchwald, "Imaging of arrhythmia: Real-time cardiac magnetic resonance imaging in atrial fibrillation," *Eur. J. Radiol. Open*, vol. 9, 2022, Art. no. 100404. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352047722000119

[48] Y. Zhao, L. Dagher, C. Huang, P. Miller, and N. F. Marrouche, "Cardiac MRI to manage atrial fibrillation," *Arrhythmia Electrophysiology Rev.*, vol. 9, no. 4, pp. 189–194, Dec. 2020, doi: 10.15420/aer.2020.21.

[49] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Inf. Sci.*, vol. 405, pp. 81–90, Sep. 2017.

[50] J. Elmadi and K. L. Satish, "Cardiovascular magnetic resonance imaging: A prospective modality in the diagnosis and prognostication of heart failure," in *Proc. Comput. Cardiology*, 2022.

[51] M. A. Ozdemir, O. Guren, O. K. Cura, A. Akan, and A. Onan, "Abnormal ECG beat detection based on convolutional neural networks," in *Proc. Med. Technol. Congr. (TIPTEKNO)*, Nov. 2020, pp. 1–4.

[52] K. Qaddoum, A. Alazzam, and R. A. Azawi, "A deep neural network heartbeat classification approach for arrhythmia detection," in *Proc. 7th Int. Conf. Inf. Technol. Trends (ITT)*, Nov. 2020, pp. 131–134.

[53] P. Bera and R. Gupta, "Improved arrhythmia detection from electrocardiogram," in *Proc. IEEE Region 10 Symp. (TENSYMP)*, Jun. 2019, pp. 547–552.

