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Deep Learning Architectures for ECG Classification in Cardiac Arrhythmia Detection: A review

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Abstract
Cardiac arrhythmias, which can lead to stroke or heart failure, require early detection for effective treatment. This study evaluates deep learning models—CNNs, RNNs, and LSTMs—for ECG classification, with LSTMs achieving top accuracy: 97.3% (PTB), 93.11% (ECG-ID), and 96.81% (MIT-BIH). Hybrid CNN-LSTM models further improve performance on imbalanced data. These results highlight deep learning's potential, particularly LSTMs, in enhancing arrhythmia detection and supporting more accurate, automated diagnoses.

Keywords: Arrythmia detection; Deep learning models; ECG Classification

1.0 Introduction
Cardiovascular diseases rank among the leading causes of death globally [1]. In particular, cardiac arrhythmias are irregular heartbeats that lead to serious health complications, including stroke and heart failure. The electrocardiogram (ECG) is a non-invasive test that analyzes the electrical activity of the heart and is essential for identifying arrhythmias in both clinical and remote monitoring situations. Early detection and accurate classification of arrhythmias through ECG analysis are vital for effective treatment and patient care. However, Traditional ECG interpretation often falls short due to signal complexity and variability. Recent deep learning advancements have transformed automated analysis by enabling accurate arrhythmia detection through automatic feature extraction from raw ECG data, eliminating the need for manual engineering.

Despite these advancements, significant challenges persist in achieving high accuracy in ECG classification for arrhythmia detection. Variability in ECG morphology across individuals, noise artifacts from ambulatory monitoring systems, and imbalanced datasets pose substantial barriers. Additionally, developing computationally efficient models suitable for deployment in real-time scenarios, such as wearable devices, remains an ongoing research focus.

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The study aims to address the challenges in arrhythmia detection by employing advanced models, including Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Transformer-based architectures. The contributions of this research are the review and evaluation of deep learning models on diverse ECG datasets to identify the most effective architectures.

This paper is designed to be a narrative review and the rest of the paper is organized as follows: Section 2 reviews related work in automated arrhythmia detection and deep learning approaches. Section 3 details the methodology, including dataset preparation, architectural design, and experimental setup. Section 4 presents the results and performance analysis, followed by a discussion in Section 5. Finally, Section 6 concludes the paper and outlines potential directions for future research.

Nomenclature

ML	Machine Learning – A subset of AI that enables computers to learn patterns from data without explicit programming.
DL	Deep Learning- A specialized branch of ML that uses deep neural networks for automatic feature learning.
ECG	Electrocardiogram – A test that records the electrical activity of the heart.
CNN	Convolutional Neural Network – A deep learning model designed for image and signal processing.
RNN	Recurrent Neural Network – A deep learning model for sequential data analysis.
LSTM	Long Short-Term Memory – A type of RNN designed to capture long-term dependencies in sequences.

2.0 Background and related work

2.1 Cardiac Arrhythmia

Cardiac arrhythmia refers to an abnormal variation in heart rate caused by an irregular heartbeat that impairs blood flow [2]. In a normal heartbeat, the heart's electrical system ensures the regularity and timing of each beat. However, arrhythmia disrupts this rhythm, causing it to become abnormally fast, slow, or irregular [3]. Arrhythmias come in various forms, and each type can be identified by examining specific patterns in the ECG waveform. Table 1 shows the major types of arrhythmias. These arrhythmias can be detected and classified using ECG signals, which reflect the heart's electrical activity.

Table 1. Types of Arrhythmias

Types of Arrhythmias	Description	Types of Arrhythmias
Tachycardia	The heartbeats are beating too fast, with a rate over 100 beats per minute.	Tachycardia
Bradycardia	The heartbeats are beating slowly, commonly less than 60 beats per minute.	Bradycardia
Atrial Fibrillation (AFib)	The atria beat irregularly and too fast, which can lead to poor blood flow. It is a common type of arrhythmia.	Atrial Fibrillation (AFib)

(Source:) Xiao, Q et al (2023)

2.2 Traditional ECG analysis

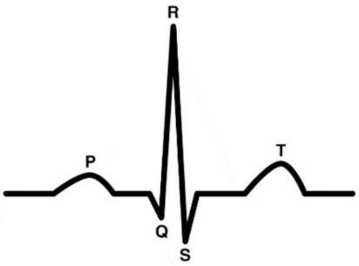

Fig. 1: ECG Waveform
(Source:) Isin et al (2017)

