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SURVEY

Deep Learning Applications in ECG Analysis and Disease Detection: An Investigation Study of Recent Advances

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ABSTRACT Effective cardiovascular health monitoring relies on precise electrocardiogram (ECG) analysis for early diagnosis and treatment of heart conditions. Recent advancements in deep learning, particularly through Convolutional Neural Networks (CNNs), have significantly enhanced the automation, accuracy, and personalization of ECG analysis. This review targets both medical professionals and a broader audience interested in deep learning applications. Our work explores the evolution of deep learning techniques in ECG analysis, from early CNN applications to current innovations in real-time processing and privacy-preserving methods. The paper discusses various deep learning models, including hybrid models, Recurrent Neural Networks (RNNs), and attention mechanisms, and their impact on diagnostic accuracy for diseases like myocardial infarction. Additionally, our paper examines ECG-based authentication systems, addressing challenges related to security and privacy, and highlighting recent technological advancements. By providing a detailed overview of these developments, the review offers valuable insights into future directions for deep learning in cardiovascular health monitoring and ECG-based authentication.

INDEX TERMS Deep learning, cardiovascular health, ECG analysis, disease detection, telemedicine, cybersecurity, ECG authentication.

I. INTRODUCTION

Cardiovascular health monitoring is crucial in modern healthcare due to the prevalence and severity of cardiovascular diseases. Electrocardiogram (ECG) analysis plays a pivotal role in the timely diagnosis and effective management of these conditions. The advent of deep learning techniques has significantly enhanced ECG analysis, ushering in an era of automation, precision, and personalized healthcare services [1].

Deep learning, led by Convolutional Neural Networks (CNNs), has revolutionized various fields, with its origins tracing back to Yann LeCun's groundbreaking LeNet-5 architecture in 1989, specifically designed for handwritten digit recognition. Subsequent breakthroughs, notably AlexNet in 2012 by Krizhevsky, Sutskever, and Hinton, demonstrated the dominance of CNNs in computer vision tasks through the ImageNet challenge [2].

In cardiovascular health, ECG analysis is indispensable across multiple domains, including disease detection, risk stratification, myocardial infarction identification, arrhythmia risk prediction, heart rate variability analysis, healthcare monitoring, and ECG-based authentication [3]. Integration of deep learning methodologies has led to a paradigm shift, enabling automated interpretation of complex ECG signals, enhancing diagnostic accuracy, and facilitating tailored medical interventions [4].

As cardiovascular diseases continue to be a leading cause of death globally, advancements in deep learning for ECG analysis present significant opportunities for improving

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patient outcomes. This paper provides a comprehensive review and analysis of the evolution of deep learning methods in ECG analysis, tracing their development from early Convolutional Neural Networks (CNNs) to current state-of-the-art techniques. It addresses the challenges encountered in the field, such as model robustness, data privacy, and real-time processing, while also exploring future directions for research and application. Designed for both medical professionals familiar with ECG and a broader audience interested in deep learning applications, this review highlights the transformative impact of deep learning technologies on cardiovascular health monitoring and ECG-based authentication. By offering insights into recent advancements, current challenges, and future research avenues, our review paper aims to bridge the gap between clinical practice and technological innovation.

The review focuses on similar works that apply deep learning to ECG signals for diverse analyses across domains. Also explores the diverse applications and methodologies employed, underpinned by deep learning techniques such as attention mechanisms, RNNs, and CNNs. Real-world case studies underscore the clinical efficacy of these approaches, illuminating their transformative impact on cardiac healthcare. An overview of the evolution of deep learning methods and applications in ECG analysis is given in Table 1.

Figure 1 illustrates the distribution of research publications published between 2017 and 2024 in three main databases (Scopus, ScienceDirect, and Web of Science) regarding ECG-based cardiovascular health monitoring and authentication systems. The graph shows the upward trend in publications over time, with the majority of papers coming from Scopus, Science Direct coming in second, and Web of Science contributing very little.

This study contributes by organizing domains for biometric and security applications in medical and healthcare settings using ECG data. Our meta-data analysis focuses on deep learning (DL) models, their performances, dataset sources, architectures, application domains, ECG signal processing techniques, and DL application tasks. Also outlines future research directions and identifies unresolved issues.

This review gives the advances enabled by deep learning in ECG analysis while also addressing the challenges of model interpretation, data consistency, demographic generalizability, and the specific requirements of ECG-based authentication. It discusses strategies to overcome these challenges and highlights ongoing advancements in deep learning algorithms to improve ECG analysis for clinical use. Table 2 gives an overview of ECG signal processing techniques along with their advantages and disadvantages. Additionally, the review explores emerging trends such as explainable AI, federated learning for privacy-preserving analysis, and real-time data integration. These innovations are envisioned to enhance ECG analysis, facilitating better patient care and outcomes. By synthesizing current research, identifying key trends, and proposing future directions, this review aims to drive the ongoing development of ECG analysis techniques, fostering innovation and effectiveness in cardiovascular medicine. Table 3 gives an overview of open-access ECG Datasets.

A. OUTLINE OF THE ARTICLE

Over 115 Springer, Science Direct, and Web of Science articles were reviewed for this study, most of which were published between 2017 and 2024. The systematic review process's PRISMA flow chart is given in Figure 2 The research article is divided into sections: Section II describes how deep learning techniques are integrated into ECG analysis to revolutionize cardiovascular health monitoring, improve diagnostic accuracy, and enable individualized medical interventions. A literature review of the ECG analysis is discussed in Section III. Research directions and a discussion are presented in Section IV. Lastly, Section V provides a summary of the findings and conclusions of the study.

II. DEEP LEARNING TECHNIQUES IN ECG ANALYSIS

A. OVERVIEW OF DEEP LEARNING ARCHITECTURES IN ECG ANALYSIS

Cardiovascular disease diagnosis and monitoring depend heavily on ECG readings. Accurate and efficient categorization of ECG signals is significantly hampered by their complexity and unpredictability. Conventional machine learning techniques might not adequately capture the complex patterns in ECG data and frequently call for substantial feature engineering. With the development of deep learning, a number of neural network topologies have demonstrated potential for raising the reliability and accuracy of ECG categorization. Tasks involving ECG signals are well-suited for deep learning techniques, particularly deep neural networks, which can automatically develop hierarchical representations from raw data. CNNs, RNNs, LSTM Networks, Hybrid CNN-RNN Models, Attention Mechanisms, GANs, Transformers, Federated Learning, and Edge Computing with Deep Learning are some of the most well-known architectures used in ECG classification. Figures 3, 4, 5, 6, 7, 8, 9, 10, and 11 illustrate the fundamental architectures of the baseline deep learning models used in ECG analysis in recent years.

1) CONVOLUTIONAL NEURAL NETWORKS (CNNs)

CNNs, or convolutional neural networks, are accurate at processing data structures that resemble grids, including pictures and ECG readings. When CNNs were first used for ECG analysis in 2016, they completely changed the field by automating the feature extraction procedure. In order to accurately classify and detect arrhythmias, they must be able to recognize spatial patterns within ECG data and learn hierarchically. These convolutional networks are robust for initial ECG classification tasks as well as arrhythmia detection since they can detect distinct features in different layers. Because of their capacity to automatically extract features from raw data, they greatly minimize the requirement for human feature

TABLE 1. An overview of the evolution of deep learning methods and applications in ECG analysis.

