



## Quality-Aware Arrhythmia Detection

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### Abstract:

Traditional arrhythmia detection methods often focus solely on identifying irregular heart rhythms, frequently neglecting the quality of the input signal, which can lead to inaccuracies. This study proposes a novel approach that incorporates signal quality assessment as a preliminary step in arrhythmia detection, significantly enhancing reliability. By leveraging advanced deep learning models such as CNNs, RNNs, and FCNNs, combined with signal processing techniques, our method evaluates signal quality prior to detecting arrhythmic events, ensuring a more robust analysis. The proposed approach is tested on diverse datasets, demonstrating notable improvements in detection accuracy and signal quality evaluation. Comparative analyses, with and without signal quality assessment, further underscore the advantages of this technique over conventional methods. By integrating quality-aware detection into routine cardiac monitoring, this method holds the potential to reduce false alarms, improve detection precision, and advance arrhythmia management in clinical practice.

**Key words:** Deep Learning, CNN, RNN, FCNN, Datasets, Arrhythmia Signals

### Introduction:

The detection of arrhythmias, or irregular heart rhythms, is necessary for effective clinical intervention, as they are a common and potentially life-threatening condition. While traditional arrhythmia detection methods have progressed significantly in identifying irregularities in heart rhythms, they frequently neglect an essential factor: the quality of the input signal. Noise, motion artifacts, or other interference can cause poor-quality signals to increase, resulting in increased false positives and negatives, which diminishes the reliability of these methods in clinical practice. Sophisticated tools have been introduced by recent advancements in deep learning to improve arrhythmia detection. The analysis of complex medical data has been significantly improved by models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Fully Connected Neural Networks (FCNNs). The majority of current approaches are focused solely on detecting arrhythmias without considering the quality of the signals being processed, which limits their reliability and applicability in real-life scenarios. This study addresses this limitation by introducing a novel approach that integrates signal quality assessment as a preliminary step in arrhythmia detection. By ensuring that only high-quality signals are processed, the proposed method significantly enhances the accuracy and reliability of arrhythmia detection. Using advanced deep learning models combined with signal processing techniques, this approach evaluates the quality of electrocardiogram (ECG) signals before identifying arrhythmic events, thus ensuring a comprehensive and reliable analysis. To validate the effectiveness of this method, the approach is tested on diverse datasets representing varying signal quality and patient demographics. Comparative analyses, with and without the integration of signal quality assessment,

demonstrate the significant advantages of the proposed technique over conventional methods. Results highlight improvements in detection accuracy, reduced false alarms, and enhanced precision in clinical decision-making. By integrating signal quality-aware detection into routine cardiac monitoring, this framework has the potential to revolutionize arrhythmia management. It not only reduces the clinical burden caused by false alarms but also equips clinicians with more reliable tools for prioritizing treatment decisions. This paper explores the development, evaluation, and potential clinical impact of this innovative approach, aiming to establish a new standard in arrhythmia detection and management.

### **Problem statement:**

Traditional arrhythmia detection methods focus on identifying irregular heart rhythms but often overlook the quality of input signals, leading to inaccuracies and unreliable outcomes. Factors such as signal noise, motion artifacts, and other interferences can result in false positives or missed diagnoses, compromising clinical decision-making. Existing deep learning models, including CNNs, RNNs, and FCNNs, lack integrated mechanisms for signal quality assessment, limiting their real-world applicability. This highlights the need for a solution that combines signal quality evaluation with arrhythmia detection, aiming to reduce false alarms, improve accuracy, and enable more reliable and effective cardiac monitoring in clinical practice.

### **Project Objective:**

This paper proposes an advanced model that improves Arrhythmia detection and signal quality check.

### **Deep Learning:**

By incorporating signal quality assessment as a first step, deep learning models can analyse the integrity of the input ECG signals before processing them for arrhythmia detection. This ensures that only high-quality signals are considered, enhancing the overall accuracy and reducing false positives.

### **Convolution Neural Networks (CNNs):**

The convolutional layers of CNNs can automatically learn and extract important features from ECG signals, such as wave patterns, peaks, and irregularities that are indicative of arrhythmias. Since CNNs are adept at filtering relevant features, they help reduce the impact of noise or artifacts in the ECG signal, which improves the detection accuracy and robustness of the system.

