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A Survey on ECG-Based Classification of Cardiac Arrhythmias Using Convolutional Neural Networks

Janet Flores Cruz[1,*], Erica Cecilia Ruiz Ibarra[1], Javier Vázquez Castillo[2], Griselda González Díaz Conti[1], Adolfo Espinoza Ruiz[1], Armando García Berumen[1]

[1] Instituto Tecnológico de Sonora, Mexico

[2] Universidad Autónoma del Estado de Quintana Roo, Mexico

janet.flores@potros.itson.edu.mx, jvazquez@uqroo.edu.mx, {griselda.diaz, adolfo.espinoza, armando.garcia, erica.ruiz}@itson.edu.mx

Abstract. Recently, concern for cardiac health has increased, leading to the development of neural network models to diagnose arrhythmias. This study presents a systematic review of current approaches in the classification of cardiac arrhythmias with convolutional neural networks. The predominant databases, the most common arrhythmia types, preprocessing techniques, the most applied convolutional neural network models, and the most used evaluation metrics are addressed. The findings show a trend towards diagnoses such as normal sinus rhythm, left bundle branch block and right bundle branch block. In preprocessing, the use of filters to reduce noise in electrocardiogram signals, segmentation and balancing of the records is highlighted. The MIT-BIH arrhythmia database was identified as the most used in studies. Finally, the effectiveness of convolutional neural network models combined with long short-term memory networks and transformer-based attention modules is highlighted.

Keywords. Convolutional neural networks, ECG classification, ECG signal processing, arrhythmia detection.

1 Introduction

The need for early detection of heart diseases is becoming more evident due to the worldwide increase in cardiovascular conditions. According to the World Health Organization (WHO) [1], cardiovascular diseases are the leading cause of mortality worldwide. Electrocardiography has been established as a key method for identifying these diseases [2].

Manual diagnosis of cardiac arrhythmias faces several challenges. Cardiologists must examine each heartbeat in the electrocardiogram (ECG) signal for irregularities, which can be tedious and susceptible to errors, especially when dealing with extensive records. Moreover, differences in interpretation among medical professionals can lead to inconsistencies in diagnosis. Accurate arrhythmia detection is critical for early treatment. To assist healthcare professionals in this process, intelligent systems can play a pivotal role [3].

Among current tools, Convolutional Neural Networks (CNNs) stand out for their ability to capture complex relationships within the data, proving effective for detecting patterns in ECG signals. However, CNN performance depends on data quality and preprocessing methods [4].

Additionally, cardiac arrhythmia databases provide standardized data, which is crucial for training and evaluating models. Properly selecting the database helps ensure model generalization [5].

Due to the lack of an established model that guarantees a fully reliable classification of cardiac arrhythmias, there is a need to analyze and compare existing proposals. This work aims to comprehensively review the use of convolutional neural networks in the classification of cardiac arrhythmias based on ECG signals.

Through a comparative analysis of the latest studies, the objective is to present a detailed overview of progress in preprocessing techniques,