Year	Key Developments/Trends	Technologies	Application Areas
2017	Early adoption of deep learning models for ECG analysis.	CNNs	Arrhythmia Classification
2018	Expansion of deep learning applications in ECG analysis.	RNNs	Myocardial Infarction Identification
2019	Advancements in model architectures and transfer learning.	Attention mechanisms, Transfer Learning	Cardiovascular Disease Detection, Risk Stratification
2020	Emergence of multimodal ECG analysis.	Multimodal fusion techniques	Heart Rate Variability Analysis, Sleep Apnea Detection
2021	Shift towards explainable AI and attention-based models.	Explainable AI techniques, Attention-based models	Telemedicine & ECG-based Diagnosis, ECG Authentication
2022	Focus on real-time applications and adaptive algorithms.	Real-time processing, Adaptive algorithms	Remote Patient Monitoring, Healthcare Monitoring
2023	Adoption of federated learning and privacy preservation.	Federated Learning, Privacy-preserving techniques	ECG Authentication, Telemedicine & ECG-based Diagnosis
2024	Integration with clinical decision support systems.	Clinical Decision Support Systems (CDSS) integration	Comprehensive Cardiovascular Health Monitoring

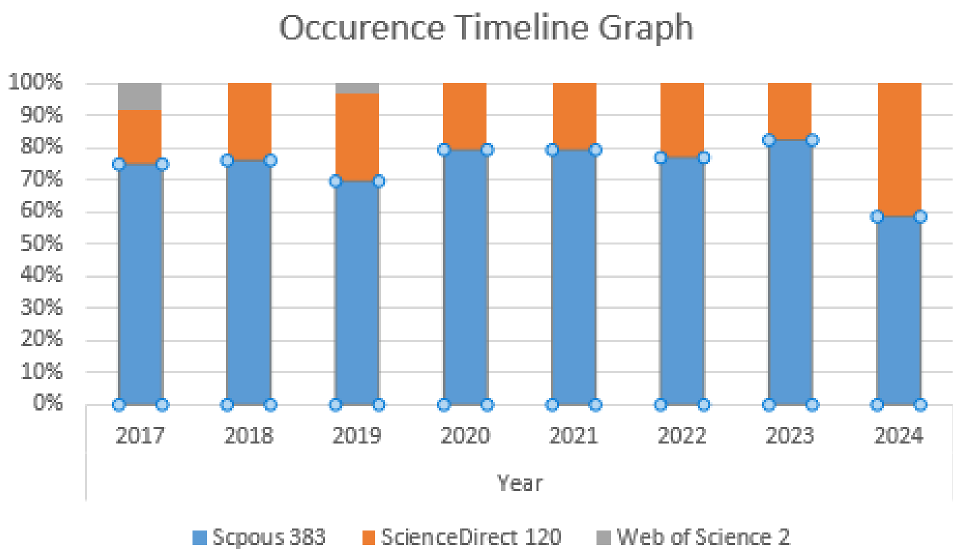

FIGURE 1. Timeline occurrence graph.

engineering, which improves the effectiveness and precision of ECG analysis [13].

2) RECURRENT NEURAL NETWORKS (RNNs)

Around 2017, RNNs gained popularity in ECG analysis because of their ability to efficiently analyze sequential data. RNNs are good at processing time-series data, like ECG signals, since they keep a kind of memory that records details about earlier inputs in the sequence. This feature makes it possible for RNNs to simulate the temporal dependencies present in ECG data, which is essential for identifying patterns over time, including irregular heartbeats. RNNs' sequential structure makes them perfect for identifying temporal patterns and abnormalities in ECG signals, which helps to provide more precise and thorough monitoring of cardiac conditions [15].

3) LONG SHORT-TERM MEMORY NETWORKS (LSTMs)

A specific kind of RNN called LSTM networks was developed to solve the vanishing gradient issue that was present in RNNs of the standard type. LSTMs were first used in ECG analysis in 2018. Their ability to hold data over long periods and identify long-term relationships makes them essential for applications involving long-sequence analysis. Long-term storage and retrieval of data is made possible by memory cells, which improves the efficiency of LSTMs in heartbeat categorization and arrhythmia detection. Because of this, long-term patterns in ECG data can be monitored with LSTMs, which enhances the ability to identify problems that develop over lengthy periods [17].

4) HYBRID CNN-RNN MODELS

In 2019, hybrid CNN-RNN models emerged as a significant advancement in ECG analysis, combining the strengths of both CNNs and RNNs. These models leverage the spatial feature extraction capabilities of CNNs alongside the temporal sequence processing expertise of RNNs. By integrating both the temporal and spatial characteristics of ECG data, this hybrid approach enhances the overall accuracy of the model. This comprehensive technique allows for a more in-depth

TABLE 2. ECG Signal Processing: Approaches, Advantages, and Disadvantages.

Approach	Advantages	Disadvantages
Signal Processing [5]	Allows for fine-grained analysis of ECG signals. Well-established methods and algorithms available.	Requires expertise in signal processing. Limited to predefined feature extraction techniques.
Wavelet Transform [6]	Captures both time and frequency information. Can handle non-stationary signals effectively.	Sensitivity to noise. Complex parameter tuning.
Deep Learning [7]	Ability to learn complex patterns automatically. High accuracy and performance in classification tasks.	Requires large amounts of labeled data. Computationally intensive.
Heart Rate Variability (HRV) [8]	Non-invasive and easy to measure. Provides insights into autonomic nervous system activity.	Susceptible to artifacts and noise. Limited to heart rhythm analysis.
Ensemble Methods [9]	Reduces overfitting and improves generalization. Can capture complementary information from different models.	Increased complexity and computational cost. Sensitivity to noisy data.
Feature Fusion [10]	Combines different information sources for better decision-making. Increases robustness and accuracy.	May lead to increased dimensionality. Requires careful feature selection and fusion techniques.
Template Matching [11]	Simple and intuitive method. Effective for specific pattern recognition tasks.	Sensitivity to signal variations. Limited to predefined templates.
Phase Space Reconstruction [12]	Captures nonlinear dynamics and chaotic behavior. Effective for time-series analysis.	Requires proper selection of reconstruction parameters. Limited to specific signal types.

TABLE 3. Overview of open access ECG datasets.

Dataset Name	Subjects	Samples	Classes	Format	Year	URL
MIT-BIH Arrhythmia Database	47	40,000	15	WFDB, CSV	1990	https://physionet.org/content/mitdb/1.0.0/
Framingham Heart Study Dataset	5,209	300,000	8	CSV, Excel	2002	https://www.framinghamheartstudy.org/
St. Petersburg INCART 12-lead Arrhythmia Database	75	75,000	12	WFDB	2008	https://physionet.org/content/incartdb/1.0.0/
E-HOL-03-0202-003	53	200,000	4	CSV	2010	https://physionet.org/content/e-hol-03-0202-003/1.0.0/
PTB Diagnostic ECG Database	290	100,000	10	CSV, XML	2012	https://physionet.org/content/ptbdb/1.0.0/
Lobachevsky University Electrocardiography Database	200	60,000	5	CSV	2015	https://physionet.org/content/ludb/1.0.1/
Cardiac Arrhythmia Risk Dataset	300	150,000	6	CSV	2016	https://archive.ics.uci.edu/ml/datasets/Arrhythmia
Sleep-EDF Database	197	80,000	2	EDF, XML	2014	https://physionet.org/content/sleep-edfx/1.0.0/
PhysioNet/CinC Challenge Database	500	120,000	5	EDF, TXT	2019	https://physionet.org/content/challenge-2020/1.0.0/
Chapman-Shaoxing and Ningbo Database	10,646	11,000,000	12	HDF5	2020	https://physionet.org/content/crcns/

understanding of ECG data by combining various types of information derived from the signals, making it particularly useful for thorough ECG analysis and disease detection [19].

5) ATTENTION MECHANISMS

When attention mechanisms were added in 2020, deep learning models for ECG analysis became much more accurate and readable. By constantly adjusting the weight assigned to various ECG signal segments, these techniques enable models to concentrate on the most pertinent portions of the input sequence. Attention processes improve the model's capacity to identify abnormalities and offer comprehensive interpretations of ECG signals by emphasizing significant portions of the data. This development is especially helpful for activities like comprehensive anomaly detection and diagnosis that call for the precise identification of particular patterns within the ECG [21].

