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REVIEW

Deep Learning-Based Detection of Arrhythmia Using ECG Signals – A Comprehensive Review

Aquib Irteza Reshad[1], Valentina Nino[1], Maria Valero[2]

[1]Department of Industrial and Systems Engineering, Kennesaw State University, Marietta, GA, USA; [2]Department of Information Technology, Kennesaw State University, Marietta, GA, USA

Correspondence: Aquib Irteza Reshad, Kennesaw State University, 1100 South Marietta Pkwy, Marietta, GA, 30060, USA, Email areshad@students.kennesaw.edu

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Abstract: Cardiac arrhythmias are a major health concern around the world, causing morbidity and mortality in a wide range of people. The timely and accurate diagnosis of arrhythmias is critical for optimal clinical management and intervention. Deep learning techniques have developed as powerful tools for detecting arrhythmias in recent years, taking advantage of advances in signal processing and machine learning. This review investigates the use of deep learning approaches to detect arrhythmias via electrocardiogram (ECG) readings. The study includes an in-depth evaluation of 30 papers retrieved from three distinct databases using a structured method. The result indicates that deep learning models can achieve high accuracy like 99.93% as well as high F1 scores such as 99.57%. Furthermore, the study examines current research trends, approaches, and developments in deep learning-based arrhythmia detection, including convolutional neural networks (CNNs), and hybrid architectures that includes RNN and CNN algorithms. Additionally, the paper investigates the strengths and limits of existing techniques, focusing on critical issues such as dataset heterogeneity, model interpretability, and real-time implementation. Future research and development directions in arrhythmia detection using deep learning are also mentioned. This study seeks to give significant insights for physicians, researchers, and policymakers involved in the development and implementation of sophisticated arrhythmia detection systems, with the ultimate goal of improving patient outcomes and cardiac healthcare.

Keywords: cardiac arrhythmia, electrocardiogram, hybrid architecture, heart disease detection, irregular heartbeat, convolutional neural networks

Introduction

Cardiac arrhythmia, defined as irregular cardiac rhythms,[1] is a major public health concern around the world, leading to morbidity and mortality in a variety of groups. Arrhythmias include a wide range of anomalies in heart rate and rhythm, from minor palpitations to life-threatening diseases like ventricular fibrillation. The detection and diagnosis of arrhythmias is critical for timely intervention and therapy, as untreated arrhythmias can lead to major problems such as heart failure, stroke, and cardiac arrest.[2] To address this critical healthcare issue, several technologies and approaches for arrhythmia detection have been developed, using advances in signal processing,[3] machine learning,[4] and data analytics.[5] Current approaches include a variety of techniques such as electrocardiogram (ECG) analysis,[6] wearable devices,[6] implantable cardiac monitors,[7] and telemonitoring systems,[8] each with its own set of benefits and applications in the clinical and ambulatory settings.

Electrocardiography (ECG) remains the gold standard for arrhythmia detection, allowing for real-time monitoring of cardiac electrical activity by non-invasive electrode implantation.[9] Advanced signal processing techniques, such as wavelet transforms and deep learning algorithms, have improved the accuracy and efficiency of ECG-based arrhythmia identification, allowing for automated analysis and interpretation of the data.[10–14] Wearable gadgets, such as smartwatches and mobile health apps, also provide continuous monitoring and early identification of arrhythmias outside of typical clinical settings, allowing people to manage their heart health more proactively.[15]

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The need for arrhythmia detection goes beyond individual patient care to include public health programs aimed at preventing cardiovascular events and lowering healthcare costs.[16] Early diagnosis of arrhythmias allows for quick commencement of relevant therapies, such as pharmaceutical therapy, lifestyle changes, and invasive procedures like catheter ablation or implanted cardioverter-defibrillator (ICD).[17,18] Furthermore, population-level arrhythmia screening programs can identify at-risk individuals and adopt preventive actions to reduce the likelihood of unfavorable cardiac events.[19]

Given the growing importance of arrhythmia identification in healthcare, this review study seeks to give a complete overview of current approaches, technologies, and breakthroughs in arrhythmia detection. This paper aims to shed light on the strengths, limitations, and future directions of arrhythmia detection research by synthesizing existing literature and reviewing major research results. Additionally, we critically examined the challenge of overfitting in deep learning models and evaluated the strategies used by authors to mitigate overfitting risks, analyzing the effectiveness of these techniques based on data size, training/test splits, and other schemes provided in each paper. Moreover, this review seeks to educate clinicians, researchers, and policymakers about developing trends and advances in arrhythmia diagnosis, thereby supporting evidence-based decision-making and propelling progress toward better cardiac health outcomes.

So, we investigate the following research concerns in this study:

RQ1: Which state-of-the-art tools are being used for detecting arrhythmias?

RQ2: What technological obstacles do researchers in this domain face when using current deep learning procedures and what strategies did, they use to overcome those obstacles?

RQ3: How can arrhythmia detection be improved for real-world applications?

Materials and Methods

We conducted a structured search to find relevant research publications in our subject field. Prior to doing the investigation, we created acceptable search phrases that included the following keywords: “Deep Learning” “heart disease” “arrhythmia detection” “cardiovascular disease” and “ECG.” To discover publications for analysis, we ran a comprehensive search across different scientific databases, using Boolean operators and pertinent keywords. Table 1 shows the keywords and Boolean expressions utilized, as well as the filters that were applied. The scientific databases used included PubMed, Web of Science, and Scopus. IEEE was removed because it is part of Scopus. To minimize the number of studies retrieved, the search was restricted to the article’s title and abstract. This is a plausible strategy, given that articles on arrhythmia detection include the keywords arrhythmia, deep learning, ECG, and heart disease in their abstracts.

Search Procedure

Initially, we discovered 276 results in Scopus. Multiple filters were used to refine the search results. The source type was limited to Journals and Conference Proceedings, and English was selected as the language. On Web of Science, we obtained 221 results. Finally, a search on PubMed yielded 151 matches. The authors searched the earlier mentioned

Table 1 Search Keywords and Results for Different Databases

	Search Keywords	Number of Papers
Web of science	TI= (Deep Learning AND ECG AND Heart Disease) OR AB= (Deep Learning AND ECG AND Heart Disease) OR AB=(Deep Learning AND ECG AND Cardiovascular Disease) OR TI = (Deep Learning AND ECG AND Cardiovascular Disease)	221
Scopus	(TITLE-ABS-KEY (deep AND learning) AND TITLE-ABS-KEY (ecg) AND TITLE-ABS-KEY (heart AND disease) OR TITLE-ABS-KEY (deep AND learning) AND TITLE-ABS-KEY (ecg) AND TITLE-ABS-KEY (cardiovascular AND disease)) AND (LIMIT-TO (LANGUAGE,“English”)) AND (LIMIT-TO (DOCTYPE,“ar”))	276
PubMed	(Deep Learning[Title/Abstract] AND ECG[Title/Abstract] AND Heart Disease[Title/Abstract]) OR (Deep Learning[Title/Abstract] AND ECG [Title/Abstract] AND Cardiovascular Disease[Title/Abstract])	151

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Table 2 Applied Conditions for Inclusion and Exclusion

Conditions for Exclusion	Conditions for Inclusion
There exists a duplicate of the paper in another database	There is no duplicate of the paper
English is not the primary language of the paper	English is the primary language of the paper
Paper used other technology than ECG	Only have used the data from ECG device as an input
Paper considered only classification of arrhythmia or monitoring of heart	Paper considered the detection of arrhythmia
Other heart diseases or diseases related to aorta, artery	No other diseases related to heart was considered

databases and formerly read works; they discovered a total of 648 titles by using the keywords shown in Table 1. After completing the initial search, we used inclusion and exclusion criteria.