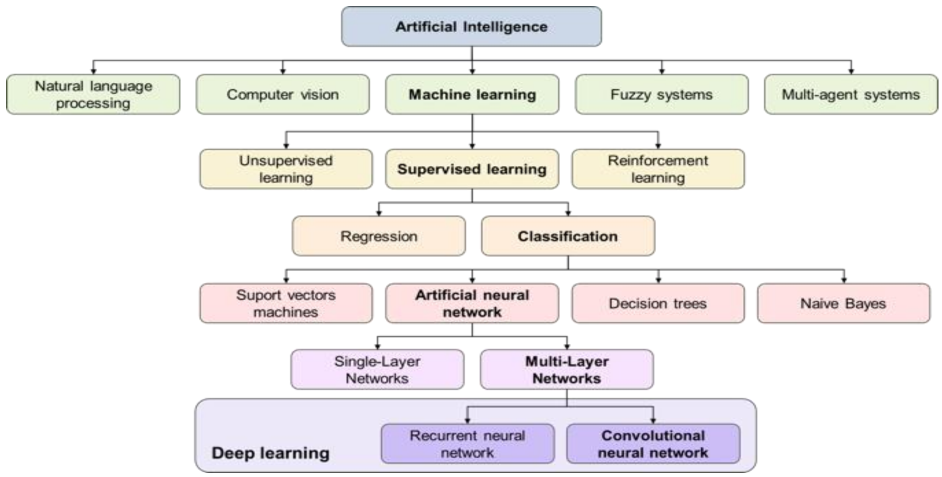

Fig. 1. Classification of artificial intelligence and machine learning methods

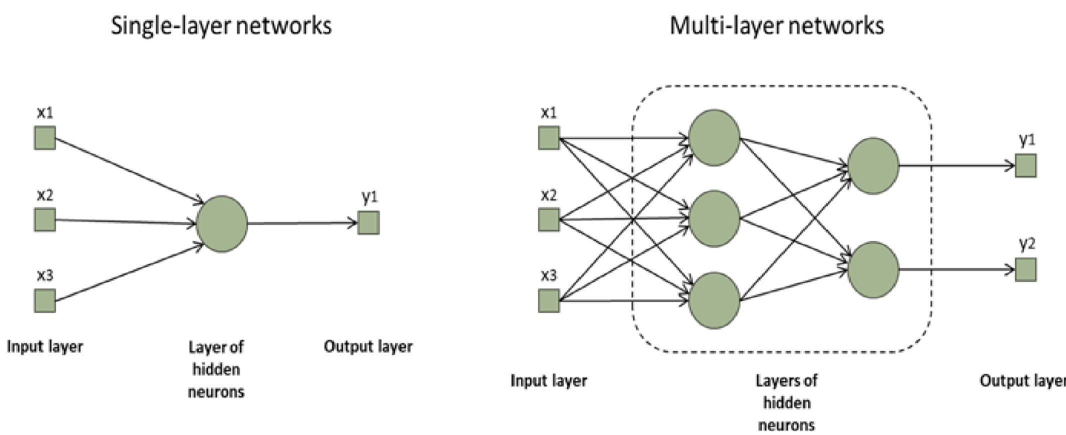

Fig. 2. Artificial neural networks: single-layer vs. multi-layer architectures

databases, and architectures. The study's contribution lies in providing relevant information that facilitates the design of more efficient models, thereby offering a solid foundation for future research.

The rest of the paper is structured as follows: Section 2 provides a general overview. Section 3 presents the related work.

Section 4 describes the methodology. Section 5 presents the main features of investigations on ECG classification using convolutional neural networks.

Section 6 discusses the results. Finally, Section 7 presents conclusions and suggests possible directions for future research.

2 Artificial Intelligence and Convolutional Neural Networks in ECG Analysis

Currently, artificial intelligence (AI) is applied in various fields and its impact on society is increasingly significant, transforming how we interact with technology. The diagram in Fig. 1 provides a clear view of how the different branches and techniques of AI contribute to the development of advanced solutions for specific tasks.

Artificial neural networks (ANN) are part of artificial intelligence. They can recognize patterns, process data, and can be trained. They are

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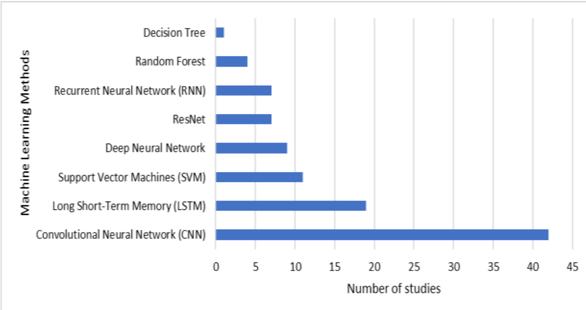

Fig. 3. Machine learning methods used in ECG analysis

composed of artificial neurons that simulate the essence of biological neurons. An ANN receives a set of inputs from various sources or from the output of previously connected neurons and produces an output that can be either the final result or considered as an input for another neuron [6].

