Computational Intelligence for Automatic Detection Cardiac Arrhythmia from ECG Signals: Taxonomy and Open Issues

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Abstract

Cardiac arrhythmia is a medical disorder, in which the heart beats sporadically or irregularly leading to serious health consequences if left untreated. Early detection of arrhythmias is essential for timely intervention and management of the condition. Recently, there has been a growing interest in using computational intelligence techniques to automatically detect arrhythmias from electrocardiogram (ECG) signals. This approach offers the potential to improve the accuracy and efficiency of arrhythmia detection, as well as reduce the workload on healthcare professionals. This work reviews the current state-of-the-art ML methods for detecting arrhythmias including deep neural networks, support vector machines, and random forests. We will also discuss the challenges associated with using these techniques, such as the need for large and diverse datasets, and the interpretation of model outputs. We also highlight the open research that require further research and development to fully realize the potential of these algorithms in clinical practice.

Keywords: Deep Learning; explainable AI; ECG classification; Arrhythmia Detection; Smart Healthcare.

1. Introduction

Cardiac arrhythmia is a common heart disorder that affects millions of people worldwide. It is characterized by an abnormal heart rhythm, which can lead to serious complications such as stroke, heart attack, and even sudden cardiac death. Early detection and management of cardiac arrhythmia are crucial for improving patient outcomes and reducing the risk of these complications. Electrocardiogram (ECG) signals are commonly used to diagnose and monitor cardiac arrhythmia. However, the interpretation of ECG signals is a challenging task that requires specialized medical expertise. Therefore, there is a need for automated tools that can accurately detect cardiac arrhythmia from ECG signals [1-2].

Computational intelligence techniques have shown great promise in the field of automatic ECG signal analysis. These techniques involve the use of machine learning algorithms and artificial intelligence to analyze ECG signals and detect abnormalities. They can be used to develop automated systems that can accurately and efficiently detect cardiac arrhythmia from ECG signals, without the need for specialized medical expertise. This has the potential to improve the accuracy and speed of diagnosis, as well as reduce the workload of healthcare professionals [3-4].

Machine learning (ML) techniques have shown great potential in the automatic detection of cardiac arrhythmia from ECG signals. ML algorithms can learn patterns and features from large datasets of ECG signals and use this knowledge to accurately classify new signals as either normal or abnormal. Various ML techniques have been used for this purpose. These techniques have demonstrated high accuracy and efficiency in detecting cardiac arrhythmia and have the potential to improve the speed and accuracy of diagnosis, as well as reduce the workload of healthcare

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professionals. However, the implementation of ML-based systems for clinical use requires careful validation and testing to ensure their safety, reliability, and interpretability. Therefore, ongoing research is needed to further improve the performance and usability of ML-based systems for automatic detection of cardiac arrhythmia from ECG signals [6-8].

In this paper, we will provide an overview of the current state-of-the-art techniques for cardiac arrhythmia detection using computational intelligence. We will discuss the advantages and limitations of each technique, as well as the challenges associated with using computational intelligence in clinical practice. We will also review recent studies on the performance of computational intelligence algorithms in detecting arrhythmias and their potential impact on patient care. Overall, the use of computational intelligence in cardiac arrhythmia detection has the potential to revolutionize how arrhythmias are diagnosed and treated, leading to improved patient outcomes and reduced healthcare costs.

2. Taxonomic Overview

A wide range of computational intelligence techniques have been developed for automated arrhythmia detection, including rule-based systems, fuzzy logic, genetic algorithms, and swarm intelligence. These techniques have been used to develop arrhythmia detection algorithms that can accurately detect and classify different types of arrhythmias from ECG signals. However, with the increasing complexity of arrhythmia detection algorithms, it is important to have a clear taxonomy of computational intelligence techniques to guide their development and evaluation. In this section, we will present a taxonomic classification of computational intelligence techniques for arrhythmia detection, and discuss their advantages, limitations, and applications in the field. We will also highlight recent advances and ongoing research in each category of computational intelligence techniques.

2.1. Signal Processing Techniques

Signal processing techniques play a crucial role in arrhythmia detection by extracting relevant features from the ECG signals. These techniques aim to enhance the quality of the signals, remove noise, and extract discriminative features that can aid in arrhythmia classification**.** Filtering is a commonly used technique that aims to remove noise and artifacts from the ECG signals. Low-pass filtering eliminates high-frequency noise, while high-pass filtering removes baseline wander and low-frequency noise. Band-pass filtering allows a specific frequency range relevant to arrhythmias to pass through while attenuating other frequencies. By applying these filters, the ECG signals are refined and focused on the components associated with arrhythmic features [9-11].