6) GENERATIVE ADVERSARIAL NETWORKS (GANs)

In 2021, the application of Generative Adversarial Networks (GANs) in generating synthetic ECG signals gained significant attention in ECG analysis. GANs, consisting of generator and discriminator neural networks, work together to produce highly realistic synthetic data. This capability

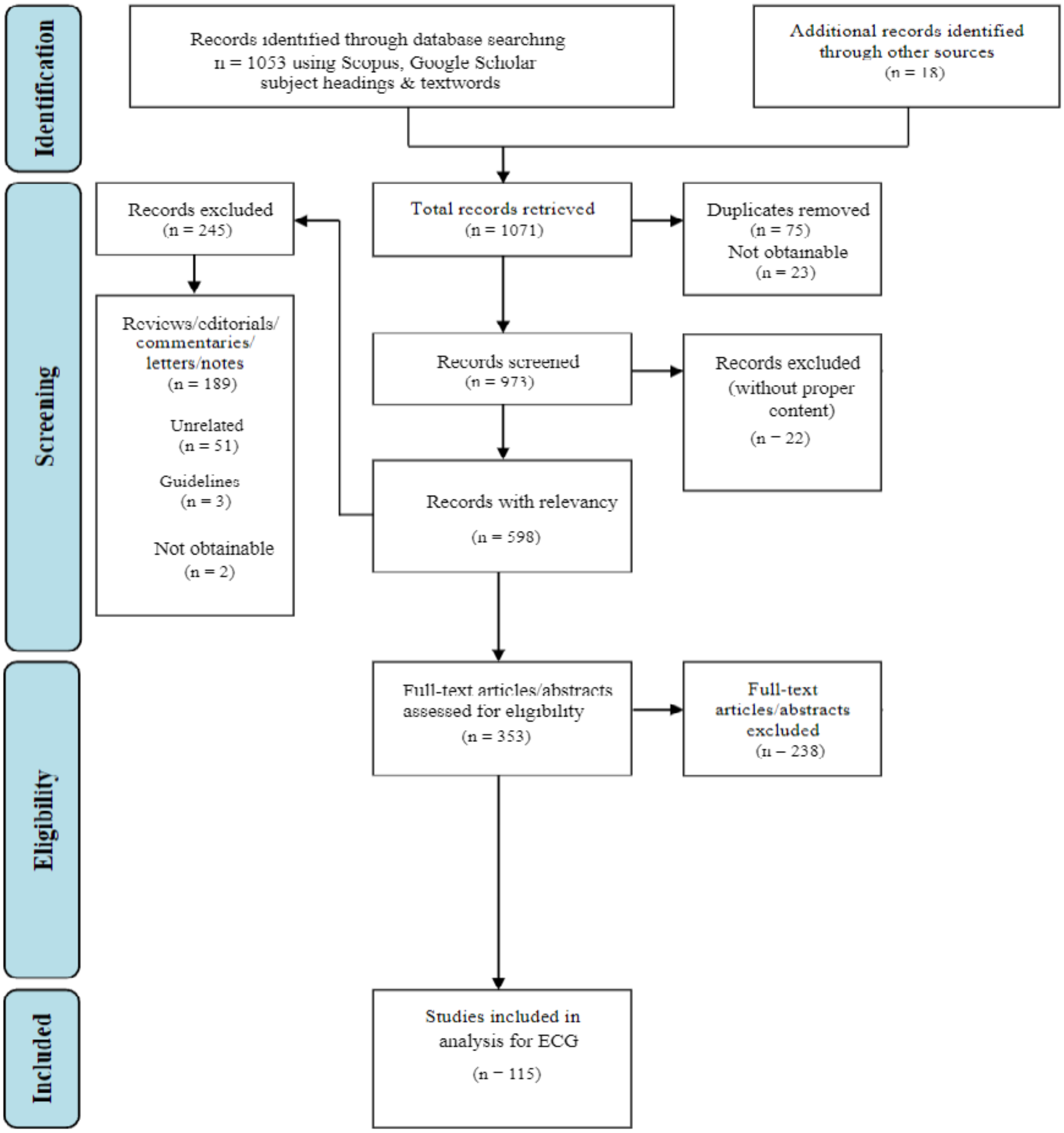

FIGURE 2. PRISMA flow chart for the systematic review process.

is particularly valuable for data augmentation, as it helps address the shortage of labeled ECG data by providing additional training examples. By generating high-quality synthetic ECG signals, GANs enhance the robustness and generalizability of deep learning models, thereby improving their performance across various ECG analysis tasks [23].

7) TRANSFORMERS

Transformers, which were first used in ECG analysis in 2022, significantly advanced the field because of how well they handled long-distance relationships. Transformers are more computationally efficient and perform better as models since they can process complete sequences in parallel, unlike regular RNNs. Because of their self-attention mechanism, they are very useful for sequence analysis and real-time monitoring since they can capture intricate connections between various ECG signal segments. Transformers are perfect for sophisticated ECG analysis because of their excellent efficiency in handling lengthy sequences, which is essential for recording complex relationships [25].

8) FEDERATED LEARNING

In 2023, federated learning became popular in ECG analysis and provides a private model training method. By enabling models to be trained across different devices without revealing sensitive data, facilitates decentralized learning. By storing patient data locally and centrally aggregating the learned models, this method improves privacy and security.

TABLE 4. Evolution of deep learning architectures in ECG analysis.

Architecture	Year	Key Features	Use Case
CNNs	2016	Automated feature extraction, hierarchical learning	Initial ECG classification and arrhythmia detection
RNNs	2017	Sequence modeling, memory retention of sequential data	Temporal pattern recognition in ECG signals
LSTM Networks	2018	Addressing vanishing gradient problem, long-term dependencies	Arrhythmia detection, heartbeat classification
Hybrid CNN-RNN Models	2019	Combining spatial and temporal features, improved accuracy	Comprehensive ECG analysis, disease diagnosis
Attention Mechanisms	2020	Focus on important signal parts, enhanced interpretability	Detailed ECG interpretation, anomaly detection
Generative Adversarial Networks (GANs)	2021	Data augmentation, synthetic ECG signal generation	Addressing data scarcity, improving model training
Transformers	2022	Parallel processing, capturing long-range dependencies	Advanced ECG sequence analysis, real-time monitoring
Federated Learning	2023	Privacy-preserving, decentralized learning	Collaborative model training without data sharing
Edge Computing with Deep Learning	2024	Real-time processing, reduced latency	On-device ECG analysis, immediate health monitoring

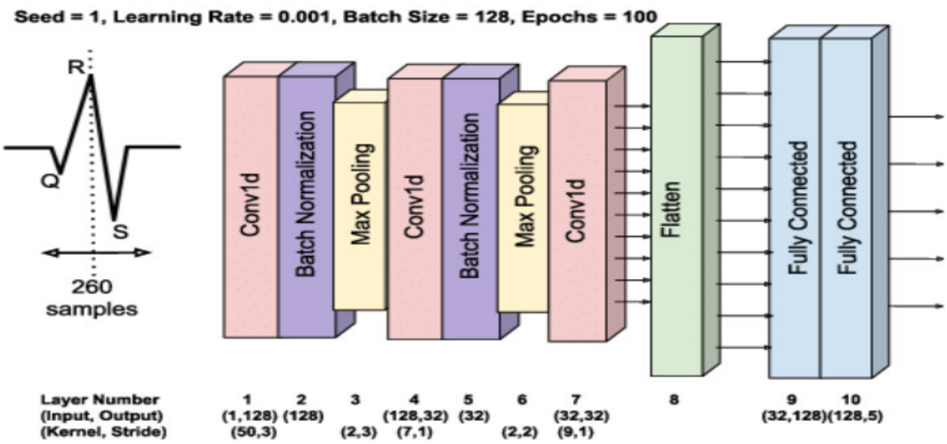

FIGURE 3. 1D CNN architecture [14].

In the healthcare industry, federated learning is especially helpful for collaborative model training because data privacy is of utmost importance. Researchers can enhance ECG analysis models without jeopardizing patient anonymity by utilizing federated learning [26].

9) EDGE COMPUTING WITH DEEP LEARNING

Introduced in 2024, edge computing in conjunction with deep learning allows for direct real-time ECG analysis on wearables and other devices. This methodology minimizes latency and bandwidth consumption by analyzing data close to the source and delivering prompt feedback and notifications. Because edge computing enables on-device ECG analysis, it is particularly useful for continuous health monitoring as it enables the delivery of real-time health insights and actions. This development makes ECG monitoring devices more useful and responsive, increasing their efficacy for prompt health care [28].

Table 5 highlights the basic equations of all the above neural networks. Significant progress has been made in ECG classification with the incorporation of these algorithms using deep learning, allowing for more accurate and effective cardiac health monitoring. This work offers a thorough analysis of different topologies, emphasizing their uses, advantages, and disadvantages in the classification of ECG signals. The table 4 and accompanying explanations provide a clear overview of the advancements in deep learning architectures for ECG analysis, highlighting their evolution, key features, and specific use cases.