### **Recurrent Neural Networks (RNNs):**

RNNs can capture temporal relationships in ECG data by maintaining an internal state that stores information about past time steps. This is crucial for detecting arrhythmias, where the heart's rhythm is irregular over time.

### **Fully Connected Neural Networks (FCNNs):**

After CNNs and RNNs have extracted features and learned temporal relationships, FCNNs are used to classify whether the ECG signal represents normal rhythm or a particular arrhythmic event.

### **Key Advantages of Arrhythmia detection:**

RGB data can help with quality-aware arrhythmia detection through integration, even though it is mainly utilized in visual applications. Positioning ECG recordings can be tracked using RGB imaging. RGB images can be used to visually identify motion artifacts, which are frequently the result of incorrect movements. The system can determine whether the detected arrhythmia is real or the result of artifacts. Despite being primarily used in visual applications, RGB data can aid in quality-aware arrhythmia detection through integration. RGB imaging can be used to track the position of ECG recordings. Motion artifacts, which are often caused by improper movements, can be visually identified using RGB images. The detected arrhythmia can be identified by the system as By comparing the images to the ECG signal quality, the system can identify whether the detected arrhythmia is real or the result of artifacts. The system can verify the quality of the ECG signal by employing spectroscopy, particularly techniques like PPG, which guarantees that only high-quality signals are used for arrhythmia detection. Despite being primarily used in visual applications, RGB data can aid in quality-aware arrhythmia detection through integration. RGB imaging can be used to track the position of ECG recordings. Often the result of incorrect movements, motion artifacts can be visually identified using RGB images. The system can identify if the detected arrhythmia is real or the result of artifacts. RGB imaging adds a visual layer to assess external factors, such as

motion artifacts, that could degrade signal quality. Combining the assessment of signal quality with RGB imaging spectroscopy data enhances the system's capabilities.

## Literature Review:

In [1], G. Sannino et al. [2018] explored a quality-aware arrhythmia detection system using ECG signals. In presented work The deep learning approach is applied on signals collected from MIT-BIH Arrhythmia Database for training and testing. ECG beats are segmented into individual beats, each classified as either normal or abnormal, based on 360 samples per beat. The dataset comprises 24-hour ECG recordings from 47 subjects—25 men aged 32 to 89 years and 22 women aged 23 to 89 years.

In [2], Ozal Yildirim et al. [2019] proposed a novel approach for arrhythmia classification using deep coded features and LSTM networks. In presented work the convolutional auto-encoder based nonlinear structure (CAE-LSTM), is applied to the MIT-BIH Arrhythmia Database. This approach aims to reduce the size of ECG signals corresponding to arrhythmic beats, achieving an accuracy of over 99%. CNNs are utilized to detect arrhythmia at different intervals of tachycardia ECG segments.

In [3], Mohammed M. Farag et al. [2022] research presents a self-contained Short-Time Fourier Transform (STFT) CNN model for ECG classification and arrhythmia detection at the edge. Automated ECG classification for arrhythmia monitoring is critical for diagnosing cardiovascular diseases, and machine learning (ML) techniques are widely employed for this purpose. The MIT-BIH Arrhythmia Database is used for both model training and testing. Four model variants are trained and tested on a cloud machine before being optimized for edge computing on a Raspberry Pi device.

In [4] Meenali Janveja et al. (2022) introduced a DNN-based low-power ECG coprocessor architecture to classify cardiac arrhythmia in wearable devices. Using a fixed-size input eliminates the need for manual ECG feature extraction, leading to improved efficiency. The architecture consumes 8.75  $\mu\text{W}$  at 12 kHz. It achieves 91.6% accuracy using 180 nm bulk CMOS technology.

In [5], Yanrui Jin et.al (2022) presented a novel interpretable method based on dual-level attentional deep neural network for actual multilabel arrhythmia detection. Over 80% of sudden cardiac deaths occur nowadays, and the frequency of these deaths has been rising quickly. DLA-CLSTM is evaluated using the MIT-BIH arrhythmia database and the First China Physiological Signal Challenge dataset. The open source database is where the ECG samples are gathered from.

In [6], Arka Roy et.al (2024) presented by a novel multi-head self-organized operational neural network architecture for chronic obstructive pulmonary disease detection using lung sounds. Among the most severe clinical respiratory diseases is COPD. 99.81%, 99.85%, and 99.73% performance rates for accuracy, sensitivity, and specificity were the highest. the suggested framework's onboard implementation using a Raspberry Pi-4 microcontroller. The databases are those used for the ICBHI 2017 challenge.