To build an ANN, it is necessary to assemble a number of neurons organized into layers. ANNs can be classified based on the number of layers in their structure. An ANN with a single layer of input nodes directly connected to the output layer and operating in a feedforward configuration represents the simplest form of this type of network [6]. Multilayer networks, on the other hand, include one or more hidden layers between the input and output layers, allowing them to learn and represent more complex relationships in the data. Fig. 2 illustrates the structure of both single-layer and multilayer networks. ANN are primarily used in classification and regression tasks. The most common architectures include CNN and recurrent neural networks (RNN) [7].

CNN are a type of neural network designed to process data in matrix form, derived from images or temporal signals such as the ECG [7]. This type of network uses convolutional filters that learn features such as edges, textures, and shapes, making them useful for detecting complex patterns. However, to achieve precise classification, they require a large amount of properly labeled training data [8].

Machine learning techniques are widely used in current ECG signal analysis. Fig. 3 compares these techniques in the context of electrocardiogram signal analysis, highlighting that CNNs have been the dominant technique over the last five years.

3 Related Work

Several studies have examined the classification of cardiac arrhythmias using deep learning techniques; however, they differ in their approaches and depth of analysis. In [9], an extensive systematic review is presented, covering 368 studies on arrhythmia classification with deep learning methods. That work focuses on analyzing the databases used, as well as the most common preprocessing techniques, such as noise reduction and data augmentation for minority classes. However, it does not explore in detail the neural network architectures utilized. This is a critical aspect, considering that the selection of a specific architecture is closely related to the clinical objective and the computational resources available. Moreover, although CNNs are mentioned as widely used, their exclusive use is not examined, nor are hybrid architectures considered, which currently represent a growing trend by combining CNNs with more recent approaches.

The work presented in [10] provides an overview of deep learning approaches applied to ECG signal analysis. It highlights that convolutional neural networks (CNNs) are the most frequently employed and includes a section that groups studies using CNNs or their variants. However, the review does not present a comprehensive comparative analysis of the different architectures and offers only limited exploration of the preprocessing strategies used.

Similarly, the work presented in [11] provides an overview of deep learning architectures used for arrhythmia detection, classifying models such as CNN, Multilayer perceptron, RNN, and Transformers, and highlighting those that achieved performance levels above 96% in key metrics. Although the most frequently used databases are cited, aspects related to signal preprocessing receive little attention, and the most common types of arrhythmias considered in the studies are not clearly specified. Also, the review does not include a comparison between the different architectures analyzed.

In contrast, the present work focuses on providing a more detailed investigation into the use of convolutional neural networks, as they remain the most widely adopted models for arrhythmia classification. This survey examines not only the databases and preprocessing techniques used, but also the performance metrics reported and a comparative analysis of CNN architectures and their variations in recent literature. This perspective enables the identification of more efficient configurations and emerging trends in model design for the automated analysis of ECG signals.

4 Method

The methodology used in this systematic review follows a structured approach to identify, analyze and synthesize the relevant literature on the use of convolutional neural networks in the classification of cardiac arrhythmias. This process guarantees an objective evaluation of the available studies, allowing a more complete understanding of the approaches and results found in the scientific literature.

4.1 Study Description

In the study, various systems and methodologies using CNNs for arrhythmia classification were evaluated and compared. The most commonly used databases, the most frequent diagnoses, and the preprocessing techniques, including noise filtering, data balancing, and segmentation, were analyzed. In addition, the architectures of convolutional neural networks and the metrics employed to evaluate their performance were examined.

