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Classification of ECG Arrhythmia using Deep Learning Techniques-Review

Anu H[1] and Rathnakara S[2]
[1]JSS Academy of Technical Education, Bangalore, Karnataka, India
Email: anuh@jssateb.ac.in
[2]Sri JCE, Mysuru, Karnataka, India
Email: rathnakara_s@sjce.ac.in

***Abstract*—Deep Learning (DL) has been suggested for the automated classification of heart abnormalities using ECG signals, although its practical applications in the medical field are limited. An extensive evaluation is presented focusing on the DL methodologies and the potential for DL-based ECG arrhythmia classification. The exploration of implementing DL-driven ECG classification involves the development of innovative DL models and further investigation into inter-patient models. Reviews rely on the MIT-BIH Arrhythmia Database for constructing DL models. Convolutional neural networks have been the predominant architecture utilized in recent research, incorporating various forms of DL. The assessment frameworks, specifically intra and inter-patient paradigms, are clearly addressed in the studies, revealing a significant gap in the inter-patient paradigm. Notably, the average F1 score in the studies reviewed is considerably lower. To enable the practical application of DL-based ECG classification in clinical settings, the exploration of diverse ECG databases, integration of novel DL frameworks, and deeper analysis of inter-patient models are potential avenues for future research.**

***Index Terms*— ECG, Arrhythmia, Deep learning, Convolution neural network (CNN), Long short-term Memory (LSTM), Optimizers.**

I. INTRODUCTION

Cardiovascular disease (CVD) is a chronic condition that presents a significant threat to human health. Electrocardiography, also known as ECG, is a non-invasive method utilized to record alterations in the bioelectric activity of the heart. Through the use of electrodes placed on the patient's skin, the electrocardiograph tracks the heart's rhythm and relaxation. Normal electrocardiogram patterns consist of various waves, including T waves, P waves, and QRS complexes. The numerical and morphological characteristics of these ECG signals serve as important indicators of cardiovascular issues. In the realm of contemporary medicine, cardiologists frequently conduct electrocardiograms on patients in order to identify heart conditions and deliver appropriate treatment, a process that demands extensive effort and specialized medical expertise. With the aging of populations, there is an expected surge in the number of patients with heart disease, underscoring the necessity for electrocardiogram diagnosis to be both effective and affordable. This study focuses on the classification of cardiac arrhythmias, a clinical approach to detecting CVD. Deep learning (DL) has exhibited remarkable success in diagnosis, particularly in recent years for identifying heart irregularities using electrocardiogram signals. By

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employing deep learning models with multiple layers of neural networks, ECG features are effectively mapped to corresponding treatment features. The training process enhances the capability of DL representations by optimizing neuron weights to minimize variance between incidental and actual data classes. When compared to traditional machine learning methods such as support vector machines (SVM) and clustering, deep learning-based ECG classification excels in categorizing ECG waves due to its efficient feature extraction and multi-level abstraction capacities.
In this context, the utilization of ECG waves in DL-based arrhythmia studies poses a distinctive challenge for cardiologists. Despite this, the categorization of arrhythmia groups from a DL perspective shares a common background and objective, emphasizing the significance of displaying ECG features for their respective groups. Thus, this study delves into existing research, challenges, and advancements in DL-centered arrhythmia classification. According to Mayo Clinic's clinical trial on artificial intelligence-enhanced electrocardiogram (AI-ECG) diagnosis, the effectiveness of AI-ECG in detecting various heart diseases has been demonstrated. However, it is acknowledged that the integration of AI for ECG analysis is still in its early stages. While the efficacy of deep learning in ECG categorization is well-established in the scientific community, its implementation in clinical settings is hindered by challenges such as competition with artificial intelligence and variability in ECG data. The development of a DL model that can accurately identify arrhythmias based on ECG waves in patients not involved in the training process is particularly complex, requiring a shift in the patient paradigm. This complexity is evident during both the training and inference phases of the DL model, leading to limitations in practical applications due to the inherent variability in ECG signals among individuals.

II. Methods and Materials

A. Investigate Strategy

This review of deep ECG arrhythmia research is centered on literature search across four major academic databases (Google Scholar, Scopus, PubMed, and Digitila Bibliography and Library Project), focusing on recent studies. Many studies did not explicitly specify classification tasks, and we first sought to include more studies and avoid studies that ignored arrhythmia classification.