[54] S. Nurmaini, A. E. Tondas, A. Darmawahyuni, M. N. Rachmatullah, R. Umi Partan, F. Firdaus, B. Tutuko, F. Pratiwi, A. H. Juliano, and R. Khoirani, "Robust detection of atrial fibrillation from short-term electrocardiogram using convolutional neural networks," *Future Gener. Comput. Syst.*, vol. 113, pp. 304–317, Dec. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X20305410
[55] H. Dang, M. Sun, G. Zhang, X. Qi, X. Zhou, and Q. Chang, "A novel deep arrhythmia-diagnosis network for atrial fibrillation classification using electrocardiogram signals," *IEEE Access*, vol. 7, pp. 75577–75590, 2019.
[56] S. Mousavi and F. Afghah, "Inter- and intra- patient ECG heartbeat classification for arrhythmia detection: A sequence to sequence deep learning approach," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 1308–1312.
[57] S. Harrane and M. Belkhiri, "Classification of ECG heartbeats using deep neural networks," *Res. Biomed. Eng.*, vol. 37, no. 4, pp. 737–747, Dec. 2021.
[58] K. Jiang, S. Liang, L. Meng, Y. Zhang, P. Wang, and W. Wang, "A two-level attention-based sequence-to-sequence model for accurate inter-patient arrhythmia detection," Tech. Rep., 2020.
[59] H. M. Rai and K. Chatterjee, "Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data," *Appl. Intell.*, vol. 52, pp. 1–19, Mar. 2022.
[60] X. Peng, H. Zhu, X. Zhou, C. Pan, and Z. Ke, "ECG signals segmentation using deep spatiotemporal feature fusion U-net for QRS complexes and R-peak detection," *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–12, 2023.
[61] Y. Zhao, J. Ren, B. Zhang, J. Wu, and Y. Lyu, "An explainable attention-based TCN heartbeats classification model for arrhythmia detection," *Biomed. Signal Process. Control*, vol. 80, Feb. 2023, Art. no. 104337. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809422007911
[62] P. M. Buscema, E. Grossi, G. Massini, M. Breda, and F. Della Torre, "Computer aided diagnosis for atrial fibrillation based on new artificial adaptive systems," *Comput. Methods Programs Biomed.*, vol. 191, Jul. 2020, Art. no. 105401. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85081004801&doi=10.1016%2fj.cmpb.2020.105401&partnerID=40&md5=35be8969be615ce124878fb75bb79190
[63] S. Kumar, B. Bhushan, L. Bhambhu, D. Singh, and D. Choubey, "A deep learning-based model for arrhythmia detection using feature selection and machine learning methods," in *Proc. 6th Int. Conf. Advance Comput. Intell. Eng.*, Sep. 2022, pp. 13–22.
[64] S. Sanamdikar, N. Karajanagi, K. Kowdiki, and S. Kamble, "Classification of ECG signal for cardiac arrhythmia detection using GAN method," in *Intelligent Communication Technologies and Virtual Mobile Networks* (Lecture Notes on Data Engineering and Communications Technologies), vol. 131, Jul. 2023, pp. 257–271. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85134775908&doi=10.1007%2f978-981-19-1844-521&partnerID=40&md5=784abe5f78f82dcb6c15d64dc1d509b1
[65] R. A. Alharbey, S. Alsubhi, K. Daqrouq, and A. Alkhateeb, "The continuous wavelet transform using for natural ECG signal arrhythmias detection by statistical parameters," *Alexandria Eng. J.*, vol. 61, no. 12, pp. 9243–9248, Dec. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1110016822001831
[66] H. Karnan, S. Natarajan, and R. Manivel, "Human machine interfacing technique for diagnosis of ventricular arrhythmia using supervisory machine learning algorithms," *Wiley Online Library*, vol. 30, pp. 1–14, Oct. 2018.
[67] G. Pan, Z. Xin, S. Shi, and D. Jin, "Arrhythmia classification based on wavelet transformation and random forests," *Multimedia Tools Appl.*, vol. 77, no. 17, pp. 21905–21922, Sep. 2018.
[68] V. Rangappa, L. Vidyapeeth, S. Prasad, A. Agarwal, L. Vidyapeeth, and L. Vidyapeeth, "Classification of cardiac arrhythmia stages using hybrid features extraction with K-nearest neighbour classifier of ECG signals," *Int. J. Intell. Eng. Syst.*, vol. 11, no. 6, pp. 21–32, Dec. 2018.
[69] S. U. Kumar and H. H. Inbarani, "Neighborhood rough set based ECG signal classification for diagnosis of cardiac diseases," *Soft Comput.*, vol. 21, no. 16, pp. 4721–4733, Aug. 2017.
[70] A. Elsayyad, A. M. Nassef, and A. K. M. A. Baareh, "Cardiac arrhythmia classification using boosted decision trees," *Int. Rev. Comput. Softw. (IRECOS)*, vol. 10, no. 3, pp. 280–289, Mar. 2015.
[71] S. Sahoo, A. Subudhi, M. Dash, and S. Sabut, "Automatic classification of cardiac arrhythmias based on hybrid features and decision tree algorithm," *Int. J. Autom. Comput.*, vol. 17, no. 4, pp. 551–561, Aug. 2020. [Online]. Available: https://www.mi-research.net/en/article/doi/10.1007/s11633-019-1219-2