Selection Procedure

To narrow down the collection of research publications for our review, we used an inclusion and exclusion approach that considered topic relevancy, duplicate elimination, and English language writing. Table 2 contains the conditions of the exclusion and inclusion criterion. After removing duplicate research, the remaining publications were filtered based on their title and abstract. Subsequently, the entire text was thoroughly examined, with an emphasis on experimental findings and conclusions. Following a rigorous screening process as per Figure 1, this review contained 30 primary studies that offered information on arrhythmia identification. We used a quality assessment approach based on the study by Kitchenham B[20] to determine the alignment of the selected papers with our research topics. The chosen ones successfully

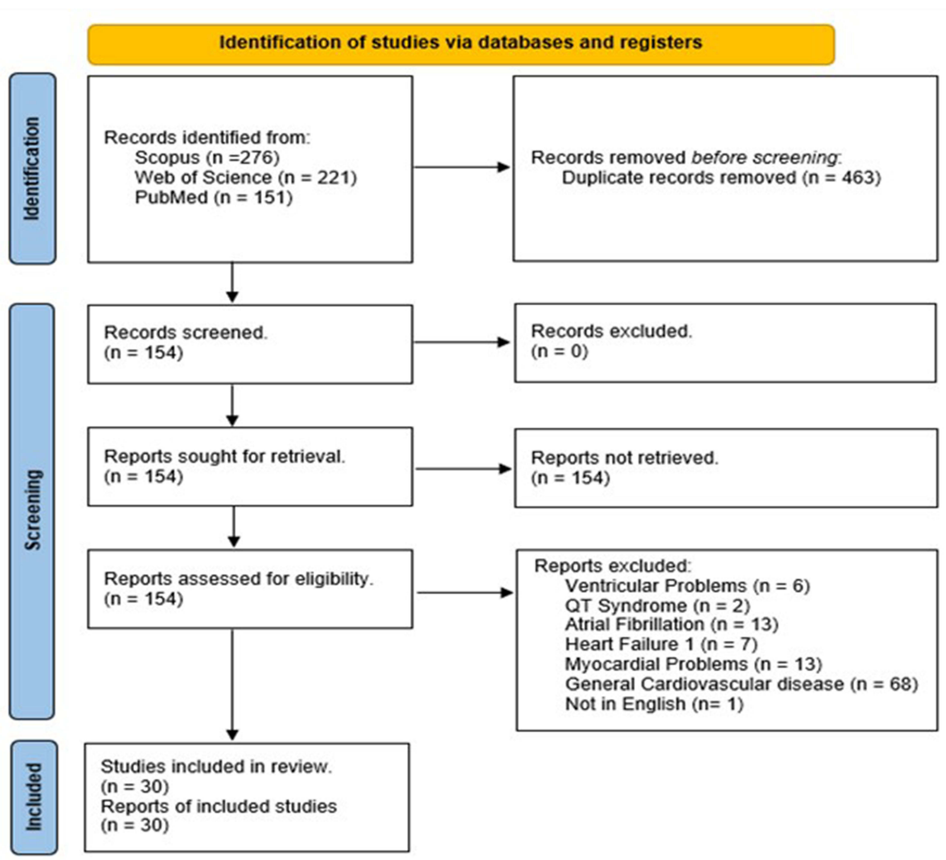

Figure 1 Flow chart for selection of papers.

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handled arrhythmia detection and provided insights pertinent to this review on arrhythmia detection based on ECG signal. To ensure appropriate interpretation and assist continued development to make detection of arrhythmia by deep learning techniques more practical, accurate and sustainable, special emphasis was made on contextual aspects, relevant frameworks, research findings, and future directions.

Results

Publication Over Time

A study of the literature on arrhythmia identification using ECG signals suggests a gradual and increasing interest in this topic in recent years that can be seen from Figure 2. In 2018, two noteworthy publications were published, indicating the start of dedicated research in this field. The next year, in 2019, the number of publications reduced somewhat to one, presumably signaling a period of methodology consolidation and refinement. However, by 2020, interest had sky-rocketed, with five notable contributions indicating advances and breakthroughs in the discipline. This tendency continued into 2021, with three major papers adding to the knowledge base. The year 2022 had a notable increase in publications, with seven significant contributions, indicating intensified research activity and the potential appearance of novel methodologies or approaches. In 2023, this trend continued with ten notable papers, illustrating the growing importance and maturity of arrhythmia detection research employing ECG signals. As of 2024, with two key articles already published, the trajectory indicates a sustained and active research landscape, with more improvements and innovations in arrhythmia detection and diagnosis via ECG signal processing.

Publications Based on Countries Associated

Figure 3 shows the diversity of countries contributing to arrhythmia detection using ECG signals which demonstrates the international extent of research in this topic. China appears as a prominent player, with ten related research contributions demonstrating its enormous investment and skill in this field. Following closely behind, India shows significant engagement with 6 linked publications, demonstrating its growing relevance as a cardiac health research powerhouse. The United States, a longstanding leader in medical research, maintains a significant presence with four related articles, trailing only China and India. Additionally, some nations, including the United Kingdom, Poland, Ethiopia, Korea, Singapore, Malaysia, Turkey, Tunisia, and Russia, have two papers related to arrhythmia detection, demonstrating a large

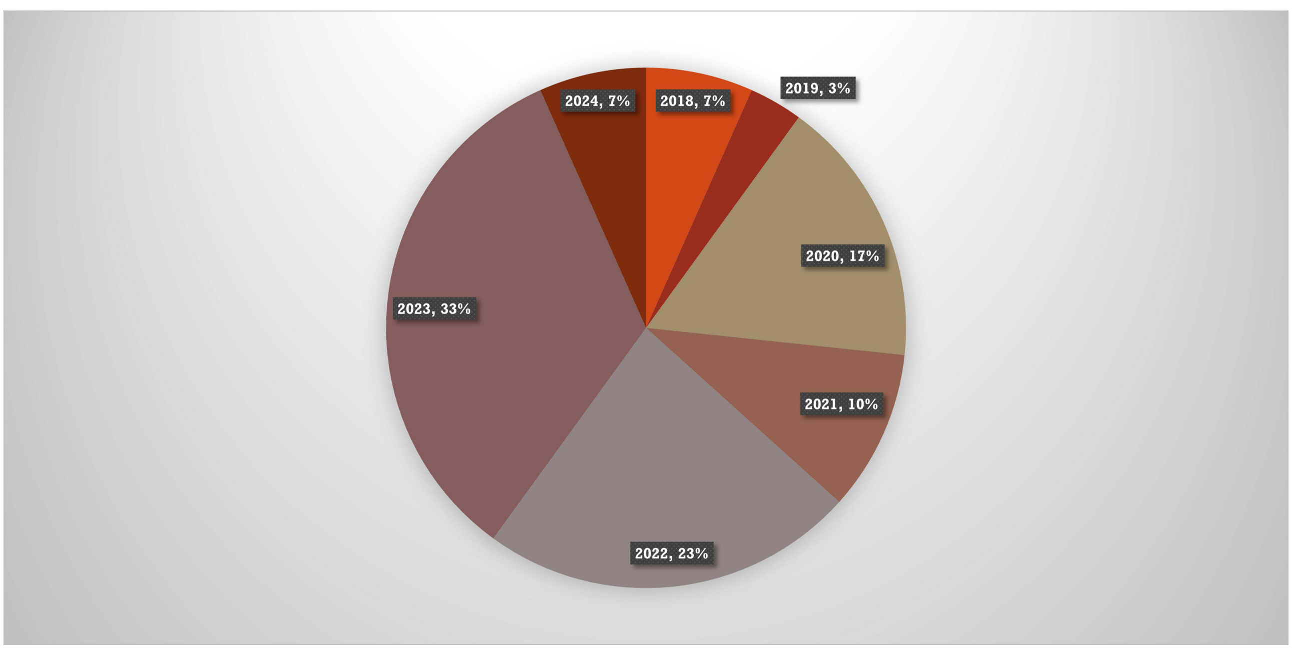

Figure 2 Publications over time for ECG based Arrythmia detection.

