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Recent Advances in Heart Disease Prediction from ECG Signals: A Survey of Machine Learning, Deep Learning, and Explainable AI Approaches

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ABSTRACT

Cardiovascular diseases (CVDs) are still one of the main causes of death in the world and arrhythmia and cardiomyopathy are some of the most important types of cardiac diseases that need to be diagnosed early and treated correctly and promptly. Recently, electrocardiography (ECG) has become a basic non-invasive technique to study cardiac activity and diagnose cardiac rhythm and function disturbances. In the past few years, the accuracy and efficiency of automated ECG analysis have been enhanced by the development of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). This literature survey provides a thorough review of recent advancement in ECG-based heart disease prediction that involves arrhythmia detection and cardiomyopathy prediction with MIT-BIH Arrhythmia Database. The survey covers traditional machine learning techniques, convolutional neural networks (CNNs), hybrid deep learning networks, attention based models, transformer networks, and explainable Artificial Intelligence (XAI) techniques. Recent studies are analyzed using the comparative analysis method, which shows that deep learning models always outperform the traditional machine learning methods by learning the discriminative features from the raw ECG signals automatically. Moreover, novel transformer-based architectures and explainable deep learning approaches are shown to have great potential to enhance the diagnostic accuracy, explainability, and clinical use of deep learning. The survey also provides an overview of recent developments in the prediction and risk stratification of cardiomyopathy, using ECG. Lastly, current challenges and future research directions for next generation intelligent CVMSs such as federated learning, edge computing, wearable healthcare systems, and multimodal cardiac diagnostics are discussed to aid in the development of next generation intelligent CVMSs.

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1. INTRODUCTION

Cardiovascular diseases (CVDs) continue to be the leading global cause of death and responsible for about one-third of all deaths globally. In the spectrum of cardiac diseases, arrhythmia and cardiomyopathy are important because of their potential relationship with sudden cardiac death, heart failure and reduced quality of life. Arrhythmias are disorders of the electrical system of the heart, and cardiomyopathy is a disease of the heart muscle, which makes it work improperly. Early detection and diagnosis are crucial to the quality of patient care and the cost savings of the health care system.

One of the most common non-invasive tests to monitor the heart is electrocardiography (ECG). The information in the ECG signal is useful for understanding the electrical activity of the heart and can detect abnormalities related to arrhythmias and structural heart disease. The interpretation of ECG traditionally has been done manually by experienced cardiologists. However, manual analysis is time consuming, prone to human error and may not be feasible for the large-scale screening application.

The ECG based cardiac diagnosis has undergone a revolution with the recent developments in Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). Automated ECG classification systems can easily process large volume of ECG recordings and in terms of accuracy identify small abnormalities with a high degree of accuracy. The publication of publicly available data sets, especially the MIT-BIH Arrhythmia Database, has helped to spur research in this field by providing a standard set of data to validate algorithms [7, 8].