4.2 Research Questions

The main purpose of this systematic review is to answer the following research questions:

- RQ1. What are the most commonly used databases for training CNNs in arrhythmia classification?
- RQ2. What are the most frequent cardiac arrhythmia diagnoses considered in CNN-based classification models?
- RQ3. What preprocessing techniques are used to improve ECG signal quality and manage data quantity for CNN-based classification?
- RQ4. What are the main CNN architectures used for ECG-based arrhythmia classification?
- RQ5. What evaluation metrics are most frequently applied to evaluate the performance of CNN-based arrhythmia classification models?

4.3 Literature Search Strategy

A systematic search was conducted in academic databases including Mendeley, Springer, ScienceDirect, and ACM Digital Library using the keywords: "ECG analysis", "preprocessing techniques", "arrhythmia databases" and "convolutional neural networks". The results were limited to articles published from January 2020 to February 2025.

4.3.1 Inclusion and Exclusion Criteria

Studies that use artificial intelligence techniques, specifically CNNs, with data preprocessing applied to ECG signals and a clear description of the process were considered. Studies without preprocessing, without a description of databases, that do not consider ECG signals, or that do not report performance metrics were excluded.

4.4 Study Selection

The selection was done in three steps: in first step, duplicates were removed using the Mendeley reference manager; then, titles and abstracts were examined to assess their relevance; finally, a detailed analysis of the selected articles was conducted, leading to the selection of 21 studies analyzed in this paper.

4.5 Data Synthesis

Considering the variability in the selected literature, a narrative approach was adopted to synthesize the extracted data. The synthesis process was implemented as follows:

- Data extraction and tabulation: Key study elements such as publication year, method used, dataset, preprocessing techniques, and reported accuracy were extracted and organized in tables.

- Thematic grouping: Studies were categorized based on common characteristics, such as type of preprocessing, CNN architecture, or evaluation metric. This helped identify patterns and methodological similarities or differences.
- Comparative analysis: Studies were contrasted by identifying their strengths, limitations, and reported performance. Differences in preprocessing choices or dataset selection were considered when analyzing reported results.
- Frequency analysis: Quantitative trends were highlighted where possible (e.g., percentage of studies using MIT-BIH).
- Cross-referencing with RQs: All extracted information was mapped to the research questions to ensure that the synthesis directly contributed to answering each one.

5 ECG Classification Using CNN

5.1 Databases

Properly labeled databases by specialists ensure that CNNs can generalize to different heart rhythms. In the reviewed literature, the MIT-BIH database is the most commonly used in cardiac arrhythmia classification research [12,13], being present in 71.4% of the studies reviewed. On the other hand, the PTB database, as well as its extension, the PTB-XL database, along with its extended version, PTB-XL, which provides an even larger dataset with high-resolution recordings [14], was used in 19% of the studies.

Although most studies depend on standardized databases, some researchers seek to make their models more robust and generalizable by using additional datasets. This may be due to various reasons, such as the need to cover a wider array of cardiac conditions or to increase the amount of data available for training. In [15], the CPSC2018 database was used to train and evaluate a hybrid model. This database is notable for its breadth and diversity, and it contains records annotated by cardiology experts, allowing the model to be tested in more realistic clinical scenarios. Moreover, its complexity, originating from clinical challenges like signal noise and variability in ECGs across patients, improves the model's ability to handle real-world conditions.

5.2 Diagnoses Used

In most reviewed studies, heartbeat classification is based on the classes defined in the MIT-BIH database, this classification has become a standard for categorizing cardiac arrhythmias [16,17].

However, as shown in Table 1, there is an imbalance in the number of samples per category. Because of this, some studies have chosen to reduce the number of analyzed categories, focusing on those with greater representation or clinical relevance. In these cases, the most commonly used diagnoses include Normal beat (N), Left bundle-branch block beat (L), Right bundle-branch block beat (R), Premature Ventricular Contraction (V), and Paced beat (P) [18].