[72] C. Usha Kumari, A. Sampath Dakshina Murthy, B. Lakshmi Prasanna, M. Pala Prasad Reddy, and A. Kumar Panigrahy, "An automated detection of heart arrhythmias using machine learning technique: SVM," *Mater. Today, Proc.*, vol. 45, pp. 1393–1398, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214785320351786
[73] A. Natarajan, Y. Chang, S. Mariani, A. Rahman, G. Boverman, S. Vij, and J. Rubin, "A wide and deep transformer neural network for 12-lead ECG classification," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[74] Z. Zhao, H. Fang, S. D. Relton, R. Yan, Y. Liu, Z. Li, J. Qin, and D. C. Wong, "Adaptive lead weighted ResNet trained with different duration signals for classifying 12-lead ECGs," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[75] Z. Zhu, H. Wang, T. Zhao, Y. Guo, Z. Xu, Z. Liu, S. Liu, X. Lan, X. Sun, and M. Feng, "Classification of cardiac abnormalities from ECG signals using SE-ResNet," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[76] M. P Oppelt, M. Riehl, F. P Kemeth, and J. Steffan, "Combining scatter transform and deep neural networks for multilabel electrocardiogram signal classification," 2020, *arXiv:2010.07639*.
[77] H. Hasani, A. Bitarafan, and M. S. Baghshah, "Classification of 12-lead ECG signals with adversarial multi-source domain generalization," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[78] S. Min, H.-S. Choi, H. Han, M. Seo, J.-K. Kim, J. Park, S. Jung, I.-Y. Oh, B. Lee, and S. Yoon, "Bag of tricks for electrocardiogram classification with deep neural networks," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[79] M. N. Bos, R. R. Van De Leur, J. F. Vranken, D. K. Gupta, P. Van Der Harst, P. A. Doevendans, and R. Van Es, "Automated comprehensive interpretation of 12-lead electrocardiograms using pre-trained exponentially dilated causal convolutional neural networks," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[80] J. Chen, T. Chen, B. Xiao, X. Bi, Y. Wang, H. Duan, W. Li, J. Zhang, and X. Ma, "SE-ECGNet: Multi-scale SE-net for multi-lead ECG data," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[81] N. Fayyazifar, S. Ahderom, D. Suter, A. Maiorana, and G. Dwivedi, "Impact of neural architecture design on cardiac abnormality classification using 12-lead ECG signals," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[82] W. Jia, X. Xu, X. Xu, Y. Sun, and X. Liu, "Automatic detection and classification of 12-lead ECGs using a deep neural network," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[83] R. Smisek, A. Nemcova, L. Marsanova, L. Smital, M. Vitek, and J. Kozumplik, "Cardiac pathologies detection and classification in 12-lead ECG," in *Proc. Comput. Cardiol.*, Sep. 2020, pp. 1–4.
[84] G. Bortolan, I. Christov, and I. Simova, "Rule-based method and deep learning networks for automatic classification of ECG," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[85] S. Kumar, B. Bhushan, L. Bhambhu, D. Singh, and D. K. Choubey, "A deep learning-based model for arrhythmia detection using feature selection and machine learning methods," in *Proc. 6th Int. Conf. Advance Comput. Intell. Eng.*, B. Pati, C. R. Panigrahi, P. Mohapatra, and K.-C. Li, Eds. Singapore: Springer Nature, 2023, pp. 13–22.
[86] E. Merdjanovska and A. Rashkovska, "Comprehensive survey of computational ECG analysis: Databases, methods and applications," *Expert Syst. Appl.*, vol. 203, Oct. 2022, Art. no. 117206. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417422005917
[87] M. A. Serhani, A. N. Navaz, H. Al Ashwal, and N. Al Qirim, "ECG-based arrhythmia classification & clinical suggestions: An incremental approach of hyperparameter tuning," in *Proc. 13th Int. Conf. Intell. Systems: Theories Appl.*, Sep. 2020, pp. 1–7.
[88] A. M. Alqudah, S. Qazan, L. Al-Ebbini, H. Alquran, and I. A. Qasmieh, "ECG heartbeat arrhythmias classification: A comparison study between different types of spectrum representation and convolutional neural networks architectures," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 10, pp. 4877–4907, Oct. 2022.
[89] M. Hammad, S. A. Chelloug, R. Alkanhel, A. J. Prakash, A. Muthanna, I. A. Elgendy, and P. Pławiak, "Automated detection of myocardial infarction and heart conduction disorders based on feature selection and a deep learning model," *Sensors*, vol. 22, no. 17, p. 6503, Aug. 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/17/6503
[90] R. R. Thirrunavukkarasu and T. Meera Devi, "Shannon entropy Morlet wavelet transform (SEMWT) and kernel weight convolutional neural network (KWCNN) classifier for arrhythmia in electrocardiogram recordings," *Biomed. Signal Process. Control*, vol. 78, Sep. 2022, Art. no. 103992. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809422004918