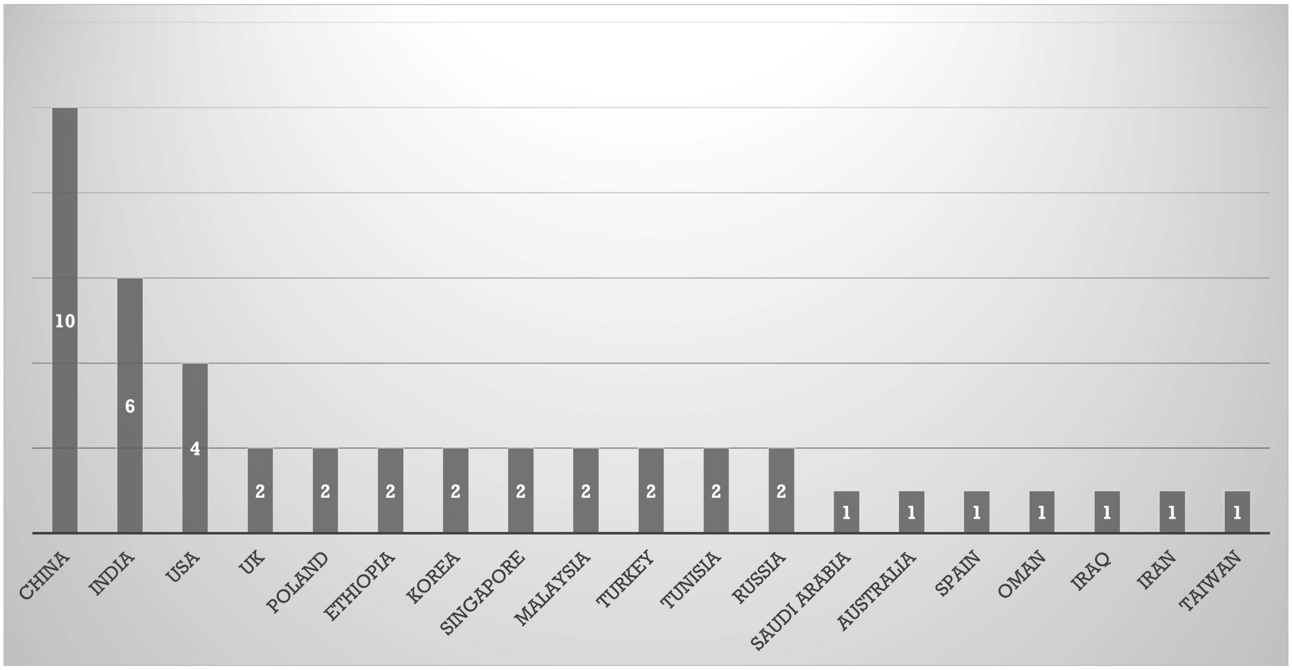

Figure 3 Countries using deep learning techniques for ECG detection of cardiac arrhythmias.

global interest and collaboration in improving this field. Furthermore, countries such as Saudi Arabia, Australia, Spain, Oman, Iraq, Iran, and Taiwan each have one connected publication, highlighting the global dispersion of research across continents. This diversified international participation highlights the collaborative aspect of scientific research and the global effort to tackle heart illnesses.

Steps for Arrhythmia Detection Using ECG Signals

Dataset

Among the 30 studies selected for arrhythmia detection using ECG signals, the vast majority, 22 papers, used the well-known MIT-BIH Arrhythmia Database for training and testing. This dataset, known for its extensive collection of annotated ECG recordings, is used as a benchmark to assess the effectiveness of various detection algorithms and models. Moreover, five studies used the CPSC2018 dataset, indicating an increasing interest in adding newer datasets to improve model validation. Moreover, four studies used the PTB dataset, demonstrating the breadth of datasets used in arrhythmia research to capture various features of cardiac abnormalities. Figure 4 shows the number of papers that have used these typical datasets for their studies.

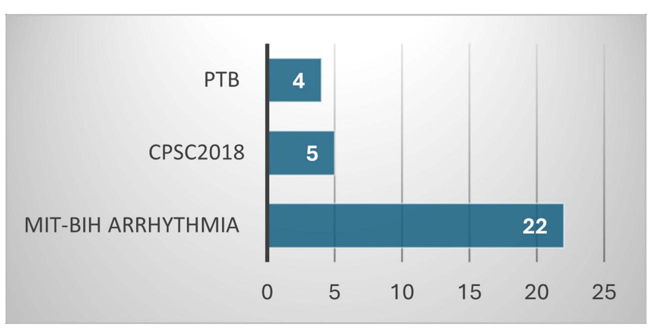

Figure 4 Datasets used in selected papers.

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Notably, the article by Tiwari S[21] stands out for its novel approach, which involves carefully placing three electrodes at the right and left clavicles, as well as the lower left rib. This novel setup aided in the detection of five distinct types of arrhythmias, emphasizing the value of specialized data collection approaches in achieving specific research goals. This paper's use of unorthodox electrode placements and multi-class classification contributes to the field by providing insights into novel methodologies for arrhythmia identification that go beyond usual dataset constraints.

Preprocessing

Preprocessing is critical for improving the quality of electrocardiogram (ECG) readings and hence detecting arrhythmias accurately. Several techniques are used to handle common issues including noise reduction, artifact removal, and baseline correction. Wavelet transform develops as a significant method, as evidenced in works by Yoo J, Yang W, Wang D and Pandey SK.[22–25]This method decomposes the noisy signal into different frequency components using the wavelet transform, followed by effective noise removal or attenuation by wavelet coefficient thresholding. Research done by Kumar S[26] also use Infinite Impulse Response (IIR) notch and Finite Impulse Response Filters to remove superfluous noise components. Besides,[27] recommends the use of low-pass filters to reduce noise by suppressing frequencies above 50 Hz. Notably, some researchers, such as that study of Shchetinin EY[28] used preprocessed signals, implying differing levels of preprocessing across different research attempts. Overall, these preprocessing techniques maintain the integrity and reproducibility of ECG signals, providing the groundwork for future analysis and arrhythmia detection algorithms.

Segmentation

In the context of ECG signal processing, segmentation refers to the dividing of data into separate segments, which are often determined by the identification of specific cardiac events such as the R-peak. The R-peak acts as an important anchor point for locating entire heartbeats in the signal.[29] Yang W[23] illustrate a variety of strategies for detecting R-peaks, including the Pan-Tompkins method. Once the R-peaks have been discovered, segmentation will extract appropriate segments for further study. For example, Pandey SK[25] divided data into 360 random samples after identifying R peaks[30] collected 90 (250 ms) samples before and 144 (400 ms) after the R-peak to represent a full pulse. Furthermore, Mohan Rao B[31] divided datasets into time intervals of 2 seconds, 5 seconds, 5 minutes, and 8 minutes from the total length of the data. These segmentation methods allow for the isolation of individual cardiac events or intervals, making it easier to analyze and interpret ECG signals for arrhythmia detection and diagnosis.

Augmentation

Augmentation is an important approach for increasing dataset diversity and enhancing model robustness by injecting variations into existing data samples. One widely used technique, SMOTEENN (Synthetic Minority Over-sampling Technique), used by He J,[30] Zeng W[32] and Ma C,[33] focuses on improving data with few samples by oversampling minority heartbeats to establish a balanced distribution. Besides, Kumar S[26] used common data augmentation techniques such cropping, resizing, shifting, and horizontally flipping the ECG images to add variability and enhance the dataset. Similarly, Pandey SK[25] used the Pandas library's dataframe.resample() function to rebalance the dataset, guaranteeing a balanced representation of different classes. These augmentation approaches make a major contribution to reducing class imbalances, boosting model generalization, and increasing the overall performance of arrhythmia detection algorithms trained using ECG data.

Classification

To diagnose arrhythmias, ECG signals are classified based on various cardiac abnormalities. The difficulty of classification varies throughout studies, with different research projects using varying numbers of classifications to capture the wide range of arrhythmia types. Zeng W[32] and Pławiak P[34] used a thorough 17-class classification approach to emphasize the complex nature of arrhythmia subtypes. In contrast,[35] used a significantly reduced 16-class classification scheme[36] reduced the classification job by focusing on binary classification, which divides ECG data into two classes, most likely normal and abnormal rhythms. Surprisingly, a large proportion of the examined publications chose classification methods that included either five or four different kinds of arrhythmia which is shown in Figure 5. Seven articles used a five-class ((Normal Rhythm (NOR), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC) and Atrial Premature Contraction (APC)) categorization

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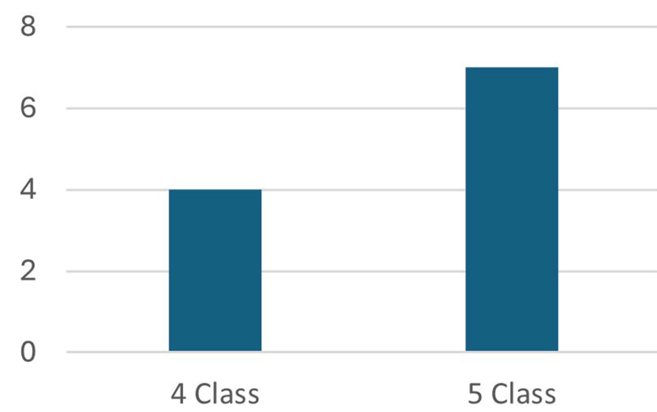

Figure 5 Different classes were used in the selected papers.