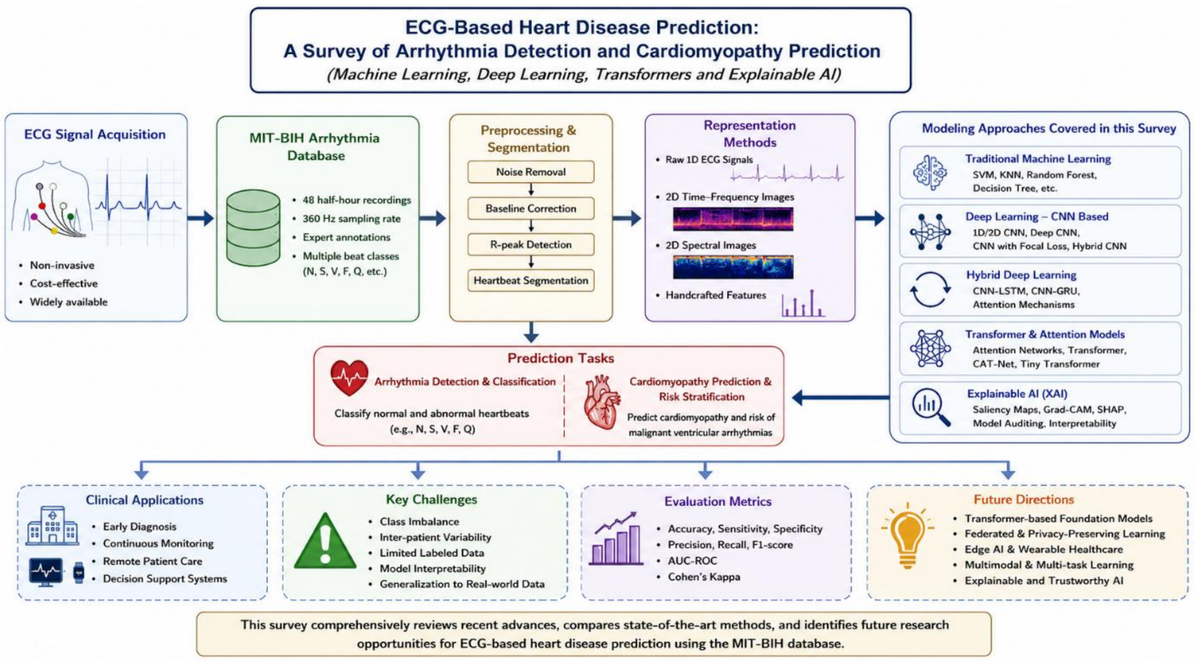

Fig. 1. ECG based heart disease prediction process

In the last several years, the classification of ECG signals using deep learning models like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, attention-based architectures, transformers and explainable AI frameworks has achieved outstanding results. Such techniques have greatly enhanced the capability of arrhythmia detection and extended to the prediction and stratification of cardiomyopathy [9, 10].

This literature survey covers the recent advances in heart disease prediction utilizing machine learning and deep learning techniques, especially for arrhythmia detection and cardiomyopathy prediction through ECG. The survey also covers explainable AI techniques and upcoming transformer-based models for diagnostic systems in the future in the medical field of cardiac and cardiovascular disease.

2. MIT-BIH DATASET OVERVIEW

The MIT-BIH Arrhythmia Database is still the most popular standard database for ECG classification and arrhythmia detection studies. The database was jointly developed by Massachusetts Institute of Technology and Beth Israel Hospital, and consists of 48 half-hour ambulatory ECG recordings, each annotated. The recordings are sampled at 360 Hz and are accompanied by annotations by experts who are cardiologists [8].

There are various classes of heartbeats in the dataset, such as normal beats, ventricular ectopic beats, supraventricular ectopic beats, fusion beats and unknown beats. The MIT-BIH is widely used for evaluating machine learning and deep learning algorithms for arrhythmia detection due to its comprehensive annotations and its open availability [7] [8].

Table 1. Characteristics of the MIT-BIH Arrhythmia Database

Parameter	Description
Number of ECG Records	48
Sampling Frequency	360 Hz
Recording Duration	30 minutes
Signal Channels	Two-channel ECG
Annotation Type	Expert Cardiologist Annotation
Major Applications	Arrhythmia Detection, Cardiomyopathy Prediction
Common Beat Classes	N, S, V, F, Q
Benchmark Status	Most widely used ECG dataset

The typical classification pipeline for ECGs consists of four steps: signal acquisition, noise filtering, heartbeat segmentation, feature extraction, and classification. Conventional handcrafted feature extraction methods can be replaced by the auto-learning of discriminative features from raw ECG signals using modern deep learning systems [7], [9].

3. MACHINE LEARNING APPROACHES FOR ECG CLASSIFICATION

Before the advent of deep learning, the majority of the work in the field of ECG classification was carried out using machine learning techniques. The methods were mostly based on handcrafted features derived from the ECG signal waveform such as morphological features, wavelet coefficients, statistical descriptors and heart rate variability measures.