B. APPLICATION AREAS

- Identification of Cardiovascular Disease: Deep learning models have significantly advanced the detection of cardiovascular diseases (CVDs) through sophisticated analysis of ECG data. For instance, CNNs are employed to detect supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB) with high accuracy. These advancements in DL not only enhance the accuracy of diagnosis but also enable early intervention by identifying patterns indicative of CVDs.
- Using Risk Stratification: Patients are categorized according to their risk of developing cardiovascular

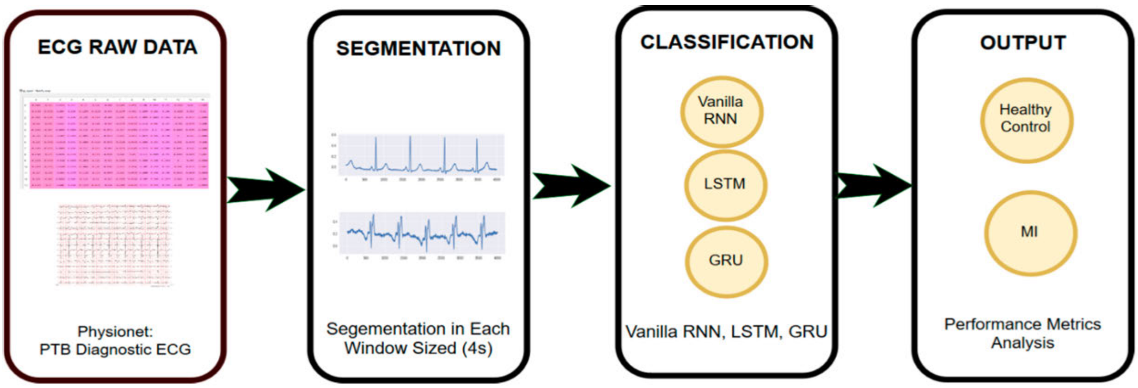

FIGURE 4. RNN architecture [16].

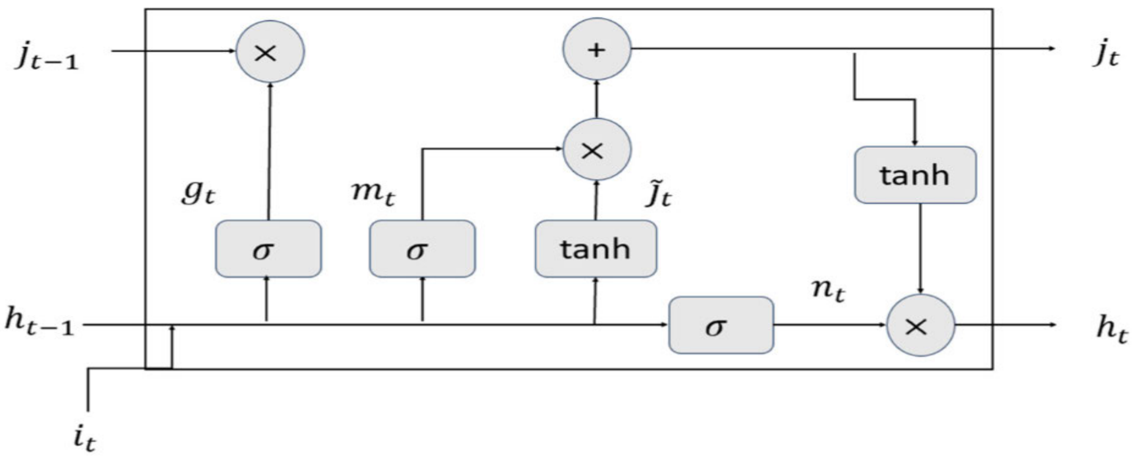

FIGURE 5. LSTM architecture [18].

events in a process known as risk stratification. DL models help with early intervention and individualized treatment regimens by analyzing past ECG data to forecast future cardiac episodes. Proactive healthcare management has been made possible by the development of prediction models that evaluate the risk of myocardial infarction using CNNs and RNNs.

- Identification of Myocardial Infarction: By examining ECG data, DL methods have greatly enhanced the detection of myocardial infarction (MI). To improve diagnostic speed and accuracy, models like RNNs and CNNs are being trained to identify tiny variations in ECG waveforms that are indicative of MI.
- Predicting Arrhythmia Risk: It is essential to predict the likelihood of arrhythmias to avoid unexpected cardiac events. DL models evaluate ECG data and forecast the likelihood of arrhythmias, particularly those that use RNNs and LSTMs. By accurately capturing the temporal dependencies present in the data, these models enable risk evaluations.
- Analysis of Heart Rate Variability: One important measure of the health of the autonomic nervous system is heart rate variability (HRV). DL models, such as CNNs and RNNs, have been used to assess HRV from ECG signals, offering predictions about prospective heart problems and insights into cardiovascular health.
- Classification of Arrhythmias in Healthcare Monitoring: The categorization of arrhythmia using ECG signals is the main application of DL in healthcare monitoring. By analyzing ECG data, methods such as CNNs, RNNs, as well as hybrid models can identify various arrhythmias, enhancing the precision and effectiveness of monitoring systems.
- Classification of Arrhythmias via Remote Patient Monitoring: By integrating DL with wearable technology, patients can be continuously monitored and their ECG data can be analyzed in real-time. This is especially helpful for remotely identifying arrhythmias so that prompt medical attention can be given. DL models improve the quality of distant medical care by classifying arrhythmias using data collected by wearable ECG monitors.
- Diagnosis based on ECG and Telemedicine: By enabling precise ECG-based diagnoses via telemedicine, DL

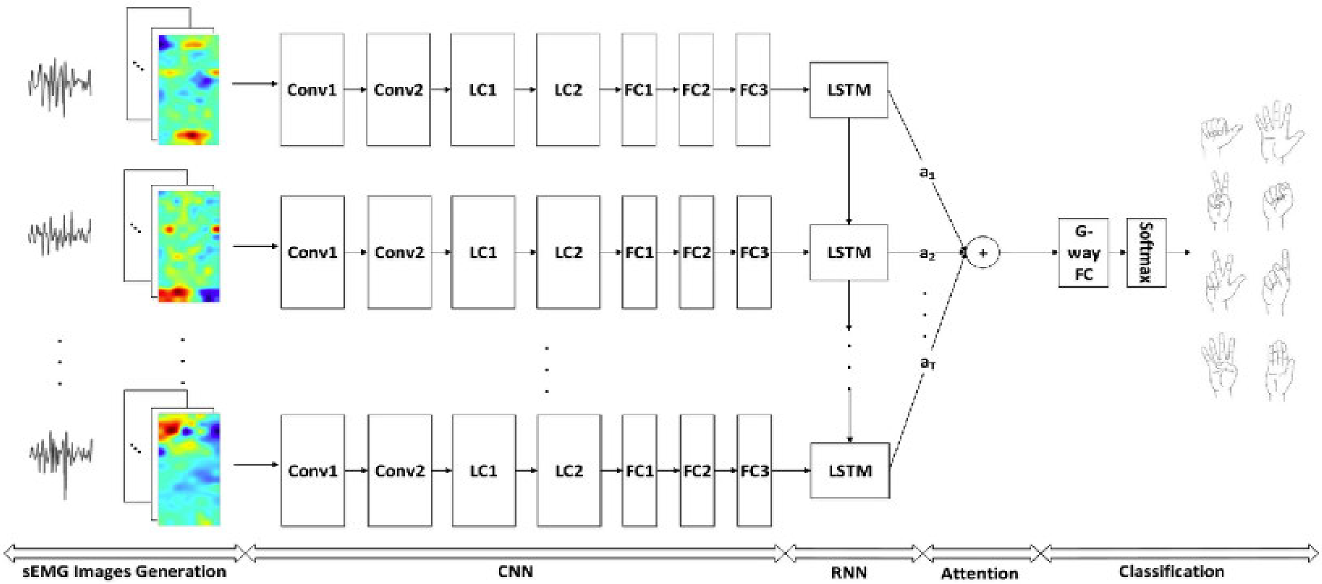

FIGURE 6. Hybrid CNN-RNN architecture [20].

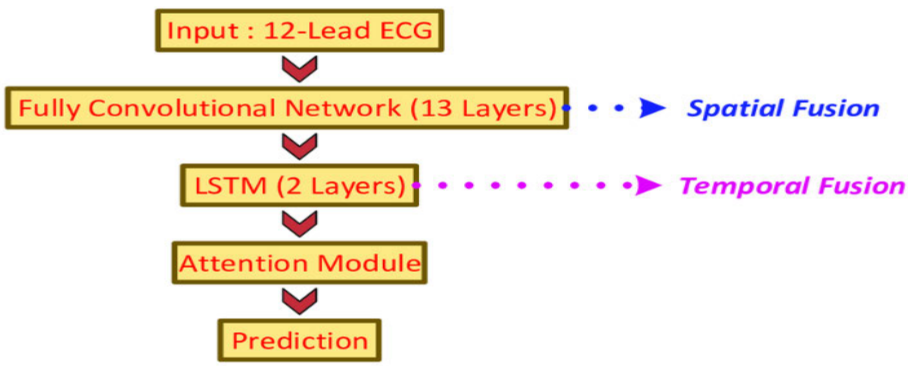

FIGURE 7. Attention architecture [22].

algorithms help narrow the communication gap between patients and medical professionals. Real-time diagnostic help is provided by models that analyze ECG recordings collected through telehealth systems, such as transformer-based models and bidirectional RNNs with attention mechanisms.