B. Data Extraction

Data was also extracted from carefully chosen studies. This evaluation concentrates on various aspects such as overall evidence, ECG databases, DL methods, measurement methods, and performance metrics.

1. *ECG Database:* Review published reports, electrocardiogram databases, and public databases of popular electrocardiogram in formation utilized for arrhythmia categorization.
2. *DL Methodology*: Search for and type the selected study. Various DL models provide insight into optimization and arrhythmia classification.
3. *Evaluation Paradigm*: The data determined ECG analysis be able to categorized into inter and intra-patient paradigms dependent on in what way the testing and training ECG information from patients are systematized.
4. *Performance Metric*: The widely utilized performance metrics is overall accuracy and F1-score of the chosen studies.

III. Deep Learning Centered Methodology

DL representations play a crucial role in the process of categorizing ECG arrhythmias in a DL-centric pipeline. These representations consist of multi-layer or multi-level compositions, where each layer or level acts as a morphological feature extractor aimed at effectively capturing signal characteristics. Leveraging the foundational components of neural networks, the DL categorization representations identified in various studies can generally be classified into distinct categories such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), Bidirectional LSTM (BiLSTM), Long Short-Term Memory (LSTM), as well as "hybrid" models combining different DL architectures, transformers, and other less common representations like constrained Boltzmann machines and Deep-Belief Networks. A comprehensive examination of these DL representations for ECG arrhythmia classification is presented as follows:

CNN

CNN, or Convolutional Neural Network, is a widely utilized DL framework for tasks involving image classification, natural language processing, and signal analysis. In CNNs, each layer generally comprises a

Convolutional filter followed by pooling operations to extract both local and global features. CNNs can be categorized as 1D or 2D based on the spatial extent of the filtering operations.

1D CNNs are well-suited for processing raw or filtered ECG signals with a single feature dimension. Adaptive 1D CNN models have been proposed for organizing ECG data and detecting anomalies at varying sampling rates. Additionally, lightweight 1D CNN architectures have been developed, incorporating methodologies like channel shuffling and depth-wise convolutions, with input segments representing 2-second ECG signals.

On the other hand, 2D-CNNs are employed when the input data resembles an image, such as spectrograms or scalograms of ECG waveforms. One approach involves transforming 1D ECG signals into 2D scalograms using continuous wavelet transform. These resulting 2D scalograms are treated as 3-channel color images for classification tasks employing standard 2D-CNN architectures like AlexNet. Another strategy includes directly converting 1D ECG recordings into 2D gray-level images, which are then processed by a 2D-CNN model. Furthermore, multi-lead CNNs have been developed to handle matrix input of multi-lead ECG signals, utilizing sub-2D convolutions and asymmetric pooling to extract features at multiple scales.

When compared to 2D-CNNs, 1D-CNNs involve simpler operations and fewer trainable parameters, leading to faster computation. This characteristic makes 1D CNNs suitable for real-time ECG classification tasks and facilitates their deployment on various computing hardware.

RNN/LSTM/BiLSTM

Recurrent Neural Network (RNN), is a DL construction that considers the response as a time series, considering the temporal correlation of attribute sequences. ECG signals being time series in characteristics, their temporal relationship within the waves can provide valuable information about their categories. In distinctive RNNs, the information in the hidden layer at the existing moment depends not only on the current input but also on the information from previous time instances. This sensitivity to temporal features makes RNN beneficial in capturing hidden time-based data in ECG features. The long short-term memory (LSTM), an improved version of RNN, is more popular due to its enhanced capability in analysing time series. LSTM includes three gate structures that control the flow of output, forget information in stored memory cells and input. Compared to RNN, LSTM can handle longer signal sequences by selectively acquiring valuable data from historical involvements.