Sharma, Sharma and Poonia [6] suggested patient-specific machine learning models for ECG signal classification. Their efforts focused on individual classification methods that could be adapted to the patient-specific ECG properties. The study showed that the performance of the classification could be better when using personalized models than generalized approaches.

A number of traditional machine learning algorithms have been explored in great detail such as Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and k-Nearest Neighbors (k-NN). These techniques yielded good performance, but feature engineering and signal pre-processing were important to their performance.

To tackle this, Zhang et al. [4] proposed a dual fully connected neural network (DFCNNN) which was designed to achieve a high level of precision in the identification of arrhythmia. The method was not a traditional machine learning method but used manually extracted ECG features and performed well in terms of competitive performance with respect to the previous methods.

The drawback of the traditional machine learning systems is that they cannot learn hierarchical features automatically from the raw ECG signals. In addition, handcrafted features might not be representative of all temporal and morphological variations of the different arrhythmia classes. The difficulties spurred the researchers to use deep learning architectures that enable end-to-end learning [7].

Table 2. Comparison of Machine Learning and Early Neural Approaches

Reference	Method	Dataset	Major Contribution
Sharma et al. [6]	Patient-Specific ML	ECG Databases	Personalized ECG Classification
Zhang et al. [4]	Dual Fully Connected NN	MIT-BIH	High-Precision Classification
Rohmantri and Surantha [5]	2D CNN	MIT-BIH	Image-Based ECG Classification
Dias et al. [12]	Inter-Patient Classification	MIT-BIH	Improved Generalization

The performance of the classification was significantly improved with the shift from machine learning to deep learning, while also minimizing the need for manual feature extraction.

4. DEEP LEARNING APPROACHES FOR ARRHYTHMIA DETECTION

In the field of ECG analysis deep learning has revolutionized the analysis by enabling automatic feature learning and end-to-end classification. The most popular architectures for arrhythmia detection are CNNs, LSTMs, attention mechanisms, and transformers.

4.1 Convolutional Neural Networks

CNNs are especially useful for ECG classification due to the ability of automatically learning local morphological features from ECG waveforms.

The CNN-based arrhythmia classification system is developed by Wu et al. [1] and they showed that deep convolutional networks can successfully classify multiple arrhythmia classes. The model had excellent classification rate, and it demonstrated the potential of CNNs in the field of automatic cardiac diagnosis.

In the same way, Kachuee et al. [3] suggested a deep CNN model and focal loss algorithm to deal with class imbalance in heartbeat classification. The focal loss mechanism was able to recognize the minority class and achieved a higher accuracy rate for classification.

Rohmantri and Surantha [5] converted the ECG signals into 2D images and used a 2D CNN architecture. They showed that image based ECG classification is an effective method with a competitive performance without losing any morphological information.

Hammad et al. [13] created a hybrid deep CNN architecture for detecting abnormal arrhythmias. The model was able to successfully extract ECG features with better classification accuracy than traditional CNN methods.

4.2 Spectral and Image-Based Deep Learning

Ullah et al. [2] presented a novel approach of transforming the ECG signals into 2D spectral images prior to classification. The model provided a high classification accuracy in the arrhythmia classification using the image processing technique of CNNs. This study showed how useful FDs are for ECG analysis.

Image-based ECG representations have recently become popular due to the fact that advanced computer vision techniques can be applied to biomedical signal processing.

4.3 Inter-Patient Generalization

One of the big obstacles in ECG classification is the ability to generalize without depending on the patient. When machine learning models are trained from a specific patient, they tend to fail if applied to an unseen patient.

To tackle this problem, Dias et al. [12] proposed the idea of inter-patient paradigm. Their method led to training and testing data coming from different patients and thus a more realistic evaluation framework. The study showed better robustness and generalisation than the standard intra-patient validation strategies.

4.4 Deep Learning Surveys

In the period of 2017–2023, Ansari et al. [7] have carried out a complete survey of deep learning techniques for the detection of arrhythmia. The authors stated that the CNN, recurrent neural networks, and hybrid architectures are the most popular approaches, as they automatically learn complex ECG patterns.