Table 2. ECG Waveform Key Component

Key Components	Description	Key Components
P Wave	It represents the electrical activity that leads to the contraction of the atria which is the upper chamber of the heart.	P Wave
QRS Complex	Depicts the electrical impulses responsible for contraction of the ventricles (the heart's lower chambers) which are vital for pumping blood through the body.	QRS Complex
T Wave	Shows the process of ventricular repolarization, where the ventricles recover T prepares for the next heartbeat.	T Wave

(Source:) Isin et al (2017)

2.3 Deep learning for ECG classification

Deep learning, a subset of artificial intelligence (AI), mimics how the human brain processes information using artificial neural networks with many layers. These models automatically learn from large datasets, identifying intricate patterns in ECG signals without manual feature extraction. The deeper the network, the more complex features it can recognize, improving its accuracy in tasks like ECG classification.

The emergence of deep learning has opened up new avenues for improving the accuracy and efficiency of ECG classification. Bizopoulos and Koutsouries offered a comprehensive summary of how deep learning is utilized in cardiology, highlighting the various methodologies and architectures employed in their systematic review. Unlike traditional machine learning techniques, deep learning models possess the ability to automatically learn from large datasets and identify complex, intricate patterns within ECG signals. This capability makes them particularly effective at detecting subtle irregularities in the heart's rhythm, which may indicate various types of arrhythmias that could otherwise be overlooked by conventional methods.

One of the key advantages of deep learning is its ability to automatically extract relevant features from raw ECG data, eliminating the need for manual intervention. This feature is critical in detecting subtle heart conditions and ensuring robust detection across diverse patient populations. Deep learning models also handle learning the variability in ECG signals, improving generalization and reducing misdiagnosis. Several deep learning architectures have been employed for ECG classification tasks, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory networks (LSTMs).

CNNs are a type of deep learning model particularly well-suited for analyzing spatial data, such as images or signals like ECG. CNNs use convolutional layers to automatically detect spatial features within the input data, making them highly effective in tasks that require understanding local dependencies. For instance, in the context of medical data like ECG signals, CNNs can identify patterns related to heartbeats by processing the data through multiple convolutional layers, each layer progressively capturing more complex features. This allows CNNs to excel in tasks like image recognition and signal classification [6][7].

RNNs are designed to process sequential data by maintaining a form of memory of previous inputs through internal states making RNNs particularly powerful in applications where the order of data points matters, such as time-series analysis or natural language processing. In medical applications, RNNs can analyze sequences of ECG signals over time, helping to detect anomalies or patterns associated with different types of arrhythmias. However, traditional RNNs can struggle with long-term dependencies due to issues like vanishing gradients [7].

As the last model, LSTM networks are a specialized type of Recurrent Neural Network (RNN) designed to process sequential data. LSTMs are specifically aimed at addressing the limitations of traditional RNNs. To overcome the limitations of standard RNNs, particularly in capturing long-term dependencies, LSTMs introduce mechanisms like gates that regulate the flow of information, allowing the network to maintain relevant information over longer sequences. This capability makes LSTMs especially effective in tasks where it is crucial to remember information over extended periods, such as predicting future events based on long sequences of past data [6][7].

Usually, a deep learning model goes through the same steps as a machine learning model. Three processing steps, including data understanding and preprocessing, deep learning model building and training, and validation and interpretation, make up a deep learning workflow to address real-world issues, according to Sarker I.H. (2021) [19] as shown in Figure 2. Nevertheless, feature extraction in the deep learning model is automated as opposed to manual, in contrast to machine learning modelling. Examples of machine learning techniques that are frequently employed in a variety of application areas include k-nearest neighbour, support vector machines, decision trees, random forests, naive Bayes, linear regression, association rules, and k-means clustering. Convolution neural networks, recurrent neural networks, autoencoders, deep belief networks, and many more are included in the deep learning model, talked about in brief with their possible areas of application.

Table 3. Key Properties and Dependencies of Deep Learning

Key Properties and Dependencies of DL	Description
Data Dependencies	Deep learning needs large datasets for good performance
Hardware Dependencies	Deep learning requires extensive computation for large datasets, making GPUs essential for efficient training.
Featuring Engineering Process	Feature engineering involves extracting attributes from raw data using domain knowledge.