approach, while four used a four-class (Normal Beat, Supraventricular Ectopic Beat, Ventricular Ectopic Beat and Fusion Beat) classification system. This variability in classification methodologies highlights the complexities of arrhythmia detection and the significance of customizing classification schemes to specific research goals and therapeutic applications. In addition to the various classification algorithms used in arrhythmia detection, the distribution of datasets for training and testing varies throughout studies, suggesting varied approaches to model evaluation and validation. 80/20 division emerges as a popular option (Figure 6), with 17 papers using this split ratio. This approach uses 80% of the dataset to train the classification model and the remaining 20% to evaluate its performance. Other research, on the other hand, has used different split ratios, such as 70/30[37] and,[36] 85/15,[38] and 90/10,[39] to demonstrate a variety of distribution strategies for balancing model training and evaluation. Only one research[21] among the selected ones had used data from different sources for the testing purpose. More information about this data has already been discussed in section 3.3.1. Furthermore, some papers use custom split ratios customized to their individual research goals, underscoring the versatility and adaptability of dataset partitioning in arrhythmia classification studies. These various techniques to dataset partition show the significance of strong evaluation procedures as well as ensuring sufficient data for both training and testing in order to obtain meaningful model performance assessment in arrhythmia detection. Since different papers have

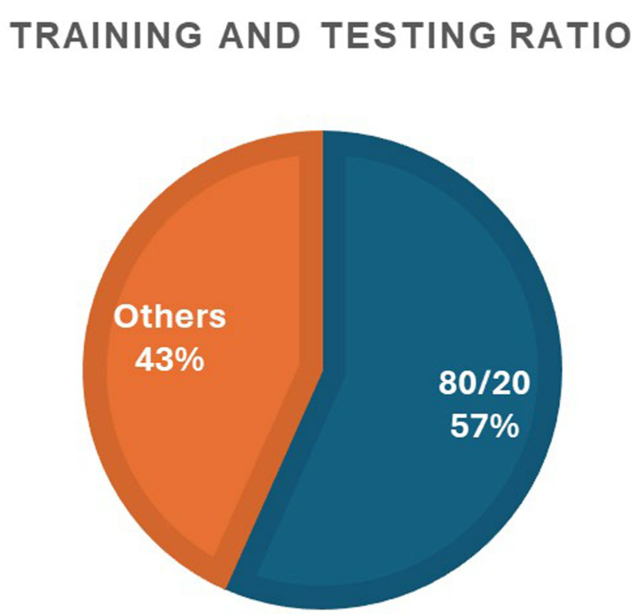

Figure 6 Perveance of 80/20 splitting of data among the selected papers.

used different classification techniques that are shown in Table 3 for the detection of arrythmias, we will be discussing three of them which have the highest accuracy.

Chenbin Ma. 2022[33] **(Accuracy: 99.89%)**

Notably, unlike some other approaches, Ma C[33] did not use noise reduction algorithms or time-frequency transformations, indicating a concentration on using raw data for categorization. By integrating CNN-based feature extraction with

Table 3 Selected Papers and Their Used Method, Accuracy, F-Score

Author and Year	Reference	Dataset	Method	Accuracy	F Score
Kumar, S., 2023	[23]	MIT-BIH	Deep learning and fuzzy clustering (Fuzz-ClustNet)	98.66	96.34
Tison, G.H., 2023	[38]	CMR study data	Deep convolutional neural network (CNN)	N/A	0.77
Chen, T.-M 2020	[39]	CPSC2018	Combined architecture of five CNN blocks, followed by a bidirectional gated recurrent unit (GRU), an attention layer and finally a dense layer.	N/A	83.7
Yıldırım, Ö, 2028	[34]	MIT- BIH	1D-Convolutional Neural Network model (1D-CNN)	91.33	85.38
Wang, D, 2020	[21]	"Hefei high tech Cup" ECG Human-Machine Intelligence Competition	Multi-resolution representation (MRR) of ECG signals	N/A	91.07
Ramkumar, M, 2023	[24]	MIT-BIH arrhythmia	Support vector machines (SVM), Naive Bayes (NB), and random forest (RF)	99.71	N/A
Zhang, S, 2024	[40]	PTB-XL dataset CPSC dataset Chapman dataset	Multi-scale convolutional Transformer network (MCTnet) and CNN	N/A	84.18
Zhuang, J., 2023	[33]	MIT-BIH	Intelligent system based on deep learning and machine learning methods	97.02	97
Pandey, S.K., 2023	[22]	MIT-BIH	SoftMax and machine learning classifiers	99.4	98.74
Zheng, X., 2023	[37]	MIT-BIH	Deep shrinkage network	99.86	N/A
Tiwari, S., 2023	[18]	MIT-BIH One electrode (red color-RA) is placed on the right clavicle near the right shoulder, the second on the left clavicle (yellow color-LA) near the left shoulder, and the third (green color-LL) is on the lower side of the left rib	Smart Cardiovascular Disease Detection System (SCDDS) ensembled with Convolution Neural Network architecture (ConvNet) and Long Short-Term Memory Networks (ConvNet-LSTM) architecture	N/A	97
Daydulo, Y.D., 2023	[41]	MIT-BIH MIT-BIH normal sinus rhythm database BIDMC	ResNet 50 and AlexNet	99.2	99.2
Alamatsaz, N., 2024	[35]	MIT-BIH arrhythmia database and the long-term AF database	Combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM).	97.5	N/A
Zeng, W., 2023	[29]	MIT-BIH	One-dimensional (1D) convolutional neural networks (CNN) and long short-term memory (LSTM)networks	97.2	97.2
Midani, W., 2023	[42]	MIT-BIH	Deep learning-based approach called "DeepArr"	99.46	97.63
Ma, C., 2022	[30]	PLAGH (PLA General Hospital) dataset CPSC 2018 dataset was chosen to test the MIT-BIH	End-to-end Multi-Scale Convolutional Neural Network-Sequence to Sequence architecture for heartbeat classification	99.89	99.57
Mohan Rao, 2022	[28]	MIT-BIH Hypertension NSR database BIDMCCHF	ResNet-50	99.93	N/A

(*Continued*)

Table 3 (Continued).

Author and Year	Reference	Dataset	Method	Accuracy	F Score
Shchetinin, E.Y., 2022	[25]	MIT-BIH	Machine learning and deep learning methods such as Support Vector Machines (SVM), Random Forests, Light Gradient Boosting Machine (LightGBM), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BLSTM)	98.4	90.7
Omar Hashim Yahya., 2023	[32]	Yfa Hospital in Russia	Convolutional neural network (CNN) and long-short-time memory (LSTM)	90.85	N/A
Dong, Y., 2022	[43]	CPSC-2018	Multi-branch signal fusion network (MBSF Net)	N/A	98.4
Toma, T.I., 2022	[44]	MIT-BIH	Parallel cross convolutional recurrent neural network	99.71	95.22
Gao, J., 2019	[36]	MIT-BIH	Long short-term memory (LSTM) recurrence network model with focal loss (FL)	99.26	N/A
Wang, R., 2020	[45]	CPSC_2018 CinC_2017	End-to-end Deep Multi-Scale Fusion convolutional neural network (DMSFNet) architecture	N/A	82.8
Yoo, J. 2021	[19]	CPSC 2018	End-to-end convolutional neural network (CNN), xECGNet	N/A	77.4
He, J., 2020	[27]	MIT-BIH-AR	Dynamic Heartbeat Classification with Adjusted Features (DHCAF) and Multi-channel Heartbeat Convolution Neural Network (MCHCNN).	91.4	N/A
Meng, Y., 2021	[46]	Chinese Cardiovascular Disease Database (CCDD) (MIT-BIH)	Deep convolutional neural network	98.84	N/A
Pławiak, P., 2020	[31]	MIT-BIH	Three-layer deep genetic ensemble of classifiers (DGEC)	95	N/A
Yang, W., 2018	[20]	MIT-BIH	Principal component analysis network (PCANet) for feature extraction and to improve the classification speed, a linear support vector machine (SVM) was applied	97.77	N/A
Saravana Ram, R., 2023	[47]	MIT-BIH PTB-ECG	Multi-layer Perceptrons (MLPs), Deep Belief Networks (DBNs), and Restricted Boltzmann Machines (RBMs)	98.6	97.4
Fradi, M., 2022	[48]	MIT-BIH PTB The improved PTB database	Convolutional neural network (CNN) based Fully Connected layers architecture, using different networks optimizer.	99.5	99

RNN-based sequence modeling, the proposed hybrid model achieves excellent accuracy in arrhythmia identification, demonstrating the effectiveness of deep learning architectures in dealing with sequential data such as ECG signals.

Xiaoyang Zheng, 2023[40]**(Accuracy: 99.86%)**

The second publication by Zheng X[40] describes DS-ECGNet, a deep learning architecture designed exclusively for electrocardiogram (ECG) signal analysis. DS-ECGNet is intended to categorize noisy ECG signals without preprocessing for noise reduction. The fundamental innovation is the incorporation of soft thresholding into a deep fully convolutional neural network (DFCNN), which successfully removes noise from input signals during classification. By skipping the typical noise reduction phase and immediately tackling noise inside the classification model, DS-ECGNet provides a streamlined approach to arrhythmia identification, potentially lowering computational complexity and increasing efficiency.