Noise removal techniques are employed to suppress unwanted noise components in the ECG signals. Adaptive filtering utilizes adaptive algorithms to estimate and suppress noise adaptively based on the signal characteristics. Wavelet denoising, on the other hand, applies wavelet transform to decompose the ECG signal into different frequency bands and selectively removes noise in each band. These techniques effectively improve the signal quality, ensuring accurate analysis and detection of arrhythmias. Another critical aspect in arrhythmia detection is baseline wander correction. Baseline wander refers to the slow-varying variations in the ECG signal caused by factors such as respiration or electrode movement. Polynomial fitting and moving average filtering are commonly employed techniques to estimate and remove the baseline wander components. By eliminating these slow-varying variations, the true arrhythmic features become more prominent, facilitating accurate detection [10].

Feature extraction, on the other hand, is a fundamental step in arrhythmia detection. Various time-domain, frequency-domain, and wavelet-based features are extracted from the processed ECG signals to capture relevant information for classification. Time-domain features include statistical measures such as mean, standard deviation, skewness, and kurtosis, as well as morphological features like QRS duration and amplitude. Frequency-domain features involve calculating power spectral density, spectral entropy, dominant frequency, or frequency band power using Fourier transform or other spectral analysis techniques. Wavelet-based features extract information from the coefficients obtained through wavelet transform at different scales and orientations, capturing both time and frequency information. These features provide insights into the temporal and spectral characteristics of the ECG signals, aiding in the identification and classification of arrhythmias [12]. Table 1 summarizes different aspects of signal processing techniques for arrhythmia detection.

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Table 1: Review of different aspects of signal processing techniques for arrhythmia detection.

Signal Processing Technique	Advantages	Limitations	Applicability	Computational Complexity	Real-time Capability	Interpretability	Robustness to Noise
Filtering	Improves signal quality	May alter or distort signal characteristics	General-purpose, noise reduction	Low	Yes	High	High
Noise Removal	Preserves relevant arrhythmic features	May inadvertently remove true arrhythmias	Noisy ECG signals	Low to Moderate	Yes	Moderate	Moderate
Baseline Wander Correction	Enhances signal clarity	Can introduce artifacts or distortions	ECG signals with baseline wander	Low to Moderate	Yes	Moderate	Moderate
Time-Domain Features	Provides simple and interpretable features	Limited representation of complex dynamics	Basic arrhythmia characterization	Low	Yes	High	High
Frequency-Domain Features	Provides frequency-based insights	Less effective for non-stationary signals	Frequency-specific analysis	Low to Moderate	Yes	Moderate to Low	Moderate
Wavelet-Based Features	Suitable for analyzing transient phenomena	Requires careful selection of wavelet basis	Transient or frequency-based analysis	Moderate to High	Yes	Moderate	High

2.2. Machine Learning Algorithms

ML algorithms have been widely used for automated arrhythmia detection and classification. These algorithms can be broadly categorized into two types: supervised and unsupervised learning.

Supervised learning algorithms, such as support vector machines (SVMs), artificial neural networks (ANNs), and random forests, rely on labeled datasets to train algorithms to recognize specific arrhythmia types. These algorithms typically require large amounts of labeled data for training but can achieve high accuracy in detecting and classifying arrhythmias. Unsupervised learning algorithms, such as k-means clustering and self-organizing maps (SOMs), do not require labeled data and instead group similar ECG signals together based on their features. These algorithms

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can be useful for identifying novel arrhythmia types or detecting abnormal ECG signals that may not fit into known arrhythmia categories. However, unsupervised learning algorithms may be less accurate than supervised learning algorithms and require more manual interpretation of the results. In addition to these traditional machine learning algorithms, deep learning algorithms have recently emerged as a powerful tool for arrhythmia detection. These algorithms use deep neural networks to automatically learn features from raw ECG signals and have shown promising results in detecting and classifying arrhythmias. Despite the advances in machine learning algorithms for arrhythmia detection, there are still several challenges that need to be addressed. One of the main challenges is the availability of high-quality labeled datasets for training and testing algorithms. Another challenge is the generalizability of algorithms across different patient populations and recording settings. Additionally, the clinical relevance and usefulness of arrhythmia detection algorithms needs to be carefully evaluated, and algorithms should be integrated with clinical decision support systems to guide patient management and treatment [11-15].