- Identifying Sleep Apnea: In sleep studies, DL techniques use ECG data to identify sleep apnea. By analyzing the ECG data, models like CNNs and RNNs can detect apnea episodes and offer a non-invasive method of diagnosing sleep problems and enhancing treatment.
- Classification of Sleep Stages: To better understand sleep patterns and pathologies, DL approaches are used to identify phases of sleep based on ECG signals. In this regard, CNNs and RNNs work very well, allowing for precise classification of various sleep stages.

The integration of DL techniques in the analysis of electrocardiograms (ECGs) has significantly transformed cardiovascular diagnostics. By utilizing sophisticated computational models, deep learning has markedly improved the accuracy, efficiency, and predictive power of cardiovascular disease (CVD) diagnoses, effectively addressing several shortcomings of traditional diagnostic methods.

Several specific examples highlight the substantial advancements facilitated by deep learning in this field. For example, Leon et al. reported that a CNN based model achieved an exceptional sensitivity of 99.0% and a positive predictivity of 96.5% in QRS detection. Additionally, this model demonstrated a sensitivity of 85.8% and a positive predictivity of 64.5% in identifying ventricular ectopic beats, underscoring its capability in detecting rare arrhythmias [30].

Similarly, Long Short-Term Memory (LSTM) networks have been highly effective in detecting atrial fibrillation (AF). Hannun et al. utilized an LSTM model to analyze long-term ECG recordings, achieving a sensitivity of 94% for AF detection. This underscores the potential of LSTM models in monitoring and diagnosing specific arrhythmias [19].

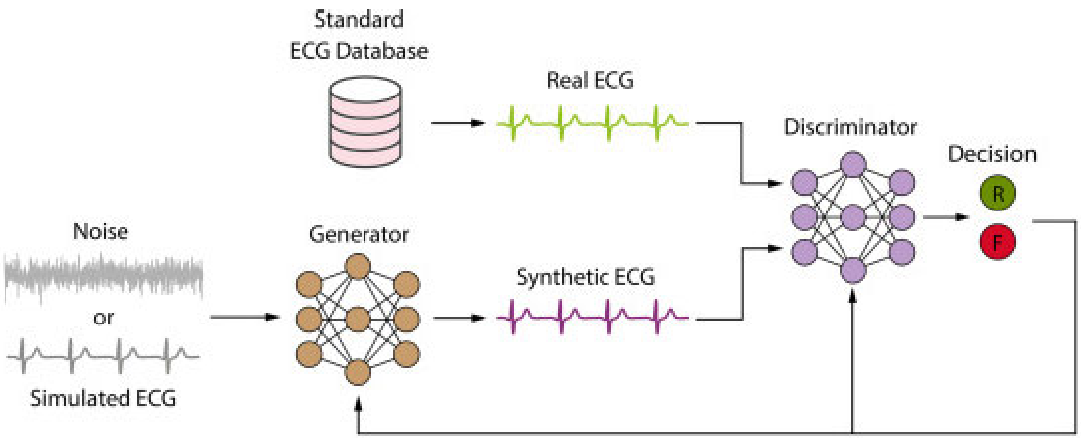

FIGURE 8. GAN architecture [24].

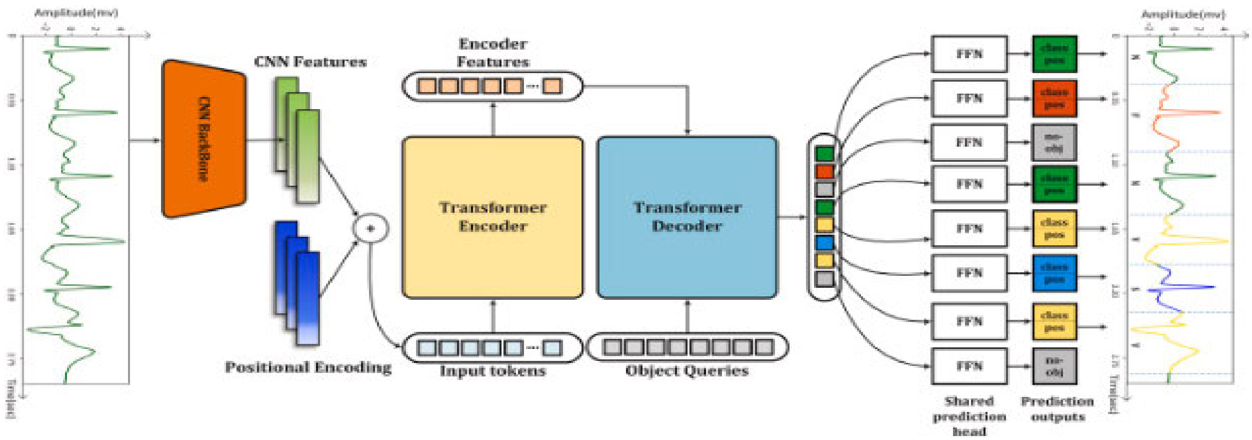

FIGURE 9. Transformer architecture [25].

Further advancements include the work of Saravana Ram et al., who employed a hybrid model combining CNNs and LSTMs. This model achieved impressive accuracies of 98.6%, 97.4%, and 96.2% on the MIT-BIH dataset, and 97.1%, 96.4%, and 95.3% on the PTB-ECG dataset, respectively [31].

Another notable application is in the detection of MI. Chen et al. developed a deep neural network (DNN) model that analyzed a large dataset of 64,121 ECG records from 29,163 subjects, achieving an area under the curve (AUC) of 0.96. This demonstrates the model's high accuracy and its potential for real-time monitoring and diagnosis of MI [32].

For arrhythmia classification, Prifti et al. employed a CNN model on the Generepol cohort, achieving an AUC of 0.9. This model effectively identified various types of arrhythmias, showcasing its utility in comprehensive cardiovascular diagnostics [33].

Lastly, the application of deep learning for remote patient monitoring has been explored by Shaik et al. Their study utilized various DL models, including CNNs, LSTMs, and DNNs, achieving the highest accuracy of 99.69% for arrhythmia classification. This highlights the potential of deep learning in telemedicine and remote healthcare applications [34].

The broader impact of deep learning in ECG analysis is illustrated by comprehensive summaries provided in various studies. Table 7, Table 8, and Table 9 present detailed overviews of deep learning applications, including specific tasks, models, datasets, performance metrics, limitations, and future directions.

III. RELATED WORK

Machine learning techniques have significantly advanced the classification of ECG signals, leading to numerous healthcare innovations. Mincholé et al. explored recent advancements in machine learning systems applied to ECG analysis, discussing their benefits and limitations [35]. Dissanayake et al. demonstrated the potential of machine learning to capture complex physiological responses through an ensemble learning approach for human emotion recognition using ECG signals [36]. Wasimuddin et al. presented a comprehensive model for ECG signal analysis, covering signal acquisition,

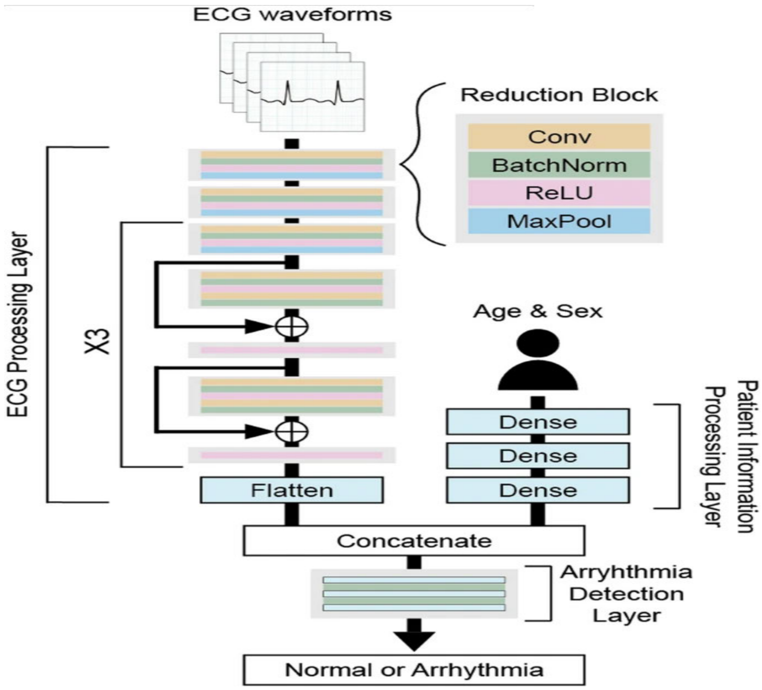

FIGURE 10. **Federated learning architecture [27].**

processing, feature engineering, and classification, thus charting the evolution of ECG analysis techniques [2].