B Mohan Rao, 2022[31] **(Accuracy: 99.93%)**

The third publication by Mohan Rao B[31] proposes ResNet-50, a convolutional neural network (CNN) architecture known for its deep and efficient learning capabilities. ResNet-50, a member of the ResNet (Residual Network) family, is distinguished by its deep structure of 50 layers. One of the distinguishing characteristics of ResNet-50 is the use of skip connections, also known as shortcuts, which allow the network to bypass one or more layers during training. This allows the network to learn both the original and residual properties of the input data, making it easier to train deeper networks without running into vanishing gradient difficulties. ResNet-50's resilience and effectiveness in handling complicated datasets make it an invaluable tool for arrhythmia identification, providing cutting-edge performance and scalability.

Hyperparameter Optimization

Hyperparameter optimization is crucial for fine-tuning machine learning models to obtain peak performance. Various methodologies are used throughout research to find the optimal collection of hyperparameters for a specific model. For example, Kumar S[26] used the RandomSearch heuristic, a popular method for hyperparameter tuning, to quickly explore the hyperparameter space and determine the best configuration. In contrast,[28] used three-fold randomized search cross validation, a technique that divides the dataset into three subsets and iteratively tunes hyperparameters using random combinations of values. Shchetinin EY[41] optimized the Adam optimizer, a prominent optimization technique, to improve model training efficiency and convergence. Yoo J[22] used a five-fold cross-validation strategy to find optimal hyperparameters, with repeated validation runs to assure robustness. Additionally, Pławiak P[34] investigated three distinct optimization approaches - particle swarm optimization, genetic algorithm, and grid search - to discover the best successful approach for hyperparameter tuning. These various methodologies highlight the need for thorough hyperparameter research and optimization for maximizing model performance in arrhythmia identification.

Evaluation Metrices

Arrhythmia detection models are frequently evaluated using important performance criteria such as accuracy, precision, recall, F1 Score, and Area Under the Receiver Operating Characteristic Curve (AUC). Among these measures, Accuracy is a key indicator of overall model correctness, showing the proportion of properly categorized examples among all occurrences. Precision measures the accuracy of positive predictions, whereas recall reflects the fraction of true positives properly detected by the model. The F1 Score, which is the harmonic mean of Precision and Recall, gives a balanced evaluation of model performance, especially in the situation of imbalanced datasets. Finally, AUC measures the model's ability to differentiate across classes, with larger values indicating superior performance. Notably, the publications produced by Mohan Rao B,[31] Ma C[33] and Zheng X[40] achieved extraordinary high Accuracy scores of 99.93%, 99.89%, and 99.86%, respectively, demonstrating the usefulness of their different methodologies in reliably classifying arrhythmias. Additionally, Ma C[33] achieved remarkable F1 scores of 99.57%, demonstrating the model's robustness in obtaining both high precision and recall. Similarly, Gao J[39] and Daydulo YD[42] achieved F1 Scores of 99.30% and 99.2%, respectively, demonstrating the outstanding efficacy of their arrhythmia detection models. These findings highlight the amazing advances in arrhythmia identification made possible by deep learning approaches, paving the path for more accurate and dependable clinical diagnosis and treatment.

Discussion and Future Research

Limitations of Existing Literature and Future Research

The field of arrhythmia detection research has some major limitations, as well as intriguing avenues for future inquiry and improvement. One such constraint is the disparity between the number of leads or channels used in research settings vs practical clinical conditions. While many studies use a small number of leads, usually two or one, clinical practice frequently employs a more comprehensive 12-lead arrangement for complete cardiac monitoring that has been used only in the studies of Tiwari S[21] and Yoo J.[19] This discrepancy raises questions about the generalizability and applicability of research findings to real-world healthcare settings, emphasizing the need for greater alignment between research methodologies and clinical practices to ensure the relevance and effectiveness of arrhythmia detection systems.

Another restriction is the range of arrhythmia types considered in research studies. Despite the fact that there are over 20 different forms of arrhythmia,[43] studies frequently focus on a subset of these diseases, thereby missing out on less prevalent but clinically significant arrhythmias. This narrow focus may limit the applicability of study findings and impede the development of comprehensive detection algorithms capable of detecting a wide spectrum of cardiac problems. Future research efforts could benefit from larger inclusion criteria that include a wider range of arrhythmia types, increasing the clinical utility and effectiveness of detection systems.

Furthermore, the demographic composition of sample populations in arrhythmia detection research frequently displays a lack of diversity, with datasets such as the MIT-BIH containing data from persons in the United States and the CPSC datasets primarily representing Chinese populations. This homogeneity restricts the generalizability of research findings and may obscure significant differences in arrhythmia presentation and detection among demographic groups. To address this constraint, larger efforts must be made to collect and analyze data from varied people around the world, ensuring that detection algorithms are resilient and successful across demographic and ethnic backgrounds.

Additionally, the lack of real-time detection capabilities and testing with real-world data creates substantial obstacles in turning research findings into actual clinical applications. While some studies have made progress in real-time identification,[25,34] the majority of research is still focused on offline analysis of pre-recorded datasets. Real-time detection is critical for timely intervention and management of arrhythmias in clinical settings, emphasizing the need of creating algorithms for accurate and efficient real-time monitoring.

Moreover, the sparse mention of energy usage in arrhythmia detection systems highlights a need in current research.[21] Given the growing demand for portable, energy-efficient medical equipment, future research should look into ways to reduce energy consumption while maintaining detection accuracy and performance.

Finally, resolving these constraints opens up new venues for future arrhythmia detection research. Researchers can promote the creation of more robust, accurate, and practical arrhythmia detection systems by broadening the range of arrhythmia types studied, diversifying sample populations, incorporating real-time detection capabilities, and optimizing energy consumption. Finally, these efforts have the potential to improve patient outcomes, improve clinical decision-making, and pave the path for more effective cardiac arrhythmia management across several healthcare settings.

Challenge of Overfitting

One of the major challenges for deep neural networks is overfitting, which occurs when a model performs exceptionally well on training data but struggles to generalize to new, unseen data. In the context of arrhythmia diagnosis based on ECG signals, researchers have implemented various methods to mitigate overfitting and improve model generalization. For example, dropout layers, as seen in studies [29,35,42], randomly disable neurons during training, forcing the network to rely on more diverse feature sets and enhancing its ability to generalize. Another commonly used technique involves ReLU activation functions combined with Local Response Normalization (LRN), as shown in [41] using AlexNet. This not only accelerates training but also reduces overfitting by normalizing neuron outputs across the network. A detailed discussion is given on Table 4.

Max-pooling layers, which downsample input vectors to reduce the parameter count, have also been used to optimize the cost function and reduce model complexity, as demonstrated by Midani W[44] and Fradi M.[45] Similarly, batch normalization, employed in study by He J,[30] addresses internal covariate shifts by standardizing inputs across layers, helping stabilize training and improve generalization. Additionally, L2 regularization, applied by Zeng W[32] and Mac C,[33] penalizes large weights in the loss function, effectively reducing model complexity and preventing overfitting.

Ensemble learning techniques, discussed in article by Ramkumar M,[27] offer another effective strategy by combining the outputs of multiple models. This approach not only reduces the risk of overfitting but also lowers the complexity of individual models, leading to more robust and reliable predictions. These comprehensive techniques, when used together, significantly enhance the performance and resilience of deep learning models for detecting arrhythmias from ECG signals, ensuring that they generalize well to real-world clinical settings.