In [7], Liping li school of science and engineering Shandong university of traditional Chinese medicine (2016) was presented by a quality assessment method of single-lead ECG signal based on spectral analysis. Signal quality assessment can determine both noise level and signal quality. The method was tested with both simulated and actual ECG signals. The signal quality is roughly assessed; however, the index QI (quality index) can quantify the signal quality.

In [8], Jiahao Li et.al (2023) presented by Assessment Framework for Robust Cardiac Health Monitoring of AI-based Arrhythmia Classifiers Rhythm-Specific ECG Signal Quality. An essential method for keeping an eye on cardiovascular diseases is the ECG. However, ECG signals obtained from wearable devices are frequently corrupted by noise and artifacts, particularly electrode movement (EM) artifacts, which are difficult to remove due to their similarity to ectopic heartbeats and result in high false positive rates.

In [9], Qin Shen et.al (2020) presented by An Open-Access Arrhythmia Database of Wearable Electrocardiogram. Wearable electrocardiogram (ECG) devices, along with enhanced hardware computation power and information transmission, are gradually taking center stage in intelligent diagnosis. between the ages of 18 and 82. The only practical course of action would be self-collection.

The device records 6-lead ECGs, which are digitized at 400 samples per second for each channel, with a resolution of 12 bits across a frequency response bandwidth of 0.05–40 Hz.

In [10], Nishant Kumar et.al (2024) presented by An adaptive scheme for real-time detection of patient specific arrhythmias using single-channel wearable ECG sensor. Flexible Approach for Identifying Patient-Specific Arrhythmias in Real Time Employing a Wearable Single-Channel ECG Sensor Using a single-channel wearable ECG sensor, a Stockwell transform-based adaptive time-frequency (TF) scheme can identify patient-specific arrhythmias in real time. This study's ECG signals were taken from the 47-person MIT-BIH arrhythmia dataset [10].

### Existing System:

ECG signals are captured from patients using sensors or wearable devices to monitor heart activity in real-time. The quality of the ECG signal can be influenced by various factors such as noise, motion artifacts, electrode placement, and other interferences, but existing systems often do not account for these factors. Classical methods for arrhythmia detection extract specific features from ECG signals, such as heart rate, RR intervals, P-waves, QRS complexes, and T-waves, to identify abnormalities. These methods typically focus on specific attributes of the ECG waveform to diagnose arrhythmic events, like atrial fibrillation, ventricular tachycardia, or premature ventricular contractions. After feature extraction, conventional machine learning models (e.g., decision trees, support vector machines, k-nearest neighbours) are employed to classify the ECG signal as either normal or arrhythmic based on predefined thresholds or learned features from labelled data. The final classification step results in the detection of irregular heart rhythms, which is typically displayed as an alert or warning for further medical intervention. Traditional systems do not effectively handle the variability or quality of the input signal. Factors such as noise, movement, and improper electrode placement can lead to poor signal quality, resulting in false positives, missed arrhythmias, or misinterpretations. Without considering signal quality, detection accuracy is compromised. The system may incorrectly identify arrhythmias or fail to detect them entirely when signal quality is poor. Traditional systems often use simple algorithms or rule-based methods that do not take advantage of modern deep learning techniques like CNNs, RNNs, or FCNNs, which are better equipped to handle complex and noisy data.