Khalil et al. introduced an end-to-end deep learning method for heart disease diagnosis from single-channel ECG signals, utilizing 1D-CNN and Stationary Wavelet Transform for feature extraction [37]. Latif et al. explored decision trees for classifying ECG and electroencephalogram (EEG) signals, showcasing the versatility of machine learning algorithms in physiological data analysis [38]. Nurmaini et al. implemented deep learning-based stacked denoising and autoencoders for ECG heartbeat classification, highlighting the potential of neural networks in feature learning [39].

Qiu et al. investigated selective encryption techniques for ECG data in body sensor networks, emphasizing the critical aspect of data security in healthcare applications [40]. Sahoo et al. conducted a comprehensive survey on machine learning approaches for detecting cardiac arrhythmias in ECG signals, providing insights into state-of-the-art methods in arrhythmia detection [41]. Subba and Chingtham distinguishes between ectopic and normal heartbeats via analysis of Electrocardiogram (ECG) signals in their study. The specificity, accuracy, and sensitivity of the LDA classifier, which was utilized to distinguish anomalies, were 98.57%, 98.77%, and 98.2%, respectively. The benchmark dataset for Arrhythmia from MIT-BIH was used to test the approach [42].

Ibrahim et al. proposed a framework for predicting acute myocardial infarction using machine learning and Shapley values, illustrating the interpretability of machine learning models in cardiovascular disease prediction [43]. Mastoi et al. employed an integrated machine learning-data mining approach for premature ventricular contraction prediction, using logistic regression and classifiers for accurate prediction [44]. Kumari et al. focused on arrhythmia classification using support vector machines (SVM) and discrete wavelet transform (DWT), aiming for precise and efficient classification [45].

Wang et al. developed a machine learning technique for improving the accuracy of PVC localization throughout the ventricle, based on 12-lead ECG data. The system classifies PVC beats into one of the 11 ventricle segments in two steps by employing six parameters, one of which is a new morphology feature termed "Peak_index." Next, a binary classifier is used to train the best classifier to distinguish between segments that are prone to confusion. The test accuracy for the first classification was 75.87%, and the accuracy for the second classification was 76.84%. 10% of the confused samples were rectified by the binary classification [46]. Feng et al. developed a sleep apnea detection method based on unsupervised feature learning and single-lead ECG signals, underscoring the importance of feature extraction in physiological signal analysis [47]. Attallah proposed an ECG-based pipeline for COVID-19 diagnosis, highlighting the potential of ECG data in disease diagnosis [48].

While traditional machine learning techniques have laid the foundation for ECG classification, deep learning methods are increasingly being employed to address their limitations. The integration of deep learning algorithms, advanced feature extraction methods, and ensemble learning approaches has

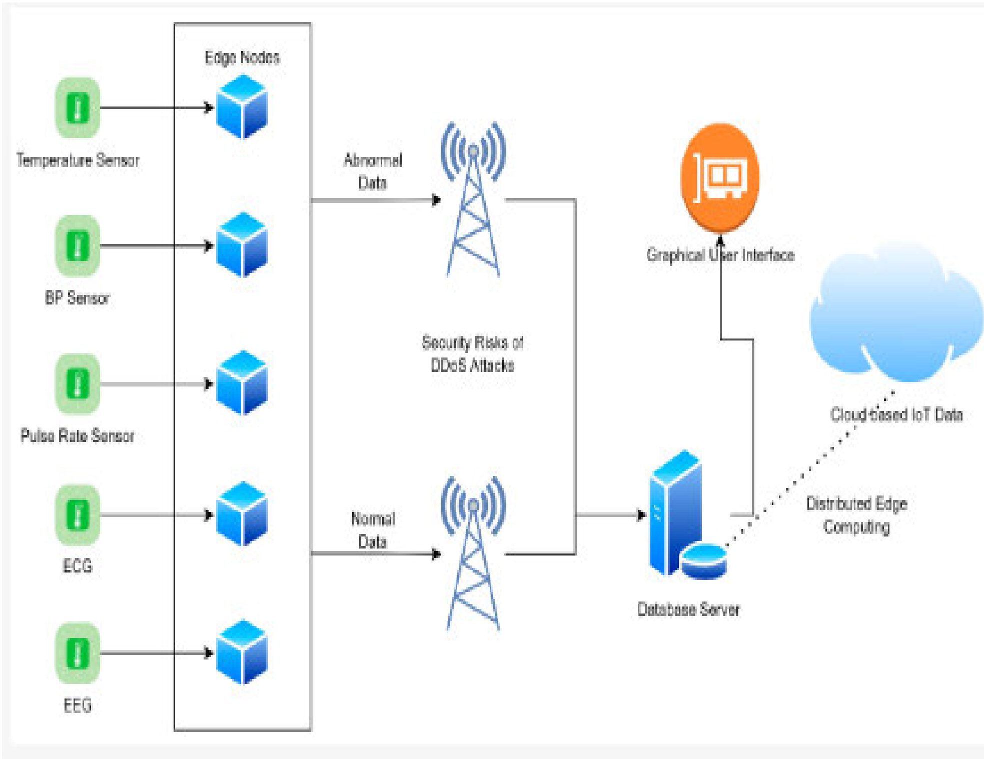

FIGURE 11. Edge computing with deep learning architecture [29].

significantly improved the accuracy and efficiency of ECG signal analysis, driving advanced healthcare innovations. A summary of Machine Learning Applications in ECG Analysis is given in Table 6.

A. INNOVATIVE APPLICATIONS OF DEEP LEARNING IN ECG CLASSIFICATION

Deep learning techniques have gained significant traction in various applications involving ECGsignals. Erdenebayar et al. demonstrated the application of deep learning methods for automatically identifying sleep apnea events from ECG signals, transforming the signal into a 2D format for analysis using a 2D CNN model [49]. Similarly, Lih et al. proposed a model for comprehensive electrocardiographic diagnosis, utilizing deep learning algorithms to classify abnormal ECG signals into conditions such as coronary artery disease (CAD), myocardial infarction (MI), and congestive heart failure (CHF) [50]. Murat et al. conducted a survey focusing on deep learning techniques for heartbeat detection and arrhythmia classification using ECG signals [51]. Strodthoff et al. aimed to establish the PTB-XL dataset as a benchmark for ECG analysis algorithms, addressing the scarcity of appropriate datasets for training and evaluation in automatic ECG analysis [52].

Belo et al. suggested two architectures, Temporal Convolutional Neural Network (TCNN) and RNN, for ECG biometrics to enhance identification and authentication processes [53]. Peimankar and Puthusserypady introduced a deep learning model for real-time segmentation of heartbeats, emphasizing its efficiency in telehealth monitoring systems [54]. Uwaechia and Ramli conducted a comprehensive survey on ECG signals as a novel biometric modality for human authentication, focusing on the challenges in ECG signal analysis for biometric recognition [55]. Furthermore, El-Rahiem et al. proposed a multimodal biometric authentication system integrating ECG and finger vein data through deep CNN models for feature extraction [56].

Panganiban et al. implemented a CNN classification approach for ECG arrhythmias without visual inspection of the ECG. By utilizing characteristic maps retrieved from pooling and convolution layers, the CNN model effectively handled noise parameters and achieved high accuracy levels during testing [57]. Ebrahimi and Bayat-Sarmadi provided an extensive review and analysis of recent deep learning techniques for classifying ECG signals, highlighting the dominance of CNNs in feature extraction across various studies [58].