[91] A. Rath, D. Mishra, G. Panda, S. C. Satapathy, and K. Xia, "Improved heart disease detection from ECG signal using deep learning based ensemble model," *Sustain. Computing: Informat. Syst.*, vol. 35, Sep. 2022, Art. no. 100732. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210537922000671
[92] S. Y. Sen and N. ÖZkurt, "Convolutional neural network hyperparameter tuning with Adam optimizer for ECG classification," in *Proc. Innov. Intell. Syst. Appl. Conf. (ASYU)*, Oct. 2020, pp. 1–6.
[93] N. Sinha, R. Kumar Tripathy, and A. Das, "ECG beat classification based on discriminative multilevel feature analysis and deep learning approach," *Biomed. Signal Process. Control*, vol. 78, Sep. 2022, Art. no. 103943. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809422004426
[94] K. Kolodiazhnyi, *Hands on Machine Learning With C++, Build, Train, and Deploy End to End Machine Learning and Deep Learning Pipelines*. Birmingham, U.K.: Packt, 2020.
[95] Z. Jiang, T. P. Almeida, F. S. Schlindwein, G. A. Ng, H. Zhou, and X. Li, "Diagnostic of multiple cardiac disorders from 12-lead ECGs using graph convolutional network based multi-label classification," in *Proc. Comput. Cardiology*, Sep. 2020, pp. 1–4.
[96] E. A. Perez Alday, A. Gu, A. J Shah, C. Robichaux, A.-K. Ian Wong, C. Liu, F. Liu, A. Bahrami Rad, A. Elola, S. Seyedi, Q. Li, A. Sharma, G. D. Clifford, and M. A. Reyna, "Classification of 12-lead ECGs: The PhysioNet/computing in cardiology challenge 2020," *Physiological Meas.*, vol. 41, no. 12, Dec. 2020, Art. no. 124003.
[97] U. Ullah and B. Garcia-Zapirain, "Quantum machine learning revolution in healthcare: A systematic review of emerging perspectives and applications," *IEEE Access*, vol. 12, pp. 11423–11450, 2024.
[98] S. S. Kumar, D. R. Rinku, A. P. Kumar, R. Maddula, and C. A. Palagan, "An IoT framework for detecting cardiac arrhythmias in real-time using deep learning Resnet model," *Measurement, Sensors*, vol. 29, Oct. 2023, Art. no. 100866.
[99] D. Li, R. Shi, N. Yao, F. Zhu, and K. Wang, "Real-time patient-specific ECG arrhythmia detection by quantum genetic algorithm of least squares twin SVM," *J. Beijing Inst. Technol.*, vol. 29, no. 1, pp. 29–37, 2020. [Online]. Available: https://journal.bit.edu.cn/jbit/en/article/doi/10.15918/j.jbit1004-0579.18156
[100] S. Sridevi, T. Kanimozhi, K. Issac, and M. Sudha, "Quanvolution neural network to recognize arrhythmia from 2D scaleogram features of ECG signals," in *Proc. Int. Conf. Innov. Trends Inf. Technol. (ICITIIT)*, Feb. 2022, pp. 1–5.
[101] S. Prabhu, S. Gupta, G. M. Prabhu, A. V. Dhanuka, and K. V. Bhat, "QuCardio: Application of quantum machine learning for detection of cardiovascular diseases," *IEEE Access*, vol. 11, pp. 136122–136135, 2023.
[102] D. N. V. S. L. S. Indira, V. S. M. Lakshmi, B. R. Markapudi, A. Yannam, M. B. Prasad, C. S. Babu, and K. K. Rao, "Detection of cardiac arrhythmia using multi-perspective convolutional neutral network for ECG heartbeat classification," *Revue d'Intelligence Artificielle*, vol. 36, no. 4, pp. 629–634, Aug. 2022. [Online]. Available: https://api.semanticscholar.org/CorpusID:252648981
[103] A. Choudhury, S. Vuppu, S. P. Singh, M. Kumar, and S. N. P. Kumar, "ECG-based heartbeat classification using exponential-political optimizer trained deep learning for arrhythmia detection," *Biomed. Signal Process. Control*, vol. 84, Jul. 2023, Art. no. 104816. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809423002495
[104] L.-H. Wang, Z.-H. Yan, Y.-T. Yang, J.-Y. Chen, T. Yang, I.-C. Kuo, P. A. R. Abu, P.-C. Huang, C.-A. Chen, and S.-L. Chen, "A classification and prediction hybrid model construction with the IQPSO-SVM algorithm for atrial fibrillation arrhythmia," *Sensors*, vol. 21, no. 15, p. 5222, Aug. 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/15/5222
[105] Z. Ozpolat and M. Karabatak, "Performance evaluation of quantum-based machine learning algorithms for cardiac arrhythmia classification," *Diagnostics*, vol. 13, no. 6, p. 1099, Mar. 2023. [Online]. Available: https://www.mdpi.com/2075-4418/13/6/1099
[106] M. Aria and C. Cuccurullo, "Bibliometrix: An R-tool for comprehensive science mapping analysis," *J. Informetrics*, vol. 11, no. 4, pp. 959–975, Nov. 2017, doi: 10.1016/j.joi.2017.08.007.