2.3. Ensemble Learning

Ensemble learning (EL) methods have gained popularity in arrhythmia detection due to their ability to improve classification performance by combining multiple individual classifiers. These techniques leverage the diversity and complementary strengths of individual classifiers to enhance accuracy and robustness. Bagging (Bootstrap Aggregating) is an EL method that involves training multiple classifiers on different bootstrap samples of the training data. Each classifier is trained independently, and their predictions are combined through majority voting or averaging. Bagging reduces the variance and helps mitigate overfitting, resulting in improved generalization performance [14].

Boosting is another EL technique that focuses on sequentially training weak classifiers to create a strong ensemble. Weak classifiers are trained iteratively, and each subsequent classifier is given more weight on instances that were misclassified by previous classifiers. The final prediction is obtained by aggregating the weighted predictions of all classifiers. Boosting aims to improve the classification performance by focusing on the instances that are more difficult to classify correctly. AdaBoost (Adaptive Boosting) is a boosting algorithm that assigns higher weights to misclassified instances during the training process. It iteratively trains weak classifiers and updates the instance weights based on their classification performance. AdaBoost places more emphasis on difficult instances, allowing subsequent classifiers to focus on the instances that were misclassified previously. The final prediction is obtained by aggregating the weighted predictions of all classifiers.

Stacking, also known as stacked generalization, involves training multiple base classifiers and a meta-classifier that combines their predictions. The base classifiers are trained on the original training data, and their outputs serve as input features for the meta-classifier. Stacking allows the meta-classifier to learn how to best combine the predictions of the base classifiers, potentially leading to improved performance.

Voting is a simple EL technique that combines the predictions of multiple classifiers using majority voting or weighted voting. Each classifier makes an independent prediction, and the final prediction is determined by the most frequent class or by considering the confidence of each classifier's prediction. Voting can be used with different types of classifiers and is straightforward to implement.