In addition, Ibtehaz et al. introduced EDITH, a deep learning-based framework for ECG biometric authentication, demonstrating its practical potential [59]. Sakr et al. proposed a cancelable ECG biometric system based on deep transfer learning approaches for human authentication [60]. Attallah introduced ECG-BiCoNet, a pipeline for COVID-19 diagnosis utilizing ECG data and extracting features from different deep learning layers [48]. Narayana et al. developed an ECG-based biometric authentication system using

TABLE 5. Basic equations for models of neural networks.

Model	Equation/Formula	Description
CNNs	**Convolution:** $S(i,j)=\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}X(i+m,j+n)\cdot W(m,n)$ **ReLU Activation:** $A(i,j)=\max(0,S(i,j))$ **Max Pooling:** $P(i,j)=\max_{0\le m<M,0\le n<N}A(i\cdot M+m,j\cdot N+n)$ **Gradient Calculation:** $\frac{\partial L}{\partial W}=\sum_{i,j}\frac{\partial L}{\partial S(i,j)}\cdot X(i,j)$	Extracts features from input data by applying filters, pooling operations, and gradient-based learning to optimize weights.
RNNs	**Hidden State Update:** $h_t=\sigma_h(W_h h_{t-1}+W_x x_t+b_h)$ **Output:** $y_t=\sigma_y(W_y h_t+b_y)$ **BPTT:** $\frac{\partial L}{\partial h_{t-1}}=\frac{\partial L}{\partial h_t}\cdot W_h$	Processes sequential data by maintaining hidden states, updating them, and making predictions based on these states.
LSTMs	**Forget Gate:** $f_t=\sigma(W_f[h_{t-1},x_t]+b_f)$ **Input Gate:** $i_t=\sigma(W_i[h_{t-1},x_t]+b_i)$ **Cell State Update:** $C_t=f_t\cdot C_{t-1}+i_t\cdot\tanh(W_C[h_{t-1},x_t]+b_C)$ **Hidden State:** $h_t=o_t\cdot\tanh(C_t)$ **Gradient Flow:** $\frac{\partial L}{\partial C_{t-1}}=\frac{\partial L}{\partial C_t}\cdot f_t$	Manages long-term dependencies using memory gates to retain and update information over extended sequences.
GANs	**Generator Loss:** $L_G=-\mathbb{E}_{z\sim p_z(z)}[\log D(G(z))]$ **Discriminator Loss:** $L_D=-\mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)]-\mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$ **Objective Function:** $\min_G\max_D L(G,D)=\mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)]+$ $\mathrm{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$	Generates realistic data through adversarial training where a generator creates data and a discriminator evaluates it.
Transformers	**Self-Attention:** $\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$ **Multi-Head Attention:** $\text{MultiHead}(Q,K,V)=\text{Concat}(\text{head}_1,\ldots,\text{head}_h)W^O$ **Positional Encoding:** $PE_{(pos,2i)}=\sin(pos/10000^{2i/d_{model}})$ $PE_{(pos,2i+1)}=\cos(pos/10000^{2i/d_{model}})$	Uses self-attention and positional encodings to manage and understand complex sequential data effectively.

CNNs - CNNs use convolutional layers for feature extraction, followed by activation and pooling operations.
BPTT - Back Propagation through time
RNNs - Recurrent Neural Networks handle sequential data through hidden state updates and backpropagation through time.
LSTMs - Long Short-Term Memory Networks incorporate memory cells and gates to manage long-term dependencies in sequences.
GANs - Generative Adversarial Networks involve a generator and a discriminator in a competitive framework to produce realistic data.
Transformers - Transformers leverage self-attention mechanisms and positional encodings for processing complex sequences.

deep learning methods, showcasing improved classification accuracy [61].

Prakash et al. presented BAED, a secured biometric authentication system utilizing ECG signals and deep learning techniques [62]. Baek et al. investigated intelligent feature selection for ECG-based personal authentication using deep reinforcement learning, optimizing features through a reinforcement learning algorithm [63]. Additionally, Agrawal et al. proposed an ECG-based user authentication system employing deep learning algorithms, offering a secure and convenient method for user authentication with ECG data [64].

Narotamo et al. evaluated various approaches to encoding ECG signals in cardiovascular diseases (CVDs) with multiple labels, including novel attention-based methods. They leveraged multimodal fusion techniques to enhance prediction capabilities across different representation networks using the publicly available PTB-XL ECG dataset [65]. Kim et al. developed a deep learning model for arrhythmia detection using RR-interval framed ECG data, emphasizing its application potential in biometric security [66].

In summary, the integration of deep learning techniques with ECG signals has demonstrated promising results across various applications, including arrhythmia detection, biometric authentication, and disease diagnosis. These advancements underscore the transformative impact of deep learning in enhancing the analysis and utilization of ECG data in healthcare and beyond. However, several limitations such as dataset biases, challenges in real-time implementation, and issues with model generalizability need

TABLE 6. Summary of machine learning applications in ECG analysis.

Year	Application Task	Machine Learning Technique	Dataset Used	Performance	Disadvantages
2016 [67]	ECG Biometric Recognition	Logistic Regression	E-HOL-03-0202-003	Accuracy: 100%	Linear decision boundary
2017 [68]	Arrhythmia Classification	k-Nearest Neighbors	MIT-BIH Arrhythmia Database (47 subjects)	Accuracy: 98.8%	Sensitive to noise
2018 [69]	Heart Rate Variability Analysis	Artificial Neural Networks	PTB Database (290 subjects)	Accuracy: 98.85%	Black-box nature
2019 [70]	Risk Stratification	Support Vector Machines	UK Biobank (47,679 subjects)	AUC: 0.742	Computationally expensive
2020 [71]	Disease Detection	Decision Trees	ECG Database (29,163 subjects)	f1-score: 0.809	Less robust for complex patterns
2020 [72]	Sleep Stage Classification	Gradient Boosting	Diverse datasets	Accuracy: 97%	Prone to overfitting
2021 [32]	Myocardial Infarction Identification	Ensemble Learning	ECG records (29,163 subjects)	AUC: 0.96	Complex tuning
2022 [33]	Arrhythmia Risk Prediction	Random Forests	Generepol cohort (990 subjects)	AUC: 0.9	Prone to overfitting

to be addressed. Future research should focus on expanding datasets, improving model interpretability, and advancing real-time processing capabilities.

B. APPLICATIONS OF DEEP LEARNING IN HEALTH STATE MONITORING USING ECG

The utilization of ECGmonitoring systems has seen a surge in the healthcare domain for continuously assessing an individual's health state. Lee and Liu proposed a real-time driver health detection system integrated into a smart steering wheel. By monitoring physiological signals including respiration, hand grip force, photoplethysmogram (PPG), and ECG, the system can detect the driver's health condition, particularly drowsiness. This illustrates the expansion of ECG applications into health monitoring beyond clinical environments [73]. Emelyanenko et al. introduced a dynamic cloud-based ECG monitoring system enabling round-the-clock measurement of the circulatory system's health using a mobile cardiograph [74]. This system transmits ECG data to a server for real-time analysis and processing, demonstrating the potential for instantaneous health monitoring.

Noh et al. developed a wearable ECG monitoring system based on Knowledge Discovery Computing, incorporating a 3-axis acceleration sensor to concurrently measure cardiac and activity information [75]. This approach aims to reduce errors in health information analysis by integrating contextual data with abnormal ECG patterns, underscoring the significance of context in health monitoring. Furthermore, Abdullah and Al-Ani proposed a CNN-LSTM-based model for ECG arrhythmias and myocardial infarction classification. Leveraging CNNs and LSTM, the system accurately classifies ECG signals for cardiac health monitoring, showcasing the potential of advanced technologies in healthcare [76]. Heart anatomy and function are vitally dependent on ECGs, which facilitate early diagnosis. Sujadevi and Soman using the dataset 'The China Physiological Signal Challenge 2018', employed deep learning approaches to enhance cardiac anomaly identification and prediction. They developed a unique architecture that combined a DNN approach to identify the minimal ECG leads for optimal accuracy, achieving 99.01% accuracy [77]. Malik et al. introduced an adaptive QRS detection algorithm for ultra-long-term ECG recordings, addressing challenges in signal processing for prolonged monitoring durations [78]. This algorithm, built upon state-of-the-art techniques with enhancements, improves the accuracy and reliability of ECG analysis for long-term health monitoring. Miao et al. investigated continuous blood pressure estimation using one-channel ECG signals and deep learning techniques. Developing a model that integrates residual networks and long short-term memory, the study aimed to estimate blood pressure non-invasively, highlighting the potential for ECG-based health monitoring beyond conventional applications [79]. In a distinct approach, Lampreave et al. introduced an AI-enabled augmented reality headset for assisting electrocardiogram interpretation. By digitizing and analyzing ECG data using artificial intelligence, the system aims to improve the efficiency and accuracy of ECG analysis, emphasizing the integration of technology in healthcare diagnostics [80].