(Source:) Sarker I.H (2021)

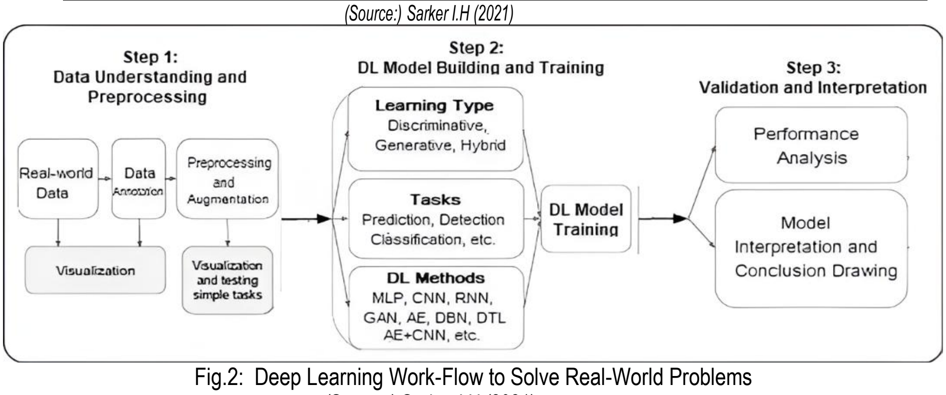

Fig.2: Deep Learning Work-Flow to Solve Real-World Problems
(Source:) Sarker I.H (2021)

As a result of its ability to process a large number of features and create an efficient data-driven model, deep learning modelling is essential when working with large amounts of data. In order to create and train DL models, it uses parallelised tensor and matrix operations, gradient computation, and optimisation [19].

In this study, the performance of CNNs, RNNs, and LSTMs in detecting arrhythmias is investigate. These models have shown potential in various time-series analysis tasks, but a comprehensive comparison in the context of ECG signals remains necessary. In this review, the hybrid models that combine the strengths of CNNs and RNNs/LSTMs to improve classification accuracy also will be explored.

3.0 Comparison of deep learning architectures for ECG classification

This study explores the benefits of hybrid models to improve the accuracy and reliability of arrhythmia detection, contributing to better cardiovascular care. Table 3 presents a detailed comparison of deep learning models for ECG classification.

CNNs have demonstrated exceptional capability in feature extraction for ECG arrhythmia classification by processing spatial data and capturing local patterns in ECG signals. Studies like Murat et al. (2020) reported an impressive accuracy of 99.26% using the MIT-BIH database, emphasizing the effectiveness of convolutional layers and pooling for dimensionality reduction. Similarly, Xu & Liu (2020) achieved accuracies ranging from 99.41% to 99.49% by incorporating dropout mechanisms to handeep learninge noise in ECG signals, while Avanzato & Beritelli (2020) highlighted real-time applications, achieving an average accuracy of 98.33% with cloud-based ECG monitoring systems.

RNNs, on the other hand, excel in analyzing sequential data and capturing long-term dependencies, making them highly suitable for ECG signals. For instance, Minic et al. (2023) utilized RNNs with particle swarm optimization (PSO) for hyperparameter tuning, achieving 91.87% accuracy and incorporating SHAP analysis to improve interpretability. LSTMs further address challenges like the vanishing gradient problem, effectively capturing temporal dependencies in ECG data. Jyotishi & Dandapat (2020) developed an LSTM model with accuracies between 91.65% and 97.3% across multiple datasets by focusing on intra- and inter-beat temporal features, while Toma & Choi (2022) incorporated LSTM layers in a hybrid model to achieve 99.58% accuracy, effectively managing imbalanced data challenges.

Comparative analysis showed LSTMs outperforming other models in ECG arrhythmia classification, achieving 97.3%, 93.11%, and 96.81% accuracy on the PTB, ECG-ID, and MIT-BIH datasets. Common evaluation metrics included Accuracy, Sensitivity, Specificity, Precision, F1 Score, and Cohen's Kappa. Hybrid models proved most effective, especially for imbalanced data and complex patterns, by leveraging the combined strengths of CNNs and RNNs/LSTMs.