Inside ECG arrhythmia classification, 6-layer LSTM has been developed to automatically recognize PVC beats grounded on ECG classifications. Bidirectional LSTM (BiLSTM), a distinct type of LSTM, involves dual LSTMs that process the response sequence in both forward and backward temporal directions. This enables BiLSTM to capture both causal and noncausal time dependency information, potentially leading to improved classification performance. BiLSTM models have been utilized in ECG categorization grounded on obtained ECG wave statistics, such as RR intervals, QR intervals, ST segment initial point, and amplitudes of Q- and R-waves. Additionally, a 2D BiLSTM has been employed for AF detection using the spectrogram of ECG signals, where the input features are the frequency components at each time instance. Another approach uses a BiLSTM that takes the sequence of RR intervals as input for AF detection.

In summary, RNN models, such as LSTM and BiLSTM, can take various types of input orders for ECG investigation, including raw ECG orders, temporal statistics, and spatial representations. These models effectively leverage the temporal nature of ECG signals to improve classification performance.

Transformer

The attention mechanism has gained significant popularity in recent DL research due to its capability to allocate higher learning weights to noteworthy features. The transformer, initially designed for natural language processing (NLP), has gained attention as it involves of only attention mechanisms and completely connected layers, offering improved performance compared to RNN/LSTM models. Consequently, it has been extended to various applications, including ECG signal analysis.

In the context of ECG arrhythmia classification, the transformer's encoder part has been utilized. Heartbeat sequences are considered as input, while RR intervals are concatenated with the morphology extracted by the attention module for ultimate classification. Another approach involves using a Random Forest Model to choose 22 significant features from ECG signals, and at that time the transformer's encoder is applied to isolate features directly from the signals. The blend of hand-crafted features and features automatically extracted by the transformer is utilized for ECG categorization.

Moreover, a proposal has been made for a wave shape transformer, in which input ECG segments are expected to form a 1D vector through a multi-layer perceptron. Subsequently, the embedded segments, in addition to positional embedding and learnable class embedding, are introduced into the transformer encoder. The features derived from the transformer are combined with 22 static attributes for the final ECG classification.

The transformer's application to ECG signal analysis is still in its early stages post its inception in 2017, with more outcomes regarding its utilization anticipated in the future. Its capacity to exploit attention mechanisms for improved feature acquisition renders it a promising avenue for ECG classification.

Hybrid DL model

Several investigations have delved into the amalgamation of multiple DL models within a singular DL network for ECG arrhythmia categorization. For example, in [30], a blend of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) is deployed to establish an encoder-decoder framework for heartbeat classification. CNN is employed for feature extraction, while RNNs convert these features into respective categories. Further instances of integrating CNN with Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) are documented in [31-33], where CNNs are placed ahead of LSTM/BiLSTM modules for feature extraction. In [25], a 1D CNN is primarily used to extract features from ECG sequences. These CNN-derived features, accompanied by positional encoding, are then utilized as input for a transformer to identify ECG arrhythmia. In [34], a 1D CNN is utilized for local attention embedding, and the transformer's encoder is employed for additional feature extraction. In [35], shallow-domain knowledge-injection attention is initially applied to derive ECG signal features. The outputs of attention from the original and smoothed ECG data are subsequently treated as multivariate inputs for 2D classification CNN. More instances of combining CNNs with transformers can be witnessed in [36,37]. CNNs are also fused with attention mechanisms in [38-40]. Among the specified studies, 82 works integrate hybrid models, encompassing diverse types of DL models for ECG arrhythmia classification. The top three prevalent hybrid models include CNN+LSTM, CNN+BiLSTM, and CNN+RNN. In most hybrid configurations, CNNs typically serve as feature extractors, followed by other models that carry out supplementary feature extraction.

Classification Categories

ECG signals are commonly divided into five distinct classes in studies utilizing the MITDB ECG database, adhering to the AAMI standards. These categories include N (Normal beat), S (Supraventricular ectopic beat), V (Ventricular ectopic beat), F (Fusion beat), and Q (unknown beat). Some research evaluates the classification performance of the major categories N, S, V, and F within the ECG database while following the AAMI guidelines. Binary classification is often used to identify specific arrhythmia types like atrial fibrillation (AF) and left ventricular dysfunction. It is widely accepted that achieving accurate multi-class arrhythmia classification poses significant challenges.