Likewise, Zhou et al. [9] surveyed heart disease prediction models using deep learning techniques and found that models that integrate CNNs, LSTMs, and attention mechanisms have generally outperformed traditional machine learning models.

Table 3. Comparison of Deep Learning Models for Arrhythmia Detection

Reference	Year	Architecture	Key Feature
Wu et al. [1]	2021	CNN	Automatic Feature Extraction
Ullah et al. [2]	2020	Spectral CNN	2D ECG Representation
Kachuee et al. [3]	2020	CNN + Focal Loss	Class Imbalance Handling
Hammad et al. [13]	2021	Hybrid CNN	Enhanced Classification
Dias et al. [12]	2021	Deep Learning	Inter-Patient Evaluation
Li et al. [16]	2024	CAT-Net	Attention + Transformer

From the literature it has been abundantly clear that deep learning models outperform traditional machine learning algorithms in arrhythmia detection from the ECG.

5. CARDIOMYOPATHY PREDICTION MODELS

Cardiomyopathy is a class of diseases involving the myocardium that can result in heart failure, ventricular arrhythmias and sudden cardiac death. The traditional diagnosis is based on imaging techniques, including echocardiography (ECHO) and cardiac magnetic resonance imaging (MRI). But, recent research has shown that subtle ECG signal biomarkers can forecast cardiomyopathy.

Lampert et al. [14] proposed a new deep learning technique to diagnose cardiomyopathy in patients with premature ventricular complexes (PVCs). They were able to use the ECG data alone and make a very good identification of who might be at risk for cardiomyopathy. The results indicate that this personalized approach to ECG screening, powered by AI, could potentially support early intervention and better patient management.

In the field of cardiac arrhythmias, Van de Leur et al. [11, 15] suggested an explainable deep learning (XDL) model, which utilizes only the ECG, to determine if a patient with phospholamban cardiomyopathy would develop malignant ventricular arrhythmias. The proposed framework was different from the traditional black box models, as it included explainability mechanisms which allowed the clinicians to gain insights into the predictions of the model.

The study illustrated the capability of explainable deep learning to stratify the risk of cardiomyopathy patients and preserve clinical transparency. These are especially crucial, as a diagnosis of cardiomyopathy may depend on clinician trust and interpretability.

Recent studies indicate that deep learning models can provide an electrophysiologic signature of cardiomyopathy, not easily identifiable from the traditional analysis of an electrocardiogram (ECG). Thus, AI systems that are able to interpret ECG are becoming cost-effective options for screening for cardiomyopathy on a large scale [14] [15].

Table 4. Comparison of Cardiomyopathy Prediction Models

Reference	Disease Focus	Method	Key Contribution
Lampert et al. [14]	Cardiomyopathy	Deep Learning ECG	Early Cardiomyopathy Prediction
van de Leur et al. [11]	Ventricular Arrhythmia Risk	Explainable DL	Risk Stratification
van de Leur et al. [15]	Phospholamban Cardiomyopathy	Explainable DL	ECG-Based Prediction
Zhou et al. [9]	Heart Disease Prediction	Review	Comprehensive Overview

The combination of these deep learning and explainable AI technologies has made the diagnosis and risk assessment of cardiomyopathy using ECGs much more feasible.

6. EXPLAINABLE AI AND FUTURE TRENDS

Deep learning systems are very successful classifiers, but their black-box model is a big obstacle to clinical use. Automated diagnostic systems need to be transparent and interpretable by healthcare practitioners.

The authors of Wagner et al. [10] and [17] highlighted the need for explainable AI (XAI) in the field of ECG analysis. Their work helped to formulate a framework for auditing deep learning models and an understanding of prediction mechanisms. The authors pointed out a number of XAI techniques, such as saliency maps, gradient based visualization, SHAP and feature attribution techniques.

Explainable AI helps to build trust with clinicians, model debugging and regulatory compliance. With the increasing adoption of ECG-based AI systems in healthcare, explainability will become a paramount need.