### Proposed System:

RGB data can help with quality-aware arrhythmia detection through integration, even though it is mainly utilized in visual applications. Positioning ECG recordings can be tracked using RGB imaging. RGB images can be used to visually identify motion artifacts, which are frequently the result of incorrect movements. The system can determine whether the detected arrhythmia is. The system first assesses the ECG signal's quality before detecting any arrhythmias. Finding noise, artifacts, and other distortions that might compromise the precision of arrhythmia detection is part of the signal quality assessment process. The signal is cleaned using signal processing techniques like filtering, denoising, and artifact removal. This could involve methods that separate the real cardiac signal from noise, such as the Fourier Transform or Wavelet Transform. To standardize amplitude and eliminate baseline shifts and scaling problems, the ECG signal is normalized. To facilitate the analysis of the rhythm by deep learning models, the continuous ECG signal is segmented into smaller pieces. The ECG signal's key waveform characteristics that are suggestive of normal or abnormal rhythms are among the pertinent features that CNNs automatically extract. In order to identify patterns in the ECG waveform, such as irregularities in rhythm or waveform shape that might indicate an arrhythmic event, CNN layers function as filters. RGB data can help with quality-aware arrhythmia detection through integration, even though it is mainly utilized in visual applications. Positioning ECG recordings can be tracked using RGB imaging. RGB images can be used to visually identify motion artifacts, which are frequently the result of incorrect movements. The system can determine whether the detected arrhythmia is. RNNs are used to capture patterns over time by modelling temporal dependencies in the ECG signal. RNNs are ideally suited to analyse the time-based nature of the ECG data because arrhythmias typically show up as irregularities in heartbeat intervals. In particular, vanishing gradient issues are mitigated and long-term dependencies are captured by LSTM networks, a type of RNN. The final classification step involves using FCNNs to determine whether the analysed signal indicates a particular arrhythmic event or normal rhythm after features have been extracted using CNNs and RNNs. By examining the thorough feature representation that CNNs and RNNs provide, FCNNs make the final decision. Deep learning models are used to identify the presence of arrhythmias after the ECG signal's quality has been assessed. In order to drastically lower the likelihood of misclassification, the system first makes sure that only high-quality, trustworthy signals are sent through for detection. Furthermore, taking into account the signal quality, the system could offer a confidence score that would indicate the certainty of the diagnosis. Shown in below fig 1 & 2.