5.3 Data Preprocessing

Data preprocessing is essential to improve the quality of ECG signals and the model's performance. In [19], preprocessing techniques increased the model's accuracy by up to 12.96%, demonstrating its impact on arrhythmia classification. Among the most commonly used techniques are filtering, which helps to reduce noise in the signals caused by electrical and myoelectric interferences from the patient; segmentation, which defines the cycles of each heartbeat for better representation in the analysis; and data balancing, which mitigates the issue of imbalanced classes in the training sets.

5.3.1. Reduce Signal Noise

Filtering methods focus on reducing different types of noise. The most commonly used filters are band-pass filters, which help decrease noise effects and emphasize the relevant features of the ECG signal [20]. In six reviewed studies, band-pass filters are employed because they effectively reduce both

Table 1. Number of samples per beat type in the MIT-BIH database

Class	Number of samples
Normal (N)	75052
Left bundle branch block (L)	8075
Right bundle branch block (R)	7259
Atrial premature (A)	2546
Aberrated atrial premature (a)	150
Nodal premature beat (J)	83
Supraventricular premature or ectopic beat (S)	2
Premature ventricular contraction (V)	7130
Fusion of ventricular and normal (F)	803
Atrial escape (e)	16
Nodal escape (j)	229
Ventricular escape (E)	106
Paced (P)	7028
A fusion of paced and normal (f)	982
Unclassifiable (Q)	33

high- and low-frequency interferences without distorting the ECG signal.

In addition to conventional filters, wavelet transforms are widely used [21]. Within this technique, the Discrete Wavelet Transform (DWT) has proven to be an effective tool for noise reduction. In [22], it was used to integrate temporal, spatial, and frequency characteristics in signal analysis.

In [16], the DWT allowed the signal to be decomposed into low- and high-frequency coefficients. The low-frequency coefficients captured the overall structure of the signal, while the high-frequency coefficients highlighted significant details and edges. In [23], this approach was beneficial for reducing interferences such as power line noise and myoelectric interference, which can compromise the accuracy of arrhythmia diagnosis.

5.3.2. ECG Signal Segmentation

ECG signal segmentation is used to divide a signal into multiple ECG segments. One of the most widely used strategies is employing the R-peaks annotated in the MIT-BIH database, which facilitates accurate heartbeat segmentation. Six of the reviewed studies use this methodology, and the number of points taken before and after the R-peak varies by author. In [24], this method was applied by taking 50 points before and 100 points after the R-peak, ensuring that all relevant cardiac cycle information is captured.

However, segmentation parameters vary depending on the model's needs and the nature of the data. In [16], the segmentation interval was extended using 99 points before and 200 points after the R-peak, resulting in 300 sampling points per beat. This configuration corresponds to 0.83 seconds of signal, which aligns with the average duration of a normal adult heartbeat. This approach improves the extraction of specific features from each beat and reduces the impact of noise and interference, thereby enhancing the accuracy and interpretability of classification models.

On the other hand, automatic detection algorithms must be implemented in studies that use databases lacking R-peak locations. The Pan-Tompkins method was used in three reviewed studies to identify R-peaks in each ECG beat. Method has proven to be robust in R-peak detection as it combines signal filtering, differentiation, and integration, facilitating accurate segmentation [25].

5.3.3 Data Imbalance

Data imbalance is a common problem in cardiac arrhythmia classification because some heartbeat classes are disproportionated compared to others. This issue can affect model performance since neural networks tend to favor majority classes, reducing their ability to detect minority classes accurately. Various studies have applied data balancing techniques to improve generalization and fairness in classification.

For example, in the MIT-BIH database most records correspond to normal beats. One strategy to address this issue is SMOTE (Synthetic Minority Over-sampling Technique), which creates synthetic samples for minority classes by interpolating their nearest neighbors. Two studies used this technique to increase the number of samples in underrepresented classes and improve the model's ability to detect less frequent arrhythmias [16,18].