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Table 4 Selected Papers and Their Data Size, Strategy Used to Reduce Overfitting

Paper	Accuracy	F-Score	Amount of Data	Class/Ca-gories	Split	Strategy Used by Paper	Discussion
[23]	98.66	96.34	87,554	5	80/20	Used several standard data augmentation techniques like cropping and resizing, shifting the image through a particular value, and horizontally flipping the ECG image	The data augmentation methods introduce enough variability to prevent the model from simply memorizing the training data. However, without additional information like a validation curve or details on how the model performed on entirely unseen data (beyond the 20% test split), we cannot definitively conclude whether overfitting has been entirely avoided. Thus, based on the provided metrics and strategies, it appears unlikely that the model is overfitted, but further validation would be required for certainty.
[38]	N/A	0.77	6,916	2	80/10/10	No Discussion on overfitting	The study did not include any discussion or mention about overfitting. Given the limited number of data and data imbalance, there might be good a chance of overfitting in the model.
[39]	N/A	83.7	6,877	8	80/10/10	CNN block contained two convolution layers that were followed by a pooling layer to reduce the amount of parameters and computation in the network and to control over-fitting	While the use of pooling layers indicates an effort to mitigate overfitting, the relatively small dataset and the F-score suggest that the model could be underperforming or not fully generalizing. It is possible that the model might not be overfitting but rather suffering from insufficient data or complexity, leading to lower performance.
[34]	91.33	85.38	1,000	17	70/15/15	Some layers have a dropout parameter to prevent the overfitting during the learning phase	Although the model's use of dropout suggests that overfitting was considered and addressed, the small dataset size and the modest F-score indicate the model may still struggle with generalization. It is possible that the dropout strategy mitigates some overfitting, but with such limited data, the model may not perform optimally across diverse or unseen samples.
[21]	N/A	91.07	29,995	34	80/20	1. Scale the original signal with a scaling factor. 2. Translation to generate more data 3. Used a Nall-zero segment of (0,1) s length fragment to randomly mask the ECG signal 4. Dropout was also introduced	The fact that the paper explicitly introduces methods to prevent overfitting, combined with the size of the dataset and variety in augmentation techniques, demonstrate that overfitting is unlikely.
[24]	99.71	N/A	109,446	4	80/20	Proposed ensemble learning technique is that it evades the overfitting problem by reducing the complexity of the model.	The model achieves an impressive accuracy of 99.71% on a large dataset of 109,446 samples with an 80/20 train-test split, using an ensemble learning technique. Ensemble methods, which combine multiple classifiers through voting mechanisms, are known to reduce overfitting by lowering the overall model complexity and increasing robustness. Given the high accuracy and the use of ensemble learning, it is unlikely that the model is overfitting, as this technique is explicitly designed to generalize well to new data.
[40]	N/A	84.18	6,877	9	80/10/10	No Discussion on overfitting	The study did not include any discussion or mention about overfitting. Given the limited number of data and data imbalance, there might be a good chance of overfitting in the model.

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[33]	97.02	97	109,446	2	70/30	Proposed a GAN-based recognition method.	By generating synthetic data for rare classes through the GAN's generator and filtering it with the discriminator, the model creates a more balanced and representative training set. This strategy not only increases the data volume but also helps mitigate the risk of overfitting, as the model is exposed to a more diverse set of examples. Given this approach and the solid performance metrics, it is unlikely that the model is overfitting. However, additional testing on unseen data would provide more conclusive evidence of its generalization capabilities.
[22]	99.4	98.74	99,567	5	80/20	Used Pooling layer and Dropout Layer	Given the high-performance metrics and the use of effective regularization techniques, it is unlikely that the model is overfitted.
[37]	99.86	N/A	31,007	8		Introduced a dropout rate of 0.5	The dropout technique, which randomly deactivates neurons with a probability of 0.5, is a widely recognized method for reducing overfitting by preventing the model from becoming too dependent on specific neurons. However, without an F1 score provided and no detailed information about external validation or testing on a separate dataset, we cannot definitively determine if the model is overfitted.
[18]	N/A	97	109,446	5	80/20	Used Augmentation and made a 20% balance for 5 classes.	Data augmentation is mentioned as a method to balance the dataset, although no specific details about the augmentation techniques are provided. While data augmentation can help prevent overfitting by increasing the variety of training data, the lack of further information about the augmentation methods and the absence of a reported accuracy score makes it difficult to determine if the model is truly overfitted or not.
[41]	99.2	99.2	3600	3	80/20	• Replaced sigmoid function by ReLU in AlexNet • Dropout was introduced • Finally, used ResNet since Overfitting was seen.	The traditional sigmoid activation function was replaced by ReLU in the AlexNet architecture, which reportedly improved training speed and helped avoid overfitting. However, the presence of overfitting was still observed, leading the authors to introduce ResNet into the model, although no discussion about ResNet's impact was provided. Despite these efforts to reduce overfitting, the fact that overfitting was mentioned but not fully addressed makes it unclear whether the issue was effectively mitigated. Based on the available information, we cannot definitively conclude if the model is still overfitted.
[35]	97.5	N/A	43,454	9	85/15	Dropout was applied and assigned higher class weights to the minority class	To address potential overfitting, dropout was implemented. Additionally, the class imbalance issue was managed by assigning class weights, which gives higher importance to the minority class. While dropout and class weights are common strategies to prevent overfitting and handle imbalanced data, the absence of the F1 score makes it difficult to evaluate the model's performance in minority classes. Therefore, based on the available information, it is not possible to conclusively determine whether the model is overfitted.
[29]	97.2	97.2	3134	17	90/10	Applied synthetic minority over-sampling technique (SMOTE) algorithm to over-sample the minority class and dropout layer with a rate of 0.5	While these strategies are designed to address overfitting and class imbalance, the high accuracy and F1 score suggest that the model performs well. However, with that limited number of data and without further details on validation methods or generalization performance, it remains difficult to definitively conclude whether overfitting occurred.

(Continued)

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Table 4 (Continued).

Paper	Accuracy	F-Score	Amount of Data	Class/Ca-gories	Split	Strategy Used by Paper	Discussion
[42]	99.46	97.63	100,062	5	90/10	At the end of each convolutional block applied Dropout with a probability of 0.1	Given the high-performance metrics, it seems that the model generalizes well. However, without further validation on unseen data or additional details on model performance across different conditions, it's difficult to definitively conclude whether overfitting occurred or not.
[30]	99.89	99.57	328,111	5	80/20	• Applied (SVM-SMOTE) • Introduced L2 regularization L2 norm to the loss function • Dropout with a rate of 0.5 was set in MSCNN-Seq2Seq.	While the use of a large dataset, SVM-SMOTE for data balancing, L2 regularization to discourage complexity, and a dropout rate of 0.5 to enhance generalization are positive strategies, without performance metrics on a separate validation or test set, we cannot definitively conclude whether the model generalizes well or has merely memorized the training data.
[28]	99.93	N/A	1,491,373	4	80/20	Added dropout layer	Although the accuracy is remarkably high, the absence of an F1 score and additional performance metrics limits our ability to fully assess the model's effectiveness, particularly regarding class balance. The use of dropout as a regularization technique is a positive step towards mitigating overfitting. However, given the extremely high accuracy, there is a concern that the model may have overfitted the training data.
[25]	98.4	90.7	109,446	5	80/20	Used ensemble algorithm	The use of an ensemble algorithm is a favorable approach for enhancing model robustness and reducing overfitting by combining the predictions of multiple models. Despite these positive aspects, without further information on how the model performed on unseen data or a validation set, we cannot definitively determine if the model is overfitting.
[32]	90.85	N/A	17 long-recorded ECG signals (24 h) from 17 subjects	16	90/10	Employed weighted loss to counter the class imbalance	While the accuracy is commendable, the very small dataset raises concerns about the model's generalizability. Without an F1 score provided and limited sample size, it is difficult to assess whether the model has overfitted or if the results are reflective of its true performance.
[43]	N/A	98.4	6,877	9	80/20	No Discussion on overfitting	The study did not include any discussion or mention about overfitting. Given the limited number of data and data imbalance, there might be a good chance of overfitting in the model.
[44]	99.71	95.22	100,501	4	80/20	A dropout layer at the rate of 0.1 and batch normalization layer was inserted in every convolutional block.	While these strategies are effective for enhancing generalization, the very high accuracy and F1 score suggest that further scrutiny is warranted. Without performance metrics on a separate validation or test set, it remains unclear whether the model has truly generalized well or if it has overfitted to the training data.
[36]	99.26	N/A	93,371	8	90/10	Used zero dropout and batch size of 128.	This study achieved the highest accuracy with a zero dropout and batch size of 128. Since an increasing number of batch sizes are prone to overfitting and dropout was zero for this high accuracy, there might be a good chance that the model was overfitting.