Evaluation Paradigm

The assessment of DL models' generalization performance is crucial for determining their effectiveness. Performance overview indicates the ability of categorization models to correctly classify new and unseen data. In the realm of ECG categorization, two evaluation paradigms have been explored: intra-patient and inter-patient paradigms. The inter-patient paradigm involves training the DL model on one group of patients' ECG signals and then testing it on different patient groups. Conversely, the intra-patient paradigm entails training and testing the DL model on ECG signals from the same patient group.Some studies focus on the inter-patient paradigm, while others prioritize intra-patient diagnosis. A few studies delve into both paradigms, while some do not specify their chosen approach.

Table 1 presents detailed information on studies utilizing the inter-patient paradigm, including the ECG data used for training, validation, and testing, the DL algorithm employed, the classification category considered, and the corresponding classification performance. The MITDS1/DS2 method is commonly used for evaluation in the inter-patient paradigm, involving the division of MITDB ECG data into two groups, DS1 and DS2. Certain studies have modified this method for ECG analysis by including different recordings in DS1 and DS2. Additionally, some research explores training DL models with ECG data from one database and testing them on different ECG databases.

As the inspirations, responsibilities, datasets, and organization methods vary across the reviewed studies, it is difficult and unfair to directly compare their classification performance. Nonetheless, comparing the average performance metrics of the selected studies in the inter-patient paradigm, irrespective of the number of categories. The average Accuracy and F1 score are 92.62% and 79.48% respectively.

In Table 2, similar information is presented for 11 studies that investigate both the inter- and intra-patient paradigms. The average classification accuracy values in the intra- and inter-patient paradigms are 98.39% and 90.15% respectively. The difference in F1 score between the two paradigms is 11.63%, which is much higher than the difference in accuracy. This indicates that the inter-patient paradigm poses a more challenging scenario, demanding more research focus and effort.

TABLE I. THE SELECTED ARTICLES FOR STUDIES IN INTER-PATIENT PARADIGM

Paper	Train/Validate data /Test Data	Algorithm	Accuracy	F1 Score (%)
47	MITB DS1/MITDB DS2	DenseNet-BiLSTM	92.37	63.29
48	MITDB DS1/MITDB DS2	CNN	88.34	-
49	FANTASIA+ INCART	CNN-LSTM	95.76	95.57
50	MITDB DS1/MITDB DS2	O-WCNN	99.43	92.05
51	MITDB DS1/MITDB DS2	CNN+BLSTM	96.77	77.89
52	PTB-XL	CNN-FWS	90.05	90.2
53	PTB	MLA-CNN-BiGRU	62.94	-
54	MITDB DS1/MITDB DS2	CNN	96.36	-
56	MITDB DS1/MITDB DS2	CNN	90.22	-
57	MITDB DS1/MITDB DS2	CNN-LSTM	95.81	71.06
58	MITDB DS1/MITDB DS2	DRCNN	88.99	-
59	MITDB DS1/MITDB DS2	OptRPC	98.48	-
60	UVA Holter Recording / MITDB	CNN+RNN	-	75.5
61	MITDB DS1/MITDB DS2	CNN	-	98.90
62	MITDB DS1/MITDB DS2	Se-ResNet	99.61	-
63	MITDB DS1/MITDB DS2	RBM	98.61	-
64	MITDB DS1/MITDB DS2	FASTER R-CNN	95.68	-
65	MITDB DS1/MITDB DS2	CNN	94.70	88.9
66	MITDB DS1/MITDB DS2	FNN+CNN	94.2	-
67	MITDB DS1/MITDB DS2	CWT+CNN	98.74	68.76
68	MITDB DS1/MITDB DS2	WaveNet-LSTM	96.80	-
69	MITDB DS1/MITDB DS2	DHCAF	93.0	-
70	MITDB DS1/MITDB DS2	CraftNet	89.24	-
71	MITDB DS1/MITDB DS2	BiLSTM	97.3	-
7	MITDB DS1/MITDB DS2	CNN	92.3	-
72	MITDB DS1/MITDB DS2	CNNs	98.6	-
73	MITDB DS1/MITDB DS2	FE-CNN	98.6	88.0
74	MITDB DS1/MITDB DS2	RBM	95.20	-
75	MITDB DS1/MITDB DS2	DNN	97.5	-
30	MITDB DS1/MITDB DS2	BiLSTM	99.53	-
76	CPSC/MITDB	RBNN	78.58	-