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2.4. Deep Networks

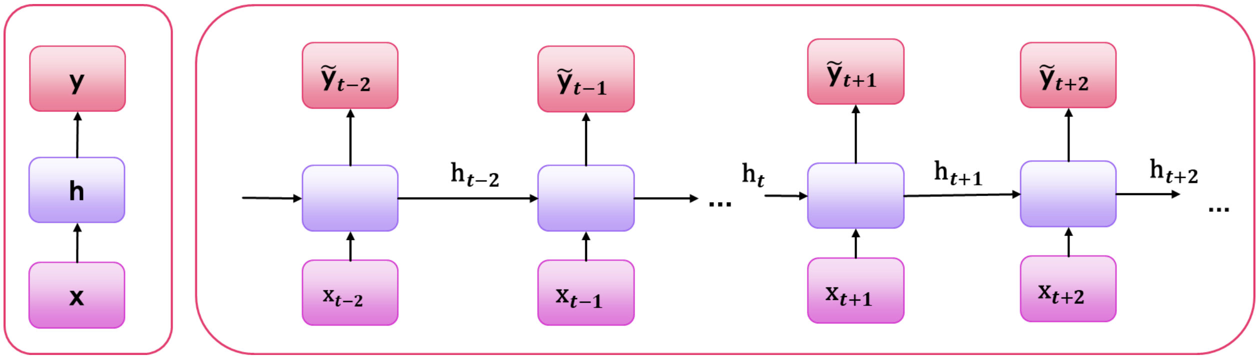

Figure 2: General architecture of recurrent neural networks

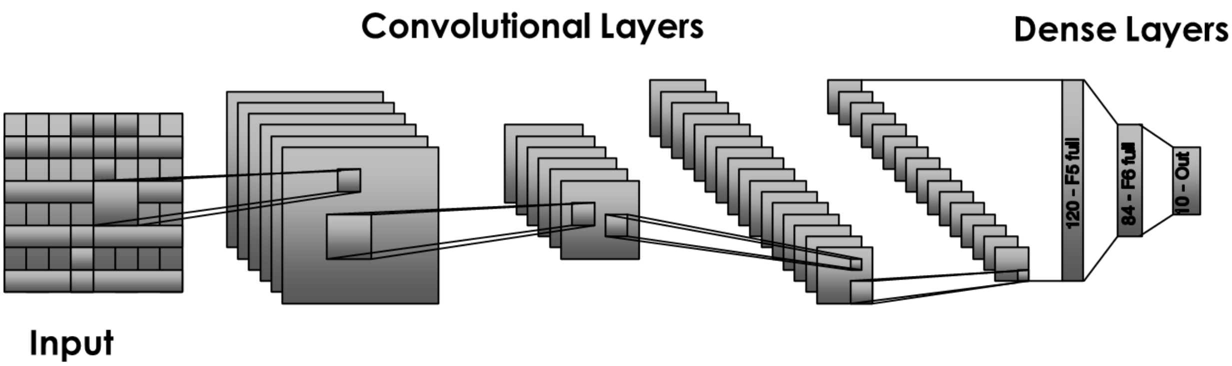

Figure 2: General architecture of convolutional neural networks

Deep networks, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown great promise in the field of arrhythmia detection. These powerful deep learning models excel at learning hierarchical representations from raw electrocardiogram (ECG) data, capturing both spatial and temporal dependencies. CNNs are particularly effective at capturing spatial patterns in ECG signals. By leveraging convolutional layers, CNNs can automatically learn relevant features from the raw ECG data without the need for handcrafted feature engineering. This ability to extract discriminative features directly from the data makes CNNs well-suited for arrhythmia detection tasks. CNN architectures typically consist of convolutional layers that perform feature extraction, pooling layers for downsampling, and fully connected layers for classification. They have been successfully applied in arrhythmia classification tasks, achieving high accuracy and robust performance. On the other hand, RNNs, especially Long Short-Term Memory (LSTM) networks, are designed to handle sequential data and are effective at capturing temporal dependencies in ECG signals. RNNs utilize recurrent connections that allow information to persist across different time steps, enabling them to model the dynamic nature of ECG sequences. LSTMs, in particular, have memory cells that can selectively remember or forget information, making them well-suited for capturing long-term dependencies in ECG data. RNNs, including LSTMs, have been successfully employed in various arrhythmia detection tasks such as heartbeat segmentation, irregularity detection, and arrhythmia classification. While CNNs excel at capturing spatial patterns and local features in ECG signals, they have limited modeling capabilities for capturing long-range temporal dependencies. RNNs, on the other hand, are designed to capture sequential dependencies but may suffer from issues such as vanishing or exploding gradients during training. Additionally, training RNNs can be slower compared to CNNs due to the sequential nature of the data processing.

To address the limitations of individual models, researchers have explored hybrid architectures that combine the strengths of both CNNs and RNNs. Convolutional Recurrent Neural Networks (CRNNs) integrate convolutional and recurrent layers, allowing simultaneous capture of both spatial and temporal information. This hybrid approach

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has shown promising results in arrhythmia detection, as it leverages the spatial pattern recognition capabilities of CNNs along with the temporal modeling capabilities of RNNs. Furthermore, advanced techniques such as attention mechanisms can be incorporated into deep networks for arrhythmia detection. Attention mechanisms allow the model to focus on important regions or time steps within the ECG signals, enhancing the model's performance by selectively attending to informative segments. Attention-based models have demonstrated improved performance in various tasks, including arrhythmia detection**.** Table 2 provides a review of cutting-edge deep learning studies for arrhythmia detection.

Table 2: Review of different deep learning techniques for arrhythmia detection.

Reference	Year	Journal	Task	Method	Dataset
[14]	2016	IEEE ACCESS	arrhythmia classification	CNN	The radar data and ECG data
[15]	2017	CinC	AF	CNN+feature	Physionet Challenge 2017
[16]	2017	CinC		CNN+RNN	
[17]	2018	CBM	arrhythmia	CNN	MIT-BIH arrhythmia
[18]	2018	IEEE ACCESS	categorize MIT-BIH arrhythmia	SDAE	
[19]	2018	PMEA		CNN+LSTM	Physionet Challenge 2017
[20]	2019	CBM		Unet	MIT-BIH arrhythmia
[21]	2019	ICASSP		CRNN	
[22]	2019	IEEE ACCESS	arrhythmia classification	CNN+features	
[23]	2019	IEEE ACCESS	categorize MIT-BIH arrhythmia	CNN	
[24]	2019	Nature medicine	classify 12 rhythm classes	RESNET	own collected
[25]	2019	CMPB	categorize MIT-BIH arrhythmia	CNN + RNN, AE	MIT-BIH arrhythmia
[26]	2019	EMBC		CNN	
[27]	2019	EMBC	AF	CNN	MIT-BIH Arrhythmia Database (DB 1-6)
[28]	2020	PlosOne	arrhythmia	CRNN	PhysioNet challenge 2015