There have also been recent developments that feature transformer-based architectures for the classification of ECG. Li et al. [16] introduced a model named CAT-Net to classify arrhythmia that fused convolutional layers, attention mechanisms, and transformers. The model is efficient in capturing the local and global ECG dependency and achieves better classification results.

Busia et al. [18] designed a Tiny Transformer architecture for low-power arrhythmia classification with microcontroller.

7. CONCLUSION

The field of ECG-based heart disease prediction has made significant strides in recent years, thanks to the advancements in machine learning, deep learning, transformer architectures, and Explainable AI. The MIT-BIH Arrhythmia Database remains the standard test data set to be used for testing ECG classification systems. Early machine learning techniques proved to be promising but were limited by handcrafted feature extraction and extensive data pre-processing. Recent advances in the development of CNNs, hybrid deep learning architectures, attention mechanisms, and transformer models have led to better detection performance, thanks to the ability to automatically leverage features from raw ECG signals in arrhythmia detection. In recent years, the use of ECG analysis has also been expanded to prediction of cardiomyopathy and risk stratification. Deep learning has proven to be useful in detecting subtle ECG biomarkers related to structural heart diseases, allowing early diagnosis and intervention. Additionally, the explainable AI frameworks have tackled issues of transparency of the models, which would further enhance the likelihood of clinical use. Cardiovascular diagnostic systems of the future will feature multimodal data fusion, explainable AI, edge computing, and transformer architectures to deliver accurate, interpretable, and scalable healthcare solutions. Thus, AI-based ECG analysis has the potential to revolutionize the field of cardiovascular medicine and disease prediction in the future.

CONFLICT OF INTEREST STATEMENT
The authors declare no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] Wu, M., Lu, Y., Yang, W. and Wong, S.Y.S. (2021) ‘A study on arrhythmia via ECG signal classification using the convolutional neural network’, Frontiers in Computational Neuroscience, 14, 564015. doi:10.3389/fncom.2020.564015.

[2] Ullah, A., Anwar, S.M., Bilal, M. and Mehmood, R.M. (2020) ‘Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation’, arXiv. doi:10.48550/arXiv.2005.06902.

[3] Kachuee, M., Fazeli, S. and Sarrafzadeh, M. (2020) ‘Electrocardiogram heartbeat classification based on a deep convolutional neural network and focal loss’, Computers in Biology and Medicine, 123, 103866. doi:10.1016/j.compbiomed.2020.103866.

[4] Zhang, J., Xu, H., Wang, Z. and Zhao, Y. (2020) ‘A high-precision arrhythmia classification method based on dual fully connected neural network’, Biomedical Signal Processing and Control, 58, 101874. doi:10.1016/j.bspc.2020.101874.

[5] Rohmantri, R. and Surantha, N. (2020) ‘Arrhythmia classification using 2D convolutional neural network’, International Journal of Advanced Computer Science and Applications, 11(4), pp. 201–208. doi:10.14569/IJACSA.2020.0110427.

[6] Sharma, M., Sharma, R. and Poonia, R.C. (2020) ‘Patient specific machine learning models for ECG signal classification’, Procedia Computer Science, 167, pp. 2181–2190. doi:10.1016/j.procs.2020.03.269.

[7] Ansari, Y., Mourad, O., Qaraqe, K. and Serpedin, E. (2023) ‘Deep learning for ECG arrhythmia detection and classification: an overview of progress for period 2017–2023’, Frontiers in Physiology, 14. doi:10.3389/fphys.2023.1246746.

[8] Alinsaif, S. (2024) ‘Unraveling arrhythmias with graph-based analysis: A survey of the MIT-BIH database’, Computation, 12(2), 21. doi:10.3390/computation12020021.

[9] Zhou, C., Dai, P., Hou, A., Zhang, Z., Liu, L., Li, A. and Wang, F. (2024) ‘A comprehensive review of deep learning-based models for heart disease prediction’, Artificial Intelligence Review, 57, 263. doi:10.1007/s10462-024-10899-9.