[107] N. J. van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, Aug. 2010, doi: 10.1007/s11192-009-0146-3.
[108] U. U. Gronthy, U. Biswas, S. Tapu, M. A. Samad, and A.-A. Nahid, "A bibliometric analysis on arrhythmia detection and classification from 2005 to 2022," *Diagnostics*, vol. 13, no. 10, p. 1732, May 2023. [Online]. Available: https://www.mdpi.com/2075-4418/13/10/1732
[109] U. R. Acharya, H. Fujita, S. L. Oh, U. Raghavendra, J. H. Tan, M. Adam, A. Gertych, and Y. Hagiwara, "Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network," *Future Gener. Comput. Syst.*, vol. 79, pp. 952–959, Feb. 2018.
[110] T. Tuncer, S. Dogan, and U. R. Acharya, "Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals," *Knowl.-Based Syst.*, vol. 186, Dec. 2019, Art. no. 104923. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950705119303727
[111] H. Zhang, W. Zhao, and S. Liu, "SE-ECGNet: A multi-scale deep residual network with squeeze-and-excitation module for ECG signal classification," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, 2020, pp. 2685–2691.
[112] R. M. Batista-Canino, L. Santana-Hernández, and P. Medina-Brito, "A scientometric analysis on entrepreneurial intention literature: Delving deeper into local citation," *Heliyon*, vol. 9, no. 2, Feb. 2023, Art. no. e13046. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405844023002530
[113] A. Y. Hannun, P. Rajpurkar, M. Haghpanahi, G. H. Tison, C. Bourn, M. P. Turakhia, and A. Y. Ng, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," *Nature Med.*, vol. 25, no. 1, pp. 65–69, Jan. 2019, doi: 10.1038/s41591-018-0268-3.
[114] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. S. Tan, "A deep convolutional neural network model to classify heartbeats," *Comput. Biol. Med.*, vol. 89, pp. 389–396, Oct. 2017, doi: 10.1016/j.compbiomed.2017.08.022.
[115] M. Hammad, R. N. V. P. S. Kandala, A. Abdelatey, M. Abdar, M. Zomorodi-Moghadam, R. S. Tan, U. R. Acharya, R. Tadeusiewicz, V. Makarenkov, N. Sarrafzadegan, A. Khosravi, S. Nahavandi, A. A. A. EL-Latif, and P. Pławiak, "Automated detection of shockable ECG signals: A review," *Inf. Sci.*, vol. 571, pp. 580–604, Sep. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0020025521004953
[116] X. Liu, H. Wang, Z. Li, and L. Qin, "Deep learning in ECG diagnosis: A review," *Knowl.-Based Syst.*, vol. 227, Sep. 2021, Art. no. 107187. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0950705121004494
[117] Z. Ebrahimi, M. Loni, M. Daneshtalab, and A. Gharehbaghi, "A review on deep learning methods for ECG arrhythmia classification," *Expert Syst. Appl., X*, vol. 7, Sep. 2020, Art. no. 100033.
[118] J. Yang, A. A. S. Soltan, and D. A. Clifton, "Machine learning generalizability across healthcare settings: Insights from multi-site COVID-19 screening," *NPJ Digit. Med.*, vol. 5, no. 1, pp. 55–59, Jun. 2022.
[119] B. Malin and K. Goodman, "Between access and privacy: Challenges in sharing health data," *Yearbook Med. Informat.*, vol. 27, no. 1, pp. 55–59, Aug. 2018.
[120] F. Chen, L. Wang, J. Hong, J. Jiang, and L. Zhou, "Unmasking bias and inequities: A systematic review of bias detection and mitigation in healthcare artificial intelligence using electronic health records," Tech. Rep., 2023.
[121] G. Ling, B. Brannan, and E. Foxton, "Real-world variability in ADAMTS13 assay methods may impact upon follow up for patients with thrombotic thrombocytopenic purpura (TTP)," *Blood*, vol. 138, p. 2085, Nov. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S000649712104043X
[122] S. Syed, M. Gatien, J. J. Perry, H. Chaudry, S.-M. Kim, K. Kwong, M. Mukarram, and V. Thiruganasambandamoorthy, "Prospective validation of a clinical decision rule to identify patients presenting to the emergency department with chest pain who can safely be removed from cardiac monitoring," *Can. Med. Assoc. J.*, vol. 189, no. 4, pp. E139–E145, Jan. 2017. [Online]. Available: https://www.cmaj.ca/content/189/4/E139
[123] D. A. Salade, K. S. Arote, P. H. Patil, V. V. Patil, and A. R. Pawar, "A brief review on pharmaceutical validation," *Asian J. Pharmaceutical Anal.*, pp. 211–217, Aug. 2022.