3. Cardiac Arrhythmia Datasets

To facilitate the development and evaluation of computational intelligence algorithms, several publicly available ECG datasets have been created, which contain recordings from patients with various arrhythmia types. These datasets have become invaluable resources for researchers and developers working on arrhythmia detection algorithms. In this section, we review some of the most widely used Cardiac Arrhythmia ECG datasets available in the literature, highlighting their key features, strengths, and limitations [20-22].

3.1. MIT-BIH Arrhythmia Database

This dataset is one of the most widely used and referenced databases in arrhythmia research. Created by the Massachusetts Institute of Technology (MIT), It consists of 48 half-hour ECG recordings collected from 47 patients. The recordings were sampled at 360 Hz and digitized with 11-bit resolution. The database includes various types of arrhythmias, such as atrial fibrillation, premature ventricular contractions (PVCs), ventricular tachycardia, and more. Each beat in the recordings is annotated with a beat type (normal, PVC, atrial premature contraction, etc.). In addition, rhythm annotations are provided for each record, specifying the overall rhythm for each section of the recording. The database also includes additional diagnostic information. It provides a good balance of common and rare arrhythmia types, allowing for evaluation of algorithms across the spectrum of arrhythmia severity. The beat-

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by-beat annotations of the recordings are highly accurate, providing a gold standard for algorithm evaluation. However, the dataset is relatively small, containing only 48 recordings, which can limit the generalizability of algorithm performance. Also, the recordings were made using ECG equipment from the 1970s, so there may be some limitations in terms of signal quality and noise [23].

3.2. PhysioNet's Computing in Cardiology Challenge (CinC)

This refers to a collection of electrocardiogram (ECG) recordings used for the annual PhysioNet/CinC challenge, which aims to advance the field of arrhythmia detection by providing a platform for researchers to develop and evaluate automated arrhythmia detection algorithms. The dataset typically contains a large number of ECG recordings, ranging from several hundred to several thousand. The recordings are often well-annotated with beat and rhythm labels, allowing for comprehensive evaluation of arrhythmia detection algorithms. The dataset may include recordings from multiple sources and with varying characteristics, providing a diverse range of arrhythmia types and ECG signal characteristics. The large number of recordings in the dataset provides a comprehensive resource for algorithm development and evaluation. However, the dataset may be focused on a specific task or arrhythmia type, which may limit its generalizability to other settings. Also, the recordings may not capture all possible variations in arrhythmia types and ECG signal characteristics, potentially limitingthe ability of algorithms to detect certain arrhythmias. It also suffers from class imbalance, with some arrhythmia types being much less common than others. It also does not includes demographic or clinical data about the patients, which may limit the ability to develop algorithms that generalize across different patient populations [24-25].

3.3. PTB Diagnostic ECG Database

The PTB Diagnostic ECG Database consists of 549 ECG recordings from 290 subjects, including patients with various cardiac conditions and healthy controls. The recordings were sampled at 1,000 Hz with 16-bit resolution. The dataset covers a wide range of arrhythmias, myocardial infarction cases, and normal sinus rhythm samples [15]. The PTB Diagnostic ECG Database is a collection of ECG recordings from patients with various cardiac conditions, including arrhythmias. Here are some of the key features, strengths, and limitations of the PTB Diagnostic ECG Database: The high sampling rate and 15-lead ECG recordings provide a rich source of information for algorithm development and evaluation. As usual, the dataset may suffer from class imbalance, with some cardiac conditions being much less common than others. Each record in the dataset is annotated with diagnostic labels, indicating the presence of specific cardiac conditions or arrhythmias [16].

3.4. The Fantasia Dataset

The Fantasia dataset includes 3,800 ECG recordings from 300 patients. It covers a variety of arrhythmias, including atrial fibrillation, ventricular tachycardia, supraventricular tachycardia, and more. The dataset offers a large and diverse collection of arrhythmia cases. The dataset provides expert annotations for each recording, specifying the presence and type of arrhythmia [20].