TABLE II. COMPARATIVE SUMMARY TABLE OF INTER/INTRA-PATIENT PARADIGMS STUDIES

<table>
<tr><th>Paper</th><th>Paradigm</th><th>Train/Validate/Test Data</th><th>Algorithm</th><th>Accuracy</th><th>F1 Score</th></tr>
<tr><td rowspan="2">47</td><td>Intra</td><td>MITDB</td><td rowspan="2">DenseNet-BiLSTM</td><td>99.44</td><td>95.89</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>92.37</td><td>63.49</td></tr>
<tr><td rowspan="2">48</td><td>Intra</td><td>MITDB</td><td rowspan="2">CNN</td><td>99.48</td><td>-</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>88.34</td><td>-</td></tr>
<tr><td rowspan="2">49</td><td>Intra</td><td rowspan="2">Fantasis +INCART</td><td rowspan="2">CNN-LSTM</td><td>99.85</td><td>99.52</td></tr>
<tr><td>Inter</td><td>95.76</td><td>95.57</td></tr>
<tr><td rowspan="2">50</td><td>Intra</td><td>MITDB</td><td rowspan="2">O-WCNN</td><td>99.58</td><td>99.28</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>99.43</td><td>92.05</td></tr>
<tr><td rowspan="2">51</td><td>Intra</td><td>MITDB</td><td rowspan="2">CNN+BLSTM</td><td>99.56</td><td>96.40</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>96.77</td><td>77.84</td></tr>
<tr><td rowspan="2">52</td><td>Intra</td><td rowspan="2">PTB-XL</td><td rowspan="2">CNN-FWS</td><td>89.92</td><td>90.70</td></tr>
<tr><td>Inter</td><td>90.05</td><td>90.20</td></tr>
<tr><td rowspan="2">53</td><td>Intra</td><td rowspan="2">PTB</td><td rowspan="2">MLA- CNN-
BiGRU</td><td>99.11</td><td>-</td></tr>
<tr><td>Inter</td><td>62.94</td><td>-</td></tr>
<tr><td rowspan="2">54</td><td>Intra</td><td>MITDB</td><td rowspan="2">CNN</td><td>99.81</td><td>-</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>96.36</td><td>-</td></tr>
<tr><td rowspan="2">55</td><td>Intra</td><td>Tongji Hospital, Database
China</td><td rowspan="2">DCNN</td><td>-</td><td>91.3</td></tr>
<tr><td>Inter</td><td>Tongji Hospital, Database
China, CPSC 2018</td><td>-</td><td>84.2</td></tr>
<tr><td rowspan="2">56</td><td>Intra</td><td>MITDB</td><td rowspan="2">CNN</td><td>99.31</td><td>-</td></tr>
<tr><td>Inter</td><td>MITDB DS1 / MITDB DS2</td><td>90.22</td><td>-</td></tr>
</table>

IV. DISCUSSION

The summary of findings in the field of DL-based ECG arrhythmia classification is presented in this section, considering various perspectives including the ECG database, DL methodology, evaluation paradigm, and performance metric. Additionally, it addresses future challenges and potential research directions in this area.

ECG Database: The quality of data is crucial for achieving high classification performance in DL-based ECG arrhythmia classification [79]. DL techniques heavily rely on training data to learn the association between data features and corresponding categories. However, collecting ECG signals, which are measured private medical information, from a diverse variety of patients with dissimilar genders and ages can be challenging. Traditional facilities and important annotation exertion from cardiologists are required to ensure unified measurement conditions and precise annotation of ECG signal illustrations [4]. Therefore, publicly available ECG databases currently serve as the primary data resources for DL-based ECG arrhythmia classification and collaboration research progress.

Amongst the numerous ECG data-banks, the MIT-DataBase is the most popular databank for DL-centered arrhythmia classification, despite being collected around 40 years before [80]. It serves as a benchmark for comparing recently designed DL approaches with well-established models. As DL models become more complex in pursuit of higher classification presentation, they require larger amounts of ECG data for training. Consequently, there have been efforts to combine datasets from multiple public ECG databases [81,82]. However, it is important not to overlook the differences in the number of leads, signal interval, measurement conditions, and patient demographic scattering among these databases.