Table 3. Comparison of Deep Learning Models

Year	Author And Tittle	Model	Dataset & collection method	Description	Evaluation Matric	Accuracy	Type Of Arrythmias
2023	Minic, A., Jovanovic, L., Bacanin, N., Stoean, C., Zivkovic, M., Spalevic, P., ... & Stoean, R. (2023). Applying recurrent neural networks for anomaly detection in electrocardiogram sensor data. Sensors, 23(24), 9878.	RNN	MIT-BIH database Collected via continuous ECG monitoring using sensors that record heart's electrical signals over time.	Uses RNNs for ECG anomaly detection, fine-tuned with a modified PSO algorithm. SHAP analysis highlights critical ECG features for better interpretability.	Accuracy Precision Recall F1 Score Cohen's Kappa	91.8695%,	The paper does not detail the specific types of arrhythmias detected
2020	Murat, F., Yildirim, O., Talo, M., Baloglu, U. B., Demir, Y., & Acharya, U. R. (2020). Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review. Computers in biology and medicine, 120, 103726.	CNN	MIT-BIH Arrhythmia Database, - The data gathered using ongoing monitoring. Sensors continuously captured the heart's electrical signals over time.	CNNs extract ECG features and reduce dimensionality, while optimized layers improve performance.	Accuracy Sensitivity (Recall) Specificity Precision F1-Score	99.26%	Normal Beats (N) Atrial Premature Beat (APB) Left Bundeep learninge Branch Block (LBBB) Right Bundle Branch Block (RBBB) Premature Ventricular

							Contraction (PVC)
2020	Murat, F., Yildirim, O., Talo, M., Baloglu, U. B., Demir, Y., & Acharya, U. R. (2020). Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review. Computers in biology and medicine, 120, 103726.	CNN-LSTM	MIT-BIH Arrhythmia Database, The data gathered using ongoing monitoring. Sensors continuously captured the heart's electrical signals over time.	Combines CNN's spatial feature extraction with LSTM's temporal analysis to improve ECG classification, particularly for detecting subtle patterns.	Accuracy. Sensitivity (Recall) Specificity Precision F1-Score	99.26%	Normal Beats (N) Atrial Premature Beat (APB) Left Bundle Branch Block (LBBB) Right Bundle Branch Block (RBBB) Premature Ventricular Contraction (PVC)
2020	Toma, T. I., & Choi, S. (2022). A parallel cross convolutional recurrent neural network for automatic imbalanced ECG arrhythmia detection with continuous wavelet transform. Sensors, 22(19), 7396.	CNN-RNN(LSTM)	MIT-BIH Arrhythmia Database Data was collected with annotated ECGs sampled at 360 Hz, using the MLII lead for analysis.	A 1D CNN with batch normalization and pooling layers achieves high accuracy and robustness for automatic heart disease detection.	Accuracy Positive Predictive Value (PPV) Sensitivity (SE) F1 Score (F1)	99.58%	Non-Ectopic Cardiac Beat (NB) Supraventricular Ectopic Beat (SVEB) Ventricular Ectopic Beat (VEB) Fusion Beat (FB) Unknown Beat (QB)
2020	Jyotishi, D., & Dandapat, S. (2020). An LSTM-based model for person identification using ECG signal. IEEE Sensors Letters, 4(8), 1-4.	LSTM	PTB Database -Includes 290 healthy and diseased subjects. Segmented ECGs MIT-BIH Arrhythmia Database -Data from 47 subjects with arrhythmias, segmented without fiducial points ECG-ID Database - From 90 healthy subjects, ECGs were segmented with sliding windows for intra/inter-session testing. CYBHi Database -Off-the-person ECGs from 63 subjects in remote settings. Sliding window segmentation	LSTM-based model for person identification using ECG, capturing intra-beat variations for better classification accuracy.	Accuracy	91.65	The paper does not explicitly detail the specific types of arrhythmias detected. However, it mentions the use of the MIT-BIH Arrhythmia Database,
2020	Avanzato, R., & Beritelli, F.	CNN	MIT-BIH Arrhythmia Database The data was collected through continuous ECG monitoring. Sensors recorded the heart's electrical signals over time.	A 1D CNN with batch normalization and pooling layers achieves high accuracy and robustness for automatic heart disease detection.	Accuracy Sensitivity (True Positive Rate) Specificity (True		Normal Atrial Premature Beat (APB) Premature Ventricular Contraction (PVC).