3.5. MIT-BIH Normal Sinus Rhythm Database

This dataset focuses specifically on normal sinus rhythm ECG signals. It contains 18 half-hour recordings from healthy subjects without any arrhythmias. The purpose of this dataset is to provide a reference for normal ECG patterns. The recordings in this dataset do not include specific beat or rhythm annotations since they represent normal sinus rhythm without arrhythmias. A summary comparison between distinctive characteristics of each of the above datasets is given in Table 3.

Table 3: review of the main characteristics of the literature datasets cardiac arrhythmia

DATASET	MIT-BIH ARRHYTHMIA DB	PHYSIONET CINC	PTB DIAGNOSTIC DB	THE FANTASIA DATASET	MIT-BIH NORMAL SINUS RHYTHM DB
DESCRIPTION	48 half-hour ECG recordings	Varies each year	549 15-lead ECGs from 290 subjects	3,800 ECG recordings from 300 patients	18 half-hour ECGs from healthy subjects

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ARRHYTHMIAS INCLUDED	Yes	Varies each year	Yes	Yes	No
OTHER CARDIAC ABNORMALITIES	Yes	Varies each year	Yes	Yes	No
ANNOTATION INFORMATION	Beat annotations,	Varies each year	Diagnostic labels	Expert annotations	N/A
	rhythm annotations,		provided by experts	for arrhythmias	
	diagnostic information				
NUMBER OF RECORDINGS	48	Varies each year	549	3800	18
NUMBER OF SUBJECTS	47	Varies each year	290	300	N/A
LEAD CONFIGURATION	Varies	Varies	15-lead	Varies	Varies
NORMAL SINUS RHYTHM INCLUDED	No	Varies each year	No	No	Yes
RESEARCH APPLICATIONS	Arrhythmia analysis,	Signal processing and	Arrhythmia analysis,	Arrhythmia classification,	Normal sinus rhythm analysis,
	algorithm development	classification tasks	diagnosis studies	algorithm development	baseline for comparison
DATASET AVAILABILITY	PhysioNet	PhysioNet	PhysioNet	PhysioNet	PhysioNet

4. Open Issues

Despite significant progress in automated arrhythmia detection, there are still open issues and future directions that need to be addressed in order to improve the accuracy and clinical utility of arrhythmia detection algorithms. One of the main challenges is the development of algorithms that can accurately detect and classify complex arrhythmia types, such as atrial fibrillation and ventricular tachycardia. Another challenge is the development of algorithms that can generalize across different patient populations, as well as different ECG machines and recording settings. Additionally, there is a need for algorithms that can provide real-time arrhythmia detection and diagnosis, as well as integration with clinical decision support systems to guide patient management and treatment. In this section, we discuss these open issues and future directions in more detail and highlight recent advances and ongoing research in the field of cardiac arrhythmia detection.

Interpretability and Explainability: Many state-of-the-art arrhythmia detection algorithms, such as deep learning models, operate as black boxes, making it challenging to understand how they arrive at their decisions. Future research could focus on developing interpretable and explainable models that provide insights into the features and patterns used for arrhythmia detection. This could enhance the trust and acceptance of the algorithms in clinical practice [25-26].

Real-Time Monitoring: Real-time detection and monitoring of cardiac arrhythmias are crucial for timely intervention and patient care. Future directions may involve the development of lightweight and efficient algorithms that can run on wearable devices or implantable cardiac devices to provide real-time arrhythmia detection and alerts. This would enable continuous monitoring and early detection of arrhythmias outside of clinical settings [13-14].

Handling Noisy and Ambiguous Data: ECG signals can be influenced by various artifacts, noise, and patient-specific factors, which can impact arrhythmia detection accuracy. Future research could focus on developing robust

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algorithms that can handle noisy and ambiguous data effectively. This may involve techniques such as signal preprocessing, denoising, and artifact removal, as well as incorporating patient-specific information for personalized arrhythmia detection [28].

Large-Scale and Diverse Datasets: Availability of large-scale and diverse datasets is crucial for training and evaluating robust arrhythmia detection algorithms. Future directions may involve efforts to curate and release publicly available datasets that cover a wide range of arrhythmias, including rare and less-studied types. This would facilitate the development and benchmarking of new algorithms and encourage collaborative research in the field [22].

Generalization to Unseen Arrhythmias: Arrhythmias can manifest in diverse forms, and the ability of detection algorithms to generalize to unseen or less common arrhythmias is crucial. Future research could focus on developing algorithms that can effectively detect and classify not only well-known arrhythmias but also emerging or rare arrhythmia patterns. This could involve exploring transfer learning techniques, domain adaptation, or the use of generative models [21].