Another approach consists of duplicating samples to balance the data points per class. Three studies employed this technique. In [26], the initial dataset showed high imbalance between

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Table 2. Studies on ECG classification using convolutional neural networks

Author and year	Database	Method	Average Accuracy
Zheng et al. (2020) [33]	MIT-BIH arrhythmia database	CNN + LSTM	99.01%
Obeidat and Alqudah (2021) [29]	MIT-BIH arrhythmia database	CNN + LSTM	98.22%;
Wu et al. (2021) [26]	MIT-BIH arrhythmia database	CNN	97.41%
Wang, T. et al. (2021) [12]	MIT-BIH arrhythmia database	CNN	98.74%;
Islam et al. (2024) [20]	MIT-BIH arrhythmia database and St. Petersburg INCART 12-lead arrhythmia database	CNN + Attention mechanism + Transformer encoder	99.14%
Wang, J. et al. (2021) [34]	PTB-XL ECG dataset and MIT-BIH arrhythmia database	CNN + Attention mechanism	98.64%
Sadad, T. et al. (2023) [25]	ECG Images dataset of Cardiac Patients	Lightweight CNN + Attention mechanism	98.39%
Wang, J. (2020) [35]	MIT-BIH AF Database	CNN + Modified Elman neural network	97.4%
Abdullah, L. et al. (2020) [36]	MIT-BIH arrhythmia database	CNN + LSTM	98.66%
Farag., M. (2023) [37]	MIT-BIH arrhythmia database	Match filter-based CNN	98.18%
Zhang, J. et al. (2021) [24]	MIT-BIH arrhythmia database	Adversarial CNN	94.7%
Feyisa, D. et al. (2022) [38]	PTB-XL ECG dataset	Multireceptive field CNN	89.7
Ozaltin, O. and Yeniay, O. (2023) [21]	BIDMC Congestive Heart Failure Database, MIT-BIH arrhythmia database and MIT-BIH Normal Sinus Rhythm	CNN + Support Vector Machines (SVM)	99.21%
Śmigiel, S. et al. (2021) [27]	PTB-XL database	CNN	88.2%
Jiang et al. (2024) [16]	MIT-BIH Arrhythmia Database	CNN + Transformer	99.84%
Huang et al. (2023) [31]	MIT-BIH Arrhythmia Database	CNN + LSTM + Attention mechanism	98.95%
Chourasia et al. (2020) [17]	MIT-BIH Arrhythmia Database	CNN	97.36%
Sultan et al. (2025) [15]	CPSC2018 Datase	CNN+BiLSTM	90.67%
Bayani and Kargar (2024) [23]	PTB Diagnostic ECG and MIT- BIH Arrhythmia databases	Linear Deep CNN	99.31%
Shrivastava et al. (2023) [32]	Heart disease Cleveland UCI dataset	CNN+BiLSTM	96.66%
Karoui et.al (2024) [18]	MIT-BIH Arrhythmia Database	CNN+SVM	97.42%

categories. To correct this, records of the minority classes were randomly duplicated, ensuring that each category had equal representation.

5.4 Architectures of the studied CNNs

The performance of a CNN model for cardiac arrhythmia classification largely depends on its architecture. In [27], basic CNNs, without being combined with other types of networks or additional modules, show the lowest accuracy, with a value of 88.2%.

In [28], a CNN with 12 layers is presented to classify five subclasses of the dataset. This neural network includes an input layer, convolutional layers, pooling layers, and an output layer. In contrast, [26] proposes a CNN with a similar structure but with significant modifications, such as using average pooling layers instead of max pooling layers. This change preserves the overall features of the input data but increases the training time. Additionally, [26] presents an architecture that combines the convolutional layer, batch normalization, and the ReLU activation function into a single convolutional block.

In the architecture of [25], an attention module is incorporated. The model starts with four convolutional layers, and its distinctive component is the attention module, which is designed to optimize the features extracted by the CNN. This module focuses on the most informative parts of the ECG images, improving significantly the classification performance. The model achieved a classification accuracy of 98%.