					Negative Rate) F1 Score False Positive Ratio False Negative Ratio		
2020	Xu, X., & Liu, H. (2020). ECG heartbeat classification using convolutional neural networks. IEEE access, 8, 8614-8619.	CNN	MIT-BIH Arrhythmia Database. Continuous ECG monitoring was used for data collection. It involved sensors tracking the heart's electrical activity over time.	CNN-based ECG classification model with noise filtering, stratified sampling, and dropout regularization to enhance generalization.	Accuracy Sensitivity Positive predictive value +FPTP	99.41%-99.49%	Non-Ectopic Beat (N) Supra Ventricular Ectopic Beat (SVEB, S) Ventricular Ectopic Beat (VEB, V) Fusion Beat (F) Unknown Beat (Q)

4.0 Discussion and future directions

Deep learning models have emerged as a transformative approach in the detection and classification of cardiac arrhythmias, leveraging their capability for automatic high-level feature extraction and robust classification. These models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), demonstrate substantial improvements over traditional machine learning methods in terms of accuracy, adaptability, and clinical utility.

4.1 Strengths of deep learning models

One of the most significant advantages of deep learning methods is their ability to extract relevant features directly from raw electrocardiogram (ECG) signals without requiring extensive domain-specific knowledge for feature engineering. For instance, CNNs have shown accuracies exceeding 95% for arrhythmias like Atrial Fibrillation (AF) and Ventricular Ectopic Beats (VEB), with small CNN architectures sometimes outperforming more complex models such as GoogLeNet, achieving over 91% accuracy. Additionally, RNNs excel in preserving temporal variations in ECG data, enabling the identification of both short-term and long-term dependencies, crucial for classifying arrhythmias like Supraventricular Ectopic Beats (SVEB) and Premature Atrial Contractions (PAC). The integration of Long Short-Term Memory (LSTM) networks further enhances performance by addressing vanishing gradient issues common in traditional RNNs [18].

Deep learning methods have also demonstrated versatility by accurately classifying a wide range of arrhythmias, including Myocardial Infarction (MI) and Premature Ventricular Contractions (PVC), across various datasets like the MIT-BIH Arrhythmia Database and INCART Database. These datasets provide a solid foundation for training and validating deep learning models, with evaluation metrics such as sensitivity, specificity, precision, and F1 scores ensuring comprehensive performance assessment.

4.2 Challenges and barriers

Despite their promise, several challenges hinder the full potential of deep learning in arrhythmia detection. The primary concern lies in the generalizability of these models. While high accuracies have been reported on specific datasets, their performance across diverse hospitals and patient populations remains inconsistent. This limitation highlights the need for larger, more diverse training datasets and domain adaptation techniques to bridge the gap between research and clinical applications.

Another critical challenge is the interpretability of deep learning models. Clinicians often require transparent and understandable decision-making processes to trust these systems fully. Current efforts to improve model interpretability, such as attention mechanisms and visualization of learned features, are promising but require further refinement.

Noise in ambulatory ECG signals presents an additional obstacle. Although deep learning models are adept at identifying hidden patterns in noisy data, the integration of advanced noise reduction techniques can further enhance their performance. Combining traditional signal processing methods with deep learning architectures offers a pathway to more reliable and noise-resilient arrhythmia detection systems.

4.3 Future directions

The integration of deep learning models with wearable devices and real-time monitoring systems holds significant potential for advancing ambulatory monitoring. RNNs, in particular, can process continuous data streams, while combining these models with electronic health records (EHRs) allows for a more comprehensive analysis of patient-specific risk factors, such as age, surgery history, and frequency of hospital visits.

Moreover, research into smaller, more efficient deep learning architectures can address computational constraints in real-time systems. Transfer learning and domain adaptation techniques should also be explored to ensure that models trained on specific datasets generalize effectively to broader clinical contexts. Finally, efforts to enhance dataset diversity, model interpretability, and noise reduction will further establish deep learning as a cornerstone in arrhythmia detection and management.

In conclusion, this narrative review highlights the potential of deep learning models—particularly CNNs, LSTMs, and Transformer-based architectures—in advancing arrhythmia detection. While these models offer high accuracy and flexibility, addressing challenges such as generalizability, interpretability, and noise resilience remains key for their clinical integration.

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