Integration with Clinical Decision Support Systems: Cardiac arrhythmia detection algorithms can serve as valuable tools within clinical decision support systems. To ensure the practical utility and clinical relevance of arrhythmia detection algorithms, extensive clinical validation studies and integration with existing healthcare systems are necessary. Future directions may involve integrating arrhythmia detection algorithms with electronic health records, telemedicine platforms, or decision support tools. This integration would enable seamless incorporation of arrhythmia detection into clinical workflows, facilitating early diagnosis, treatment, and patient management [25].

Multimodal Data Fusion: Integrating ECG signals with other physiological data modalities, such as blood pressure, respiratory signals, or even non-invasive imaging, can provide a more comprehensive view of cardiac health. Future research can investigate techniques for multimodal data fusion to enhance arrhythmia detection accuracy and enable a holistic understanding of the underlying physiological conditions [10].

Online Learning and Adaptive Systems: Developing adaptive arrhythmia detection systems that can continuously learn from new data and adapt to individual patient characteristics is a promising direction. Online learning techniques and adaptive algorithms can enable personalized arrhythmia detection, accommodating patient-specific variations and evolving conditions over time.

5. Conclusion

In brief, this work presents a concise review of the application of computational intelligence approaches for real-time detection of the Arrhythmia for 12-lead ECG signals. Our review provide taxonomy for categorizing the literature studies for detecting different kinds of arrhythmia. Then, we discuss the details of each category of methods form different design standpoints. The findings demonstrate the promise of computational intelligence techniques for enhancing patient outcomes and lowering the burden on healthcare systems. Finally, the open research issues were discussed to promote further research in this field.

References

[1] Alfaras, M., Soriano, M.C. and Ortín, S., 2019. A fast machine learning model for ECG-based heartbeat classification and arrhythmia detection. *Frontiers in Physics*, p.103.
[2] Sahoo, S., Dash, M., Behera, S. and Sabut, S., 2020. Machine learning approach to detect cardiac arrhythmias in ECG signals: A survey. *Irbm*, *41*(4), pp.185-194.
[3] Parvaneh, S., Rubin, J., Babaeizadeh, S. and Xu-Wilson, M., 2019. Cardiac arrhythmia detection using deep learning: A review. *Journal of electrocardiology*, *57*, pp.S70-S74.
[4] Subramanian, K. and Prakash, N.K., 2020, August. Machine learning based cardiac arrhythmia detection from ecg signal. In *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 1137-1141). IEEE.
[5] Pandey, S.K., Sodum, V.R., Janghel, R.R. and Raj, A., 2020. ECG arrhythmia detection with machine learning algorithms. In *Data Engineering and Communication Technology: Proceedings of 3rd ICDECT-2K19* (pp. 409-417). Springer Singapore.

Doi: https://doi.org/10.54216/IJAACI.020202
Received: June 24, 2022 Accepted: December 23, 2022