[45]	N/A	82.8	6,877	9	80/20	Used horizontal and vertical flip operation to expand small sample data, added random noise and applied random erasure strategy	These approaches are effective in mitigating overfitting by providing the model with a richer variety of training examples. However, given the modest F1 score relative to the dataset size, it is unclear whether the model effectively generalizes or has overfitted to specific patterns in the training data.
[19]	N/A	77.4	6,877	9	60/ 20/20	The models were trained up to 1000 epochs, and the training was stopped if the validation F1 score did not improve for 50 consecutive epochs	While this approach is a solid strategy for avoiding overfitting, the F1 score indicates that the model may not have achieved optimal performance. Further evaluation on independent data is necessary to assess its generalizability.
[27]	93	N/A	100,607	5	50/50	Introduced batch normalization and pooling layer.	While the accuracy appears strong, no F1 score was reported, making it difficult to fully assess the model's performance, especially concerning class balance. The mention of a batch normalization pooling layer suggests that the model employs regularization techniques aimed at improving convergence and potentially mitigating overfitting. However, without further information on the model's performance on a separate validation set, if the model is overfitting cannot be conclusively determined.
[46]	98.84	N/A	109,446	5	50/50	No Discussion on overfitting	The study did not include any discussion or mention about overfitting. Given the unusual split of data and data imbalance, there might be a good chance of overfitting in the model.
[31]	95	N/A	744	17	80/20	No Discussion on overfitting (data imbalanced)	The study did not include any discussion or mention about overfitting. Given the limited number of data and data imbalance, there might be a good chance of overfitting in the model.
[20]	97.77	N/A	107,168	5	90/10	No discussion on overfitting	The use of data augmentation through the Synthetic Minority Over-sampling Technique (SMOTE) was discussed to address class imbalance for future work. However, without information on performance metrics from a validation set and balanced dataset there might be a good chance of overfitting in the model.
[47]	98.6	97.4	268	2	66.67/ 33.33	No discussion on overfitting	The study did not include any discussion or mention about overfitting. Given the limited number of data and data imbalance, there might be good a chance of overfitting in the model.
[48]	99.5	99	109,446	5	70/ 20/10	Used Adadelta-optimizer and introduced Dropout layers.	The use of the Adadelta optimizer, known for its robustness in minimizing overfitting by eliminating the need for manual learning rate settings, suggests a thoughtful approach to training. Additionally, the incorporation of dropout further aids in regularization. While the high accuracy and F1 score indicate strong performance, the proximity of these metrics raises the possibility of overfitting.

Improving Interpretability

In the field of arrhythmia detection utilizing ECG signals, improving the interpretability of deep learning models is vital for clinician trust and acceptance.[38] According to Yoo J,[22] in the field of cardiac arrhythmia, the two inherent and interconnected components of AI - multilabel classification and interpretability - have not been adequately addressed. Various research have used different approaches to tackle this issue. Alamatsaz N[38] used Shapley values to measure the contribution of each ECG sample to model predictions, resulting in clear explanations critical for medical applications. This approach enables clinicians to determine which ECG segments have the greatest influence on the identification of complex ventricular arrhythmias (ComVE) or late gadolinium enhancement. Wang R[46] employs a parallel machine learning approach intended to improve interpretability. This strategy improves our knowledge of how models process ECG data, allowing for greater clinical integration. Yoo J[22] describes xECGNet, a model that addresses the dual issues of detection and interpretation. By fine-tuning attention mappings for concurrent labels and integrating a regularization term, xECGNet efficiently performs multilabel classification and enhances model transparency. Toma TI[47] describes MCTnet, which combines CNN and gated Transformer architectures that was developed by Wang R[48] to detect both local and global features in ECG data. This synergistic method enables good handling of long-term dependencies as well as natural interpretability via attention maps. These techniques highlight the significance of making deep learning models more transparent, which will lead to increased clinical acceptability and improved patient care in arrhythmia identification.

Limitation of This Article

This study has both advantages and disadvantages. This study used organized techniques to acquire and assess studies, although only a few electronic databases were used. One paper that was not in English was additionally turned down during full-text screening, which could have yielded valuable data. We limited our search to the title and abstract to keep the number of searches manageable. It is possible that some of the studies were missing because of our adjustments to the search technique.

In our review, we acknowledge the predominance of studies utilizing the MIT-BIH Arrhythmia Database, which appears in 22 out of the 30 selected papers. This reflects the database's well-established role in arrhythmia detection research and its widespread acceptance within the scientific community. However, we recognize that this reliance on a single dataset may underrepresent other valuable datasets that could provide additional insights and improve generalizability. Future reviews should aim to incorporate a broader range of datasets, including less commonly used ones, to ensure a more comprehensive and impartial assessment of arrhythmia detection methodologies.

Conclusion

This review investigates the use of deep learning approaches to detect arrhythmias via electrocardiogram (ECG) readings. The emphasis is on using convolutional neural networks (CNNs) or Hybrid Models that includes RNN and CNN algorithms for high-accuracy recognition of arrhythmic patterns, which is critical for accurate diagnosis and early intervention. Through a thorough study of current research trends and methodology, the review emphasizes the potential of deep learning-based approaches to revolutionize arrhythmia diagnosis by automating ECG signal analysis. The challenges of dataset heterogeneity, model interpretability, overfitting and real-time implementation are examined, as well as potential solutions and future research and development areas. This paper outlines current techniques for managing overfitting, such as dropout layers, data augmentation, and class weighting, while also identifying scenarios where overfitting may still be possible due to data size restrictions or a lack of cross-validation. This analysis intends to lead future research into using robust strategies to improve the generalizability of deep learning models, ensuring consistent results across varied datasets. Finally, this review intends to inform physicians, researchers, and policymakers about the transformative influence of deep learning in advancing arrhythmia detection, eventually improving patient outcomes, and strengthening cardiac healthcare.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors report no conflicts of interest in this work.

References

1. Antzelevitch C, Burashnikov A. Overview of basic mechanisms of cardiac arrhythmia. *Card Electrophysiol Clin*. 2011;3(1):23–45. doi:10.1016/j.ccep.2010.10.012
2. Collins KK, Dubin AM. Detecting and diagnosing arrhythmias in adults with congenital heart disease. *Curr Cardiol Rep*. 2003;5(4):331–335. doi:10.1007/s11886-003-0071-7
3. Chandrasekar A, Shekar DD, Hiremath AC, Chemmangat K. Detection of arrhythmia from electrocardiogram signals using a novel gaussian assisted signal smoothing and pattern recognition. *Biomed Signal Process Control*. 2022;73:103469. doi:10.1016/j.bspc.2021.103469
4. Sahoo S, Dash M, Behera S, Sabut S. Machine learning approach to detect cardiac arrhythmias in ECG signals: a survey. *IRBM*, 41 4 185–194 doi:10.1016/j.irbm.2019.12.001
5. Carnevale L, Celesti A, Fazio M, Villari M. A big data analytics approach for the development of advanced cardiology applications. *Information*. 2020;11(2):60. doi:10.3390/info11020060
6. Azariadi D, Tsoutsouras V, Xydis S, Soudris D. ECG signal analysis and arrhythmia detection on IoT wearable medical devices. *2016 5th International Conference on Modern Circuits and Systems Technologies (MOCAST)*. Vol. 2016:1–4. doi:10.1109/MOCAST.2016.7495143
7. Ip J, Jaffe B, Castellani M, Sheikh A, Castellani C, Ip R. Accuracy of arrhythmia detection in implantable cardiac monitors: a prospective randomized clinical trial comparing reveal LINQ and confirm Rx. *Pacing Clin Electrophysiol*. 2020;43(11):1344–1350. doi:10.1111/pace.14076
8. Ali H, Naing HH, Yaqub R. An IoT assisted real-time high CMRR wireless ambulatory ECG monitoring system with arrhythmia detection. *Electronics*. 2021;10(16):1871. doi:10.3390/electronics10161871
9. Badhwar N, Kusumoto F, Goldschlager N. Arrhythmias in the coronary care unit. *J Intensive Care Med*. 2012;27(5):267–289. doi:10.1177/0885066611402165
10. ST segment analysis using wavelet transform | semantic scholar. Available from: https://www.semanticscholar.org/paper/ST-Segment-Analysis-Using-Wavelet-Transform-Haddadi-Abdelmounim/dd8374e337b3d8d989ca46cce6379882e5e52a1d. Accessed May 5, 2024.
11. Kusuma S, Udayan JD. Analysis on deep learning methods for ECG based cardiovascular disease prediction. *Scalable Computing*. 2020;21(1):127–136. doi:10.12694/scpe.v21i1.1640
12. Al Younis SM, Hadjileontiadis LJ, Al Shehhi AM, et al. Investigating automated regression models for estimating left ventricular ejection fraction levels in heart failure patients using circadian ECG features. *PLoS One*. 2023;18(12):e0295653. doi:10.1371/journal.pone.0295653
13. Alkhodari M, Khandoker AH, Jelinek HF, et al. Circadian assessment of heart failure using explainable deep learning and novel multi-parameter polar images. *Comput Methods Programs Biomed*. 2024;248:108107. doi:10.1016/j.cmpb.2024.108107
14. Al Younis SM, Hadjileontiadis LJ, Khandoker AH, et al. Prediction of heart failure patients with distinct left ventricular ejection fraction levels using circadian ECG features and machine learning. *PLoS One*. 2024;19(5):e0302639. doi:10.1371/journal.pone.0302639
15. Kim NH, Ko JS. Introduction of wearable device in cardiovascular field for monitoring arrhythmia. *Chonnam Med J*. 2021;57(1):1–6. doi:10.4068/cmj.2021.57.1.1
16. Gangwar DS, Saini DS. Arrogyam: arrhythmia detection for ambulatory patient monitoring. In: Ranka S, Banerjee A, Biswas KK, editors. *Contemporary Computing. Vol 95. Communications in Computer and Information Science*. Berlin Heidelberg: Springer; 2010:168–180. doi:10.1007/978-3-642-14825-5_15
17. Nazarian S. New technologies and therapies for cardiac arrhythmias. *Minerva Cardioangiologica*. 2010;58(6):731–740.
18. Sridhar D, Reddy C. A study of etiology, clinical profile and complications of patients with atrial fibrillation; 2019. Available from: https://www.semanticscholar.org/paper/A-STUDY-OF-ETIOLOGY%2C-CLINICAL-PROFILE-AND-OF-WITH-Sridhar-Reddy/ccd16e8256bcdea67b85ed179c3794ecd332a5ae. Accessed June 9, 2024.
19. Staszewsky L, Pasina L, Musazzi UM, Latini R. Screening for unknown atrial fibrillation in older people: a feasibility study in community pharmacies. *Eur Geriatr Med*. 2018;9(1):113–115. doi:10.1007/s41999-017-0010-6
20. Kitchenham B, Charters S. Guidelines for performing systematic literature reviews in software engineering. 2007;2.