Another challenge with current arrhythmia-related ECG databases is the significant class imbalance. The normal category often dominates the quantity of ECG data in these databases [83]. While methods such as data augmentation and focal loss are used to address this imbalance, collecting more data in abnormal categories is the ideal solution. However, gathering specific data from patients with the exact diseases to be classified is often difficult in practice. Therefore, the imbalance of the ECG dataset is a long-term challenge that investigators should anticipate.

DL Methodology

CNNs (Convolutional Neural Networks) are widely recognized as the utmost popular DL models for ECG classification due to their strong feature extraction capabilities [85]. RNNs (Recurrent Neural Networks) are also frequently used given the sequential nature of ECG signals. The arrival of the attention mechanism has introduced transformer models into ECG classification. Moreover, hybrid DL models combining different structures are commonly employed in arrhythmia classification. Typically, CNNs function as feature extractors at the input layer, followed by the utilization of RNNs and transformers to refine features. Results indicate that in most cases, hybrid models achieve better classification performance at the expense of higher computational complexity [86,49,87–90]. However, the incorporation of novel DL models or structures for ECG classification remains limited, with potential opportunities arising from models like ViT and MLPMixer [91,92].

While the focus of most reviewed works lies in maximizing classification performance, the interpretability of DL models is generally overlooked. The integration of interpretable DL models is extremely necessary in real clinical scenarios, enabling trust in ECG classification results and aiding cardiologists in understanding hidden features of ECG signals [93].

Most reviewed studies adopt DL models within the supervised learning framework. Exploring the application of DL models in other artificial intelligence frameworks, such as active learning and reinforcement learning, represents a potential future research direction for improving the accuracy of ECG diagnosis [94,95]. Additionally, systematically optimizing DL model structures (e.g., kernel size) and hyperparameters (e.g., minibatch size, learning rate) is crucial for ECG classification.

The number of categories considered in the reviewed studies varies from 2 to 9, posing challenges as the number of categories increases. Learning the mapping for arrhythmia classification becomes more difficult [46]. MITDB, for example, encompasses a total of 26 categories, but some categories have limited ECG data. To achieve accurate classification performance with a higher number of categories, addressing challenges such as complex mapping relationships and data scarcity in minority categories requires dedicated research efforts.

Evaluation Paradigm

ECG classification can be divided into two paradigms, namely the inter-patient and intra-patient paradigms, depending on how the training and testing datasets are organized [96]. While earlier studies primarily focus on the intra-patient paradigm, more recent works explore the inter-patient paradigm due to its relevance in clinical applications [51]. However, in the inter-patient paradigm, it is observed that the values of Accuracy (Acc) and Specificity (Spe) are more than 10% higher than the F1 score. Comparing the classification performance of the same models in both paradigms from existing works reveals that the F1 scores achieved in the inter-patient paradigm are approximately 15% lower than those achieved in the intra-patient paradigm. Consequent

Consequently, further research is needed to bridge the performance gaps between the inter- and intra-patient paradigms, which presents opportunities for future investigation.

Performance Metrics

A diverse range of performance metrics is employed for comparison in the selected studies. The most frequently used metrics include overall Accuracy and F1 score. Generally, the classification accuracy of the proposed DL models in the majority of the studies reviewed surpasses 95%. However, the F1 score tends to be relatively lower, usually ranging between 80% and 95%. This emphasizes the need for further research efforts in improving F1 score performance.

V. CONCLUSIONS

DL techniques have been widely studied in the context of arrhythmia diagnosis utilizing ECG signals, showcasing their potential for medical applications. However, this survey highlights the need for further research in several key aspects of the DL pipeline to ensure reliable application in medical ECG arrhythmia classification. Specifically, forthcoming research directions and chances include leveraging varied ECG databases for training and testing, evolving novel integrated DL models, and conducting deeper investigations in the inter-patient paradigm. These efforts aim to enhance the trustworthiness of DL-based arrhythmia classification and promote its practical implementation in real medical scenarios. Special acknowledgment goes to the authors [97] for their valuable contribution to research in this field.

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