[6] Scirè, A., Tropeano, F., Anagnostopoulos, A. and Chatzigiannakis, I., 2019. Fog-computing-based heartbeat detection and arrhythmia classification using machine learning. *Algorithms*, *12*(2), p.32.
[7] Hammad, M., Iliyasu, A.M., Subasi, A., Ho, E.S. and Abd El-Latif, A.A., 2020. A multitier deep learning model for arrhythmia detection. *IEEE Transactions on Instrumentation and Measurement*, *70*, pp.1-9.
[8] Hussain, L., Aziz, W., Saeed, S., Awan, I.A., Abbasi, A.A. and Maroof, N., 2020. Arrhythmia detection by extracting hybrid features based on refined Fuzzy entropy (FuzEn) approach and employing machine learning techniques. *Waves in Random and Complex Media*, *30*(4), pp.656-686.
[9] Singh, V., Tewary, S., Sardana, V. and Sardana, H.K., 2019, March. Arrhythmia detection-a machine learning based comparative analysis with mit-bih ecg data. In *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)* (pp. 1-5). IEEE.
[10] Devi, R.L. and Kalaivani, V., 2020. Machine learning and IoT-based cardiac arrhythmia diagnosis using statistical and dynamic features of ECG. *The journal of supercomputing*, *76*(9), pp.6533-6544.
[11] Singh, N. and Singh, P., 2019. Cardiac arrhythmia classification using machine learning techniques. In *Engineering Vibration, Communication and Information Processing: ICoEVCI 2018, India* (pp. 469-480). Springer Singapore.
[12] Nandhini Abirami, R. and Durai Raj Vincent, P.M., 2020. Cardiac arrhythmia detection using ensemble of machine learning algorithms. In *Soft Computing for Problem Solving: SocProS 2018, Volume 2* (pp. 475-487). Springer Singapore.
[13] Haddi, Z., Ananou, B., Trardi, Y., Pons, J.F., Delliaux, S., Deharo, J.C. and Ouladsine, M., 2020, July. Advanced machine learning coupled with heart-inter-beat derivatives for cardiac arrhythmia detection. In *2020 American Control Conference (ACC)* (pp. 5433-5438). IEEE.
[14] Yin, W., Yang, X., Zhang, L., & Oki, E. (2016). ECG monitoring system integrated with IR-UWB radar based on CNN. *IEEE Access*, *4*, 6344-6351.
[15] Andreotti, F., Carr, O., Pimentel, M. A., Mahdi, A., & De Vos, M. (2017, September). Comparing feature-based classifiers and convolutional neural networks to detect arrhythmia from short segments of ECG. In *2017 Computing in Cardiology (CinC)* (pp. 1-4). IEEE.
[16] Warrick, P., & Homsi, M. N. (2017, September). Cardiac arrhythmia detection from ECG combining convolutional and long short-term memory networks. In *2017 Computing in Cardiology (CinC)* (pp. 1-4). IEEE.
[17] Yıldırım, Ö., Pławiak, P., Tan, R. S., & Acharya, U. R. (2018). Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Computers in biology and medicine*, *102*, 411-420.
[18] Xia, Y., Zhang, H., Xu, L., Gao, Z., Zhang, H., Liu, H., & Li, S. (2018). An automatic cardiac arrhythmia classification system with wearable electrocardiogram. *IEEE Access*, *6*, 16529-16538.
[19] Warrick, P. A., & Homsi, M. N. (2018). Ensembling convolutional and long short-term memory networks for electrocardiogram arrhythmia detection. *Physiological measurement*, *39*(11), 114002.
[20] Oh, S. L., Ng, E. Y., San Tan, R., & Acharya, U. R. (2019). Automated beat-wise arrhythmia diagnosis using modified U-net on extended electrocardiographic recordings with heterogeneous arrhythmia types. *Computers in biology and medicine*, *105*, 92-101.
[21] Mousavi, S., & Afghah, F. (2019, May). Inter-and intra-patient ecg heartbeat classification for arrhythmia detection: a sequence to sequence deep learning approach. In *ICASSP 2019-2019 IEEE international conference on acoustics, speech and signal processing (ICASSP)* (pp. 1308-1312). IEEE.
[22] He, R., Liu, Y., Wang, K., Zhao, N., Yuan, Y., Li, Q., & Zhang, H. (2019). Automatic cardiac arrhythmia classification using combination of deep residual network and bidirectional LSTM. *IEEE access*, *7*, 102119-102135.
[23] Huang, J., Chen, B., Yao, B., & He, W. (2019). ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network. *IEEE access*, *7*, 92871-92880.
[24] Sun, W., Zeng, N., & He, Y. (2019). Morphological arrhythmia automated diagnosis method using gray-level co-occurrence matrix enhanced convolutional neural network. *IEEE Access*, *7*, 67123-67129.
[25] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature medicine*, *25*(1), 65-69.

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[26] Hong, S., Zhou, Y., Wu, M., Shang, J., Wang, Q., Li, H., & Xie, J. (2019). Combining deep neural networks and engineered features for cardiac arrhythmia detection from ECG recordings. *Physiological measurement*, *40*(5), 054009.

[27] Yildirim, O., Baloglu, U. B., Tan, R. S., Ciaccio, E. J., & Acharya, U. R. (2019). A new approach for arrhythmia classification using deep coded features and LSTM networks. *Computer methods and programs in biomedicine*, *176*, 121-133.

[28] Zhao, W., Hu, J., Jia, D., Wang, H., Li, Z., Yan, C., & You, T. (2019, July). Deep learning based patient-specific classification of arrhythmia on ECG signal. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 1500-1503). IEEE.

Doi: https://doi.org/10.54216/IJAACI.020202
Received: June 24, 2022 Accepted: December 23, 2022