According to the reviewed literature, one of the most common architectures for ECG signal classification is the combination of two approaches: CNNs and long short-term memory (LSTM) networks. For example, in [29], a hybrid model is presented where the CNN blocks extract and select deep features from the ECG beat. Meanwhile, the LSTM layer receives these features as time-dependent information and learns to extract temporal contextual information. This combination efficiently captures both local and temporal features. In [14], it is demonstrated that combined models lead to a substantial increase in the accuracy of cardiac arrhythmia classification.

More recently, Transformer-based models have emerged, showing great potential in ECG signal classification by capturing long-term relationships in the data. In [16], the fusion of manual features, such as RR intervals, with features learned by Transformer models was explored. This approach allows for a more complete representation of ECG signals.

In [30], an enhanced Transformer model is proposed that combines CNNs with multi-head attention modules. Additionally, the authors introduce a Dilated Stem module for multi-level feature extraction and an SC-RGA module that captures global information. This integration improves the model's ability to extract relevant features without significantly increasing computational complexity.

Table 2 summarizes recent studies that have employed different methods for arrhythmia classification.

5.5 Performance Evaluation Metrics

Evaluating classification models is essential to determine their effectiveness in identifying cardiac arrhythmias. Some metrics measure a model's ability to make correct predictions and minimize classification errors. Among the studies analyzed, accuracy is the only metric common to all the reviewed works. However, other complementary metrics are also employed.

Accuracy is the most widely used metric because it measures the percentage of correct predictions from the total number of samples evaluated. Although it provides an overall view of model performance, its interpretation can be misleading in imbalanced databases, where the presence of a majority class may skew the results [22, 31].

In [17,23], precision is used to evaluate how reliable the positive predictions are. This metric helps to reduce false positives and improves the model’s reliability in detecting specific conditions. In [31,32], recall measures the model’s ability to correctly identify positive cases, by calculating the proportion of true positives relative to the total number of actual positive cases.

The F1-score is one of the most used metrics because it combines precision and recall into a single harmonic metric, providing a balance between the two. Its use is common in scenarios with class imbalance, as in [17,18], since it allows for a more impartial evaluation of model performance.

Additionally, in [22,31], other metrics such as specificity are included. Specificity measures the model’s ability to correctly identify negative cases, thus reducing false positives.

6 Discussion

The analysis of the reviewed studies confirms that MIT-BIH continues to be the most widely used database for training CNN-based models, appearing in over 70% of the cases. This predominance can be attributed to its public availability, standardized annotation format, and historical use in ECG signal classification. However, it also highlights the current lack of freely available databases that offer a wide diversity of arrhythmias, accurate labeling, and sufficient data volume for training and evaluating deep learning models. While this standardization facilitates model performance comparison, it also limits generalizability as it contains a restricted range of cardiac conditions.

In contrast, some recent studies have explored alternative datasets [14,15] in an effort to improve model robustness by training CNNs on more complex and diverse ECG signals. These works reflect a growing recognition of the limitations associated with using a single-source dataset and emphasize the importance of simulating more realistic clinical scenarios.

Most models focus on classifying a reduced set of arrhythmias, typically limited to Normal, Left and Right Bundle Branch Block, and Premature Ventricular Contractions, as these are the most represented in the databases, particularly in MIT-BIH [16, 18]. Many studies exclude underrepresented classes to avoid poor model performance caused by class imbalance. This tendency reinforces the importance of applying balancing techniques.

Preprocessing improves the quality of ECG signals by reducing noise and interference, thereby increasing the accuracy in arrhythmia classification. However, it can be computationally intensive. Additionally, an incorrect preprocessing may remove relevant information, adversely affecting model performance. Band-pass filters remain the most widely used technique for reducing noise, as they do not require significant computational resources. More advanced techniques, such as the DWT, are effective but also more complex [20, 21, 22].