[124] N. Naik, B. M. Z. Hameed, D. K. Shetty, D. Swain, M. Shah, R. Paul, K. Aggarwal, S. Ibrahim, V. Patil, K. Smriti, S. Shetty, B. P. Rai, P. Chlosta, and B. K. Somani, "Legal and ethical consideration in artificial intelligence in healthcare: Who takes responsibility?" *Frontiers Surgery*, vol. 9, Mar. 2022. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fsurg.2022.862322

[125] D. Ivankovic, P. Garel, N. Klazinga, and D. Kringos, "Data-driven collaboration between hospitals and other healthcare organisations in Europe during the COVID-19 pandemic: An explanatory sequential mixed-methods study among mid-level hospital managers," *Int. J. Integr. Care*, vol. 23, p. 28, Jun. 2023.

[126] D. Ueda, "Fairness of artificial intelligence in healthcare: review and recommendations," *Int. J. Integr. Care*, vol. 42, p. 28, Jun. 2024.

[127] H.-T. Lee, H.-R. Cheon, S.-H. Lee, M. Shim, and H.-J. Hwang, "Publisher correction: Risk of data leakage in estimating the diagnostic performance of a deep-learning-based computer-aided system for psychiatric disorders (scientific reports, (2023), 13, 1, (16633), 10.1038/s41598-023-43542-8)," *Sci. Rep.*, vol. 14, no. 1, p. 2172. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85183000885&doi=10.1038%2fs41598-024-52295-x&partnerID=40&md5=9327cd6c39d319911d92e999f29a7184

[128] B. Haibe-Kains, G. Adam, A. Hosny, F. Khodakarami, and Levi, "Transparency and reproducibility in artificial intelligence," *Nature*, vol. 586, pp. E14–E16, May 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:222833180

[129] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *Social Netw. Comput. Sci.*, vol. 2, no. 3, May 2021.

[130] K. B. Hansen, "The virtue of simplicity: On machine learning models in algorithmic trading," *Big Data Soc.*, vol. 7, no. 1, Jan. 2020, Art. no. 205395172092655.

[131] V. Patel, "Open source frameworks for deep learning and machine learning," Tech. Rep., 2019.

[132] D. Peral-García, J. Cruz-Benito, and F. J. García-Peñalvo, "Systematic literature review: Quantum machine learning and its applications," *Comput. Sci. Rev.*, vol. 51, Feb. 2024, Art. no. 100619.

[133] R. Kharsa, A. Bouridane, and A. Amira, "Advances in quantum machine learning and deep learning for image classification: A survey," *Neurocomputing*, vol. 560, Dec. 2023, Art. no. 126843.

[134] M. Ragab, E. B. Ashary, M. Farouk S. Sabir, A. A. Bahaddad, and R. F. Mansour, "Mathematical modelling of quantum kernel method for biomedical data analysis," *Comput., Mater. Continua*, vol. 71, no. 3, pp. 5441–5457, 2022.