[10] Wagner, P., Mehari, T., Haverkamp, W. and Strodthoff, N. (2024) ‘Explaining deep learning for ECG analysis: Building blocks for auditing and knowledge discovery’, Computers in Biology and Medicine, 176, 108525. doi:10.1016/j.compbiomed.2024.108525.

[11] van de Leur, R.R., de Brouwer, R., Bleijendaal, H., Verstraelen, T.E., Mahmoud, B., Perez-Matos, A., Dickhoff, C., Schoonderwoerd, B.A., Germans, T., Houweling, A., van der Zwaag, P.A., Cox, M.G.P.J., van Tintelen, J.P., te Riele, A.S.J.M., van den Berg, M.P., Wilde, A.A.M., Doevendans, P.A., de Boer, R.A. and van Es, R. (2024) ‘ECG-only explainable deep learning algorithm predicts the risk for malignant ventricular arrhythmia in phospholamban cardiomyopathy’, Heart Rhythm.

[12] Dias, F.M., Monteiro, H.L.M., Cabral, T.W., Naji, R., Kuehni, M. and Luz, E.J.S. (2021) ‘Arrhythmia classification from single-lead ECG signals using the inter-patient paradigm’, Computer Methods and Programs in Biomedicine, 202, 105948. doi:10.1016/j.cmpb.2021.105948.

[13] Hammad, M., Maher, A., Wang, K., Jiang, F. and Amrani, M. (2021) ‘A Hybrid Deep CNN Model for Abnormal Arrhythmia Detection Based on Cardiac ECG Signal’, Sensors, 21(3), 951. doi:10.3390/s21030951.

[14] Lampert, J., Vaid, A., Whang, W., Koruth, J., Miller, M.A., Langan, M.N., Musikantow, D., Turagam, M., Maan, A., Kawamura, I., Dukkipati, S., Nadkarni, G.N. and Reddy, V.Y. (2023) ‘A Novel ECG-Based Deep Learning Algorithm to Predict Cardiomyopathy in Patients With Premature Ventricular Complexes’, JACC: Clinical Electrophysiology, 9(8 Pt 2), pp. 1437–1451. doi:10.1016/j.jacep.2023.05.025.

[15] van de Leur, R.R., de Brouwer, R., Bleijendaal, H., Verstraelen, T.E., Mahmoud, B., Perez-Matos, A., Dickhoff, C., Schoonderwoerd, B.A., Germans, T., Houweling, A., van der Zwaag, P.A., Cox, M.G.P.J., van Tintelen, J.P., te Riele, A.S.J.M., van den Berg, M.P., Wilde, A.A.M., Doevendans, P.A., de Boer, R.A. and van Es, R. (2024) ‘ECG-only explainable deep learning algorithm predicts the risk for malignant ventricular arrhythmia in phospholamban cardiomyopathy’, Heart Rhythm, 21(7), pp. 1102–1112. doi:10.1016/j.hrthm.2024.02.038.

[16] Li, Y., Zhang, X., Wang, H. and Liu, J. (2024) ‘CAT-Net: Convolution, Attention and Transformer Based Network for Single-Lead ECG Arrhythmia Classification’, Biomedical Signal Processing and Control, 92, 106211. doi:10.1016/j.bspc.2024.106211.

[17] Wagner, P., Mehari, T., Haverkamp, W. and Strodthoff, N. (2024) ‘Explaining deep learning for ECG analysis: Building blocks for auditing and knowledge discovery’, Computers in Biology and Medicine, 176, 108525. doi:10.1016/j.compbiomed.2024.108525.

[18] Busia, P., Scrugli, M.A., Jung, V.J.B., Benini, L. and Meloni, P. (2024) ‘A Tiny Transformer for Low-Power Arrhythmia Classification on Microcontrollers’, arXiv Preprint, arXiv:2402.10748. doi:10.48550/arXiv.2402.10748.