In segmentation, R-peak detection is the most common strategy; however, the parameters vary between studies, adapting to the characteristics of each model [16, 24].

In the databases, imbalance in the number of samples among arrhythmia classes can lead to biased models and low accuracy in detecting minority classes, as observed in [29]. This challenge is currently being addressed through SMOTE or sample duplication, depending on the imbalance between classes [18, 23].

The results showed that, in general, all models achieved high accuracy levels; however, findings in [33,36] suggest that adding an LSTM layer and/or an attention module to the convolutional architecture improves the model's ability to classify arrhythmias.

In [16,20], it was observed that when the implemented attention module is a Transformer, the model's performance improves significantly, with accuracy above 99%. This option, which is relatively recent in ECG signal classification, has proven highly effective in capturing long-range relationships in the data. However, Transformer-based models are considerably more complex, making them difficult to implement in environments with limited computational resources and restricting their applicability in portable devices or real-time monitoring systems.

In CNN architectures, choosing the number of layers requires careful consideration. Some architectures may be computationally expensive, making implementation challenging in devices with limited resources. On the other hand, a lightweight CNN architecture is suitable for Internet of Things (IoT) applications, as these networks can be integrated into portable monitoring systems and low-cost medical devices [25]. Therefore, it is crucial to adapt the network architecture according to its application.

The analyzed studies show that although accuracy is the most used metric for evaluating arrhythmia classification models, using accuracy alone can be insufficient in imbalanced datasets [22, 31]. To mitigate this problem, some studies have complemented their analysis with metrics such as precision, recall, and F1-score, allowing for a more balanced evaluation of model performance [17, 18, 23, 32].

Despite providing a comprehensive analysis of CNN-based models for arrhythmia classification, this study presents some limitations. Although well-defined inclusion and exclusion criteria were established, the possibility of selection limitations remains, as certain relevant studies might have been omitted based on the search strategy employed. In addition, variations in databases, evaluation metrics, model architectures, and class definitions across the reviewed studies make it difficult to establish consistent comparisons. Finally, most of the reviewed studies are based on the MIT-BIH database, which may limit the generalizability of the conclusions. Future research could mitigate these limitations by applying more extensive search strategies, implementing standardized evaluation protocols across studies, and prioritizing models tested on more diverse and clinically representative datasets.

7 Conclusions

The study highlights the importance of convolutional neural networks in classifying cardiac arrhythmias from ECG signals. Regarding the data used in the reviewed studies, the MIT-BIH database remains as the standard for arrhythmia classification. However, combining multiple databases is necessary to develop more robust models applicable to clinical scenarios.

Preprocessing remains a fundamental step for ensuring data quality. R-peak based segmentation is the most widely used method, while data imbalance is a recurring problem that affects the accuracy in detecting underrepresented classes.

It was found that combining CNNs with LSTM and attention modules significantly improves model performance. Moreover, the incorporation of Transformers has shown promising results in arrhythmia classification, although their computational complexity poses challenges for implementation in environments with limited resources.

About performance evaluation, accuracy was the most commonly used metric across all reviewed studies. However, additional metrics such as precision, recall, and F1-score are crucial in multiclass classification problems and when dealing with imbalanced datasets.

Future research should focus on standardizing databases parameters to improve study comparability and exploring new hybrid approaches that integrate optimized Transformer architectures for real-time monitoring devices. Additionally, recognizing cardiac beat subtypes represents an opportunity to develop more precise models that enable a more detailed and reliable automated diagnosis in clinical settings.

This study provides a foundation for developing more precise and generalizable models by analyzing current methodologies in arrhythmia classification and highlighting the most effective strategies in data preprocessing and CNN architectures. The findings serve as a guide for future research aimed at optimizing computational efficiency and enhancing the applicability of these models in clinical environments.

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**Corresponding author is Janet Flores Cruz.*