[135] S. Suneel, A. Balaram, M. A. Begum, K. Umapathy, P. C. S. Reddy, and V. Talasila, "Quantum mesh neural network model in precise image diagnosing," *Opt. Quantum Electron.*, vol. 56, no. 4, Jan. 2024.

[136] S.-Y. Liu and H. Fan, "The application of quantum coherence as a resource," *Chin. Phys. B*, vol. 32, no. 11, Nov. 2023, Art. no. 110304.

[137] M. A. Schalkers and M. Möller, "Efficient and fail-safe quantum algorithm for the transport equation," *J. Comput. Phys.*, vol. 502, Apr. 2024, Art. no. 112816.

[138] R. Agrawal and V. G. Diaz, *Understanding Biomedical Engineering for Quantum Computing*. IGI Global, 2023.

[139] E. S. Y. Ern and D. A. Ramli, "Classification of arrhythmia signals using hybrid convolutional neural network (CNN) model," in *Artificial Intelligence and Machine Learning for Healthcare: Volume 1: Image and Data Analytics*. Cham, Switzerland: Springer, 2023, pp. 105–132, doi: 10.1007/978-3-031-11154-9_6.

[140] S. Dhyani, A. Kumar, and S. Choudhury, "Arrhythmia disease classification utilizing ResRNN," *Biomed. Signal Process. Control*, vol. 79, Jan. 2023, Art. no. 104160. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809422006140

[141] S. Ma, J. Cui, C.-L. Chen, X. Chen, and Y. Ma, "An effective data enhancement method for classification of ECG arrhythmia," *Measurement*, vol. 203, Nov. 2022, Art. no. 111978. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0263224122011745

[142] S. Sahoo, P. Dash, B. S. P. Mishra, and S. K. Sabut, "Deep learning-based system to predict cardiac arrhythmia using hybrid features of transform techniques," *Intell. Syst. Appl.*, vol. 16, Nov. 2022, Art. no. 200127. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2667305322000643

FERNANDO VÁSQUEZ-ITURRALDE (Member, IEEE) received the B.S. degree in computer engineering from Universidad Central del Ecuador, the M.Sc. degree in electrical engineering and the Master of Business Administration (M.B.A.) degree from Escuela Politécnica Nacional (EPN), Ecuador, where he is currently pursuing the Ph.D. degree in electrical engineering. He is a Professor at the Faculty of Engineering and Applied Sciences, Universidad Central del Ecuador. His areas of interest include artificial intelligence, digital signal processing, and bioengineering.

MARCO JAVIER FLORES-CALERO received the B.S. degree in mathematical engineering from Escuela Politécnica Nacional, Quito, Ecuador, in 2001, the M.S. degree in statistics from Pontificia Universidad Católica, Santiago, Chile, in 2004, and the Ph.D. degree in electrical, electronic, and automatic engineering from Carlos III University of Madrid (Spain). Presently, he holds the position of Full Professor at Universidad de las Fuerzas Armadas (Ecuador). Throughout his academic career, he has showcased his expertise by publishing scientific papers in prestigious international journals across various domains, including artificial intelligence, digital signal processing, bioinformatics, applied mathematics, and scientific software.

FELIPE GRIJALVA (Senior Member, IEEE) received the B.S. degree in electrical engineering and telecommunications from the Army Polytechnic School, Quito, Ecuador, in 2010, and the M.Sc. and Ph.D. degrees in electrical engineering with a major in Computing Engineering from the University of Campinas, Campinas, Brazil, in 2014 and 2018, respectively. He is currently an Associate Professor with the Universidad San Francisco de Quito (USFQ), Quito. His research interests include spatial audio, machine learning, computer vision applications, and assistive technologies designed to assist visually impaired individuals.

ANDRÉS ROSALES-ACOSTA (Member, IEEE) received the doctorate degree in control systems engineering with the subject Dynamic Control of Mobile Robotic Systems: A Linear Algebra Approach from the Institute of Automatic, National University of San Juan (Argentina), in 2009. He is a Principal Professor of the Department of Automation and Industrial Control. He is an Electronics and Control Engineer from the Escuela Politécnica Nacional (Ecuador) in 2001. His interests in the field of research are oriented to robotics, cooperative systems, applied artificial intelligence, predictive control, and industrial process control.