21. Tiwari S, Jain A, Sapra V, et al. A smart decision support system to diagnose arrhythymia using ensembled ConvNet and ConvNet-LSTM model. *Expert Syst Appl*. 2023;213:118933. doi:10.1016/j.eswa.2022.118933
22. Yoo J, Jun TJ, Kim YH. xECGNet: fine-tuning attention map within convolutional neural network to improve detection and explainability of concurrent cardiac arrhythmias. *Comput Methods Programs Biomed*. 2021;208:106281. doi:10.1016/j.cmpb.2021.106281
23. Yang W, Si Y, Wang D, Guo B. Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine. *Comput Biol Med*. 2018;101:22–32. doi:10.1016/j.compbiomed.2018.08.003
24. Wang D, Meng Q, Chen D, Zhang H, Xu L. Automatic detection of arrhythmia based on multi-resolution representation of ECG signal. *Sensors*. 2020;20(6):1579. doi:10.3390/s20061579
25. Pandey SK, Shukla A, Bhatia S, et al. Detection of arrhythmia heartbeats from ECG signal using wavelet transform-based CNN model. *Int J Comput Intell Syst*. 2023;16(1):80. doi:10.1007/s44196-023-00256-z
26. Kumar S, Mallik A, Kumar A, Ser JD, Yang G. Fuzz-ClustNet: coupled fuzzy clustering and deep neural networks for arrhythmia detection from ECG signals. *Comput Biol Med*. 2023;153:106511. doi:10.1016/j.compbiomed.2022.106511
27. Ramkumar M, Alagarsamy M, Balakumar A, Pradeep S. Ensemble classifier fostered detection of arrhythmia using ECG data. *Med Biol Eng Comput*. 2023;61(9):2453–2466. doi:10.1007/s11517-023-02839-6
28. Shchetinin EY, Glushkova AG. Arrhythmia detection using resampling and deep learning methods on unbalanced data. *Computer Optics*. 2022;46.
29. Design and implementation of a novel R-peak detection algorithm. Available from: https://www.researchgate.net/publication/338796798_Design_and_Implementation_of_a_Novel_R-Peak_Detection_Algorithm. Accessed May 5, 2024
30. He J, Rong J, Sun L, Wang H, Zhang Y, Ma J. A framework for cardiac arrhythmia detection from IoT-based ECGs. *World Wide Web*. 2020;23(5):2835–2850. doi:10.1007/s11280-019-00776-9
31. Mohan Rao B, Kumar A. Detection of heart arrhythmia based on UCMFB and deep learning technique. *Sādhanā*. 2022;47(4):252. doi:10.1007/s12046-022-02027-6
32. Zeng W, Su B, Chen Y, Yuan C. Arrhythmia detection using TQWT, CEEMD and deep CNN-LSTM neural networks with ECG signals. *Multimed Tools Appl*. 2023;82(19):29913–29941. doi:10.1007/s11042-022-14227-7
33. Ma C, Lan K, Wang J, Yang Z, Zhang Z. Arrhythmia detection based on multi-scale fusion of hybrid deep models from single lead ECG recordings: a multicenter dataset study. *Biomed Signal Process Control*. 2022;77:103753. doi:10.1016/j.bspc.2022.103753
34. Pławiak P, Acharya UR. Novel deep genetic ensemble of classifiers for arrhythmia detection using ECG signals. *Neural Comput Appl*. 2020;32(15):11137–11161. doi:10.1007/s00521-018-03980-2
35. Yahya OH, Alekseev VV, Lakomov DV, et al. Deep learning approach for detecting cardiovascular arrhythmias in seven lead ECG signal from holter. *Int J Onl Eng*. 2023;19(14):160–170. doi:10.3991/ijoe.v19i14.43059
36. Zhuang J, Sun J, Yuan G. Arrhythmia diagnosis of young martial arts athletes based on deep learning for smart medical care. *Neural Comput Appl*. 2023;35(20):14641–14652. doi:10.1007/s00521-021-06159-4
37. Yıldırım Ö, Pławiak P, Tan RS, Acharya UR. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Comput Biol Med*. 2018;102:411–420. doi:10.1016/j.compbiomed.2018.09.009
38. Alamatsaz N, Tabatabaei L, Yazdchi M, Payan H, Alamatsaz N, Nasimi F. A lightweight hybrid CNN-LSTM explainable model for ECG-based arrhythmia detection. *Biomed Signal Process Control*. 2024;90:105884. doi:10.1016/j.bspc.2023.105884
39. Gao J, Zhang H, Lu P, Wang Z. An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset. *J Healthcare Engineer*. 2019;2019:1–10. doi:10.1155/2019/6320651
40. Zheng X, Ma Y, Pan Z, Xu Z. Deep shrinkage network for arrhythmia detection. *Int J Innov Comput Inf Control*. 2023;19(4):1153–63. doi:10.24507/ijicic.19.04.1153
41. Dong Y, Cai W, Qiu L, et al. Detection of arrhythmia in 12-lead varied-length ECG using multi-branch signal fusion network. *Physiol Meas*. 2022;43(10):105009. doi:10.1088/1361-6579/ac7938
42. Daydulo YD, Thamineni BL, Dawud AA. Cardiac arrhythmia detection using deep learning approach and time frequency representation of ECG signals. *BMC Med Inform Decis Mak*. 2023;23(1):232. doi:10.1186/s12911-023-02326-w
43. Arrhythmia. *Wikipedia*; 2024. Available from: https://en.wikipedia.org/w/index.php?title=Arrhythmia&oldid=1224885499. Accessed June 11, 2024.
44. Midani W, Ouarda W, Ayed MB. DeepArr: an investigative tool for arrhythmia detection using a contextual deep neural network from electrocardiograms (ECG) signals. *Biomed Signal Process Control*. 2023;85:104954. doi:10.1016/j.bspc.2023.104954
45. Fradi M, Khriji L, Machhout M. Real-time arrhythmia heart disease detection system using CNN architecture based various optimizers-networks. *Multimed Tools Appl*. 2022;81(29):41711–41732. doi:10.1007/s11042-021-11268-2
46. Tison GH, Abreau S, Barrios J, et al. Identifying mitral valve prolapse at risk for arrhythmias and fibrosis from electrocardiograms using deep learning. *JACC*. 2023;2(6):100446. doi:10.1016/j.jacadv.2023.100446
47. Zhang S, Lian C, Xu B, Su Y, Alhudhaif A. 12-Lead ECG signal classification for detecting ECG arrhythmia via an information bottleneck-based multi-scale network. *Inf Sci*. 2024;662:120239. doi:10.1016/j.ins.2024.120239
48. Liu M, Ren S, Ma S, et al. Gated transformer networks for multivariate time series classification. *ArXiv*. Available from: https://www.semanticscholar.org/paper/Gated-Transformer-Networks-for-Multivariate-Time-Liu-Ren/f4299e47a76d5d7cf1638ba347d9848903ef5a60. Accessed June 11, 2024.

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