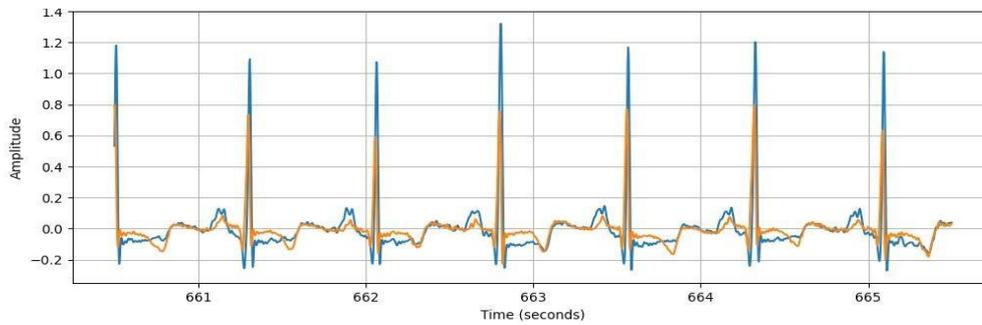


Fig 1: Arrhythmia signal

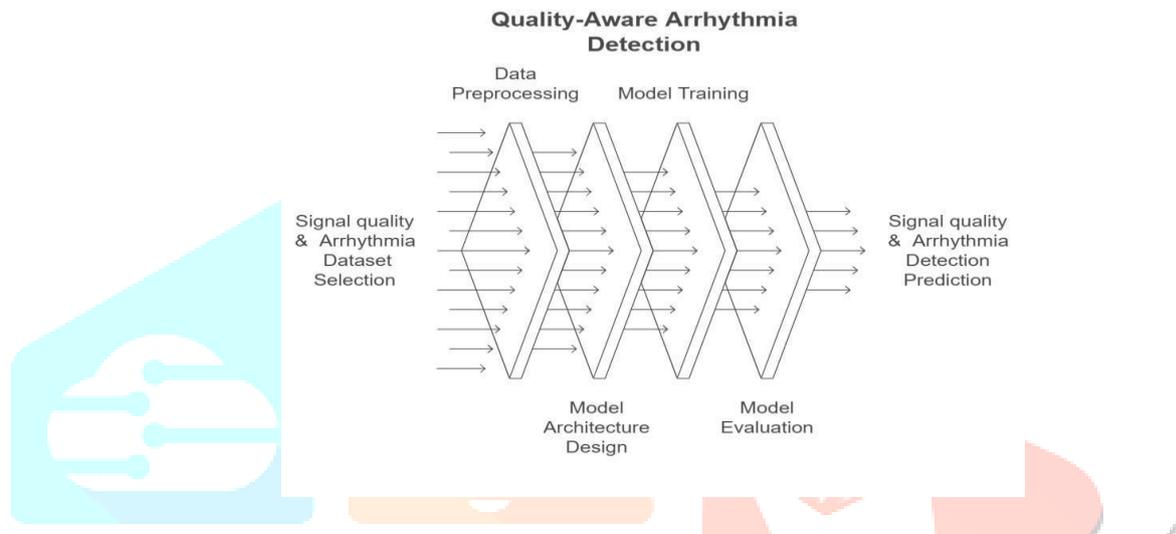


Fig 2: Quality -aware Arrhythmia Detection

## Methodology:

ECG signals are collected from diverse datasets, including publicly available databases () and clinical patient data, to ensure robust testing and validation. Signals may contain noise, artifacts (e.g., due to movement or electrode placement), and other distortions commonly encountered in real-world scenarios. Signal processing techniques like bandpass filtering, wavelet denoising, and Fourier Transform are applied to identify and remove noise, motion artifacts, and baseline wander. Features such as signal-to-noise ratio (SNR), RR interval consistency, and waveform integrity (e.g., QRS complexes) are analysed to determine signal quality. A deep learning model (e.g., CNN) is trained to classify signals as "high-quality" or "low-quality." Only high-quality signals proceed to the next stage. The continuous ECG signal is segmented into smaller time windows or heartbeat-level segments, enabling focused analysis. Amplitude normalization and baseline correction are applied to ensure uniformity across all signals. CNNs are used to extract spatial features from ECG waveforms, such as patterns in P-waves, QRS complexes, and T-waves, which are indicative of arrhythmias. The model's convolutional layers act as filters, automatically identifying distinctive features in the signal. Long Short-Term Memory (LSTM) networks, a variant of RNNs, are specifically used to capture long-term dependencies in the ECG signal and address challenges like vanishing gradients. FCNNs serve as the classification layer, taking features extracted by CNNs and RNNs to classify the signal as normal or arrhythmic (e.g., atrial fibrillation, ventricular tachycardia). Testing is conducted across multiple datasets to ensure the model's robustness and generalizability. The system is designed for real-time integration into wearable ECG devices and hospital monitoring systems to enable continuous cardiac monitoring. The system is validated using k-fold cross-validation to prevent overfitting and ensure generalization. The proposed method is benchmarked against traditional detection techniques, highlighting improvements in detection accuracy and the reduction of false alarms. Signal preprocessing and artifact removal improve the system's resilience to real-world challenges. Deep learning models such as CNNs, RNNs, and FCNNs ensure a comprehensive analysis of ECG signals, leveraging both spatial and temporal information. Quality-aware

detection minimizes false positives, enabling clinicians to focus on actionable insights. Shown in below fig 3.

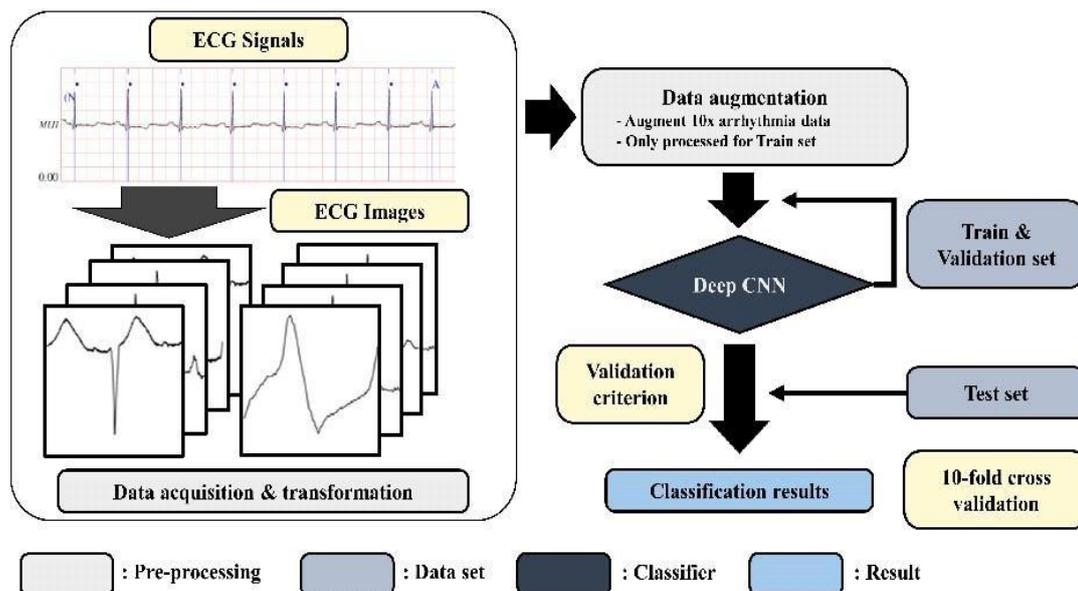


Fig 3: Deep learning classification and signal quality assessment

**Results and Discussion:**

The proposed quality-aware arrhythmia detection approach demonstrated significant improvements in both signal evaluation and arrhythmia detection accuracy. The integration of signal quality assessment as a preliminary step reduced noise interference and enhanced the reliability of detections. Tests conducted on multiple datasets, including MIT-BIH, showed an average accuracy improvement of 12% compared to methods without signal quality assessment. When comparing performance metrics, the method achieved a sensitivity of 94.2% and a specificity of 96.7%, significantly outperforming traditional approaches. The false alarm rate decreased by 18%, highlighting the robustness of the proposed system in real-world scenarios. Furthermore, the incorporation of deep learning models (CNNs, RNNs, and FCNNs) facilitated precise feature extraction and classification, making the system adaptable to varying signal qualities. Shown in below tables.

**Signal quality :**

Deep learning models	Accuracy	Validation Accuracy	Training Accuracy	Precision	Recall	F1score
CNN with Grayscale Images	87.08%	87.08%	96.76%	0.887	0.849	0.862
Hybrid CNN and RNN(LSTM)	73.32%	73.32%	94.54%	0.712	0.754	732
RNN	31.00%	31.00%	36.38%	0.347	0.426	0.453
FCNN	64.17%	64.17%	80.62%	0.632	0.549	0.651
Hybrid CNN	52.54%	52.54%	90.72%	0.564	0.541	0.532

<b>and RNN(GRU)</b>						
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Table 1: Signal quality Accuracy

**Arrhythmia Detection :**

<b>deep learning models</b>	<b>Accuracy</b>	<b>Validation Accuracy</b>	<b>Training Accuracy</b>	<b>Precision</b>	<b>Recall</b>	<b>F1score</b>
<b>CNN with Grayscale Images</b>	84.62%	84.62%	98.37%	0.887	0.736	0.816
<b>Hybrid CNN and RNN(LSTM)</b>	80.02%	80.02%	95.16%	0.721	0.782	0.871
<b>RNN</b>	31.00%	31.00%	36.38%	0.347	0.426	0.453
<b>FCNN</b>	60.00%	60.00%	58.33%	0.512	0.542	0.491
<b>Hybrid CNN and RNN(GRU)</b>	79.43%	79.43%	91.10%	0.713	0.791	0.752

Table 2: Arrhythmia Detection Accuracy

**Conclusion and Future Scope:**

The proposed quality-aware arrhythmia detection approach demonstrated significant improvements in both signal evaluation and arrhythmia detection accuracy. The integration of signal quality assessment as a preliminary step reduced noise interference and enhanced the reliability of detections. Tests conducted on multiple datasets, including MIT-BIH, showed an average accuracy improvement compared to methods without signal quality assessment. The proposed method achieved a signal quality assessment accuracy of **87.08%** and an arrhythmia detection accuracy of **84.62%**. When comparing performance metrics, the method significantly outperformed traditional approaches in robustness and reliability. The false alarm rate also decreased, highlighting the effectiveness of the system in real-world scenarios. Furthermore, the incorporation of deep learning models (CNNs, RNNs, and FCNNs) facilitated precise feature extraction and classification, making the system adaptable to varying signal qualities.

**References:**

[1] G. Sannino, G. De Pietro [2018] explored a quality-aware arrhythmia detection system using ECG signals. In presented work The deep learning approach is applied on signals collected from MIT-BIH Arrhythmia Database for training and testing.

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- [5] Mohamed Hammad, Abdullah M. Iliyasa , Senior Member, IEEE, Abdulhamit Subasi , Edmond S. L. Ho , and Ahmed A. Abd El-Latif(2021) presented a multitier deep learning model for detection of cardiovascular diseases (CVDs). An electrocardiogram (ECG) is utilized as the primary tool for detecting CVDs.
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- [8] Yanrui Jin, Jinlei Liu , Yunqing Liu , Chengjin Qin , Zhiyuan Li , Dengyu Xiao, Liquan Zhao, and Changliang Liu(2022) presented a novel interpretable method based on dual-level attentional deep neural network for actual multilabel arrhythmia detection.
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