The progress of ECG monitoring systems has also spurred the development of predictive cyber-physical systems for specific health conditions. Hussain and Park presented Big-ECG, a system for stroke management integrating wearable ECG sensors, data analytics, and health advisory services. This system exemplifies the potential of ECG-based monitoring in forecasting and managing health conditions proactively [81]. Moreover, Ibaida et al. proposed a privacy-preserving compression model for efficient IoMT ECG sharing, addressing concerns regarding data security and network efficiency. Employing shallow neural networks for ECG data compression, the system ensures privacy while optimizing data transmission, underscoring the importance of data protection in healthcare applications [82].

A significant aspect of everyday living is stress analysis, which involves feature extraction that can be time-consuming. Ishaque et al. implemented a method that transforms 1D ECG data collected by WESAD into 2D images using model compression and transfer learning. They achieved a classification accuracy of 90.62%, illustrating the potential of deep learning techniques for edge computing and mobile applications on low-end hardware [83]. With cardiac telemonitoring, medical personnel evaluate measurements from a distance for monitoring patients and decision-making. Belaid et al. suggested a learning-based electrocardiogram classification method in conjunction with a virtual platform called MCPCS to identify MI. They utilized the ADS1298 chip to detect ECG signals when an arrhythmia manifests, with R-peak detection and ECG noise reduction achieved by the wavelet transform technique. The model was tested on 50,728 cases from the PTB database, achieving a mean accuracy of 96.67% [84].

Begum et al. implemented two suggested models for the automatic identification and categorization of irregular heartbeats in ECGs using the MIT-BIH Dataset. Model A achieved an accuracy of 99.68%, while Model B achieved 99.51%. This study aims to shorten the time it takes to diagnose patients through automation [85]. In summary, predictive analytics, disease classification, and real-time health monitoring are all being revolutionised in the medical field by ECG monitoring technologies. The accuracy of diagnoses and ongoing monitoring are enhanced by deep learning techniques. To improve the efficacy and dependability of ECG-based health monitoring systems, future research should address issues including variation in data and contextual data integration.

C. APPLICATIONS OF DEEP LEARNING IN ARRHYTHMIA DETECTION

Arrhythmias, irregular heart rhythms, pose significant health risks. Recent research has concentrated on detecting them via ECGsignals, with diverse methodologies proposed for enhanced accuracy and efficiency. Sharma et al. devised a robust system employing wavelet decomposition filter banks to extract features from ECG signals, aiming to classify shockable and non-shockable arrhythmias more accurately than existing methods [86]. Similarly, Prakash et al. suggested a technique based on the Association for the Advancement of Medical Instrumentation (AAMI) standard, incorporating pre-processing, feature extraction, and classification stages to improve arrhythmia recognition [87].

Machine learning has been extensively explored for arrhythmia detection. Sahoo et al. surveyed contemporary methods, offering insights for researchers [41]. Zheng et al. developed a classification method utilizing a combination of CNN and LSTM technology, showcasing the potential for precise arrhythmia diagnosis [88]. To diagnose left ventricular diastolic dysfunction noninvasively, Zheng et al. introduced a CatBoost model based on phonocardiogram (PCG) transfer learning. They utilized convolutional neural networks trained on deep features and four distinct spectrogram representations to identify patterns. After applying principal component and linear discriminant analysis to several feature subsets, the model achieved a sensitivity of 0.821, an AUC of 0.911, specificity of 0.927, accuracy of 0.882, and F1-score of 0.892, demonstrating significant performance improvement [88]. Personalized approaches have also been pursued. Hori et al. proposed an individualized ECG abnormality judgment method employing deep learning tailored to each patient's unique ECG patterns [89]. This personalized approach aimed to identify abnormalities potentially missed by generic methods. To categorize ECGs, a deep-learning-based method named Multi-ECGNet was created by Cai et al. The model was able to classify 55 different types of arrhythmias with a high micro-F1-score of 0.863. [90]. Additionally, Kumar et al. reviewed impactful research papers on arrhythmia detection using ECG signals, underlining ECG's significance in detecting heartbeats via skin electrical changes [91]. Baek et al. proposed an algorithm to identify minute variations in paroxysmal AF. The internal and external validation datasets showed that the AI-based algorithm performed well in identifying AF, with the area under the receiver operating characteristic curve being 0.79 and 0.75, recall being 82% and 77%, specificity being 78% and 72%, F1 score being 75% and 74%, and overall accuracy being 72.8% and 71.2%, respectively [92]. Arrhythmias and other cardiovascular illnesses are the leading causes of death globally. Murawwat et al. suggested a hybrid method for detecting and categorizing arrhythmias that combined Multivariate Empirical Mode Decomposition (MEMD) with Artificial Neural Networks (ANN) [93]. To distinguish between bradycardia and tachycardia, MEMD pulled characteristics from ECG data such as heart rate and RR interval. Utilizing ANN pattern recognition, the method outperformed earlier approaches like DWT and LDA, achieving an accuracy of 89.8%. Furthermore, ensemble learning models have been suggested for precise arrhythmia detection. Ramkumar et al. introduced an Ensemble classifier, implementing the AD-Ensemble SVM-NB-RF method [94]. Similarly, Mandala et al. presented an enhanced ensemble learning approach utilizing multi-lead ECG data and a novel feature extraction technique to enhance detection accuracy [9].

D. APPLICATIONS OF DEEP LEARNING IN ECG BIOMETRIC AUTHENTICATION AND IoT

Biometric authentication utilizing ECG signals has garnered significant interest recently due to its distinctive attributes and potential applications across various domains. Samarin and Sannella conducted a study exploring ECG signals as a biometric for authentication, gathering data from 55 participants across two sessions four months apart. They aimed to assess the stability of ECG signals as a dependable biometric identifier [95].

Al Alkeem et al. took this further by integrating machine learning techniques into the ECG-based authentication system, underscoring the significance of biometric authentication in supplanting traditional methods and highlighting its applicability in security protocols and medical environments [96]. Similarly, Kim et al. proposed an improved machine learning-based biometric authentication system utilizing RR-interval framed electrocardiograms, achieving accuracy rates of up to 95% through streamlined data analysis [97].

Wang et al. concentrated on developing a simplified ECG biometric authentication method for IoT edge devices, achieving an impressive authentication accuracy of 99.63% with a cohort of 290 subjects from the Physionet PTB ECG database [98]. This study underscored the potential of ECG-based biometrics for securing IoT devices at the edge. In a comparative analysis by Ingale et al., a new extensive off-the-person ECG dataset was curated to advance research in ECG biometrics, highlighting the speed and convenience of biometric authentication and its low susceptibility to circumvention [99].

Barros et al. proposed a data enhancement model for ECG biometric identification, aiming to improve the performance of biometric systems with a larger subject pool, mirroring real-world security scenarios [100]. Shdefat et al. investigated the challenges and opportunities of deploying ECG biometric authentication in IoT and 5G environments, focusing on obtaining vital ECG signals through wearable devices compatible with 5G technology and addressing factors impacting signal acquisition [101]. Additionally, Chandrakar et al. presented a secure ECG-based smart authentication scheme for IoT devices, stressing communication, computation, storage costs, and security features in the protocol's performance assessment [102]. The integration of ECG biometrics with other modalities was explored by El-Rahiem et al., who advocated for a multimodal biometric authentication system merging ECG and finger vein biometrics utilizing a CNN model for feature extraction, thereby enhancing the authentication process [56].

Dhanke et al. introduced a new supervised learning platform that combines information from several systems to provide a distinct characteristic for ECG-based biometric authentication. The system achieved a 99.4% prediction performance with excellent quality and memory with the usage of an SVM for verification, highlighting the need for a reliable approach that takes into account individual ECG differences for successful verification in real-time software [103].

In summary, research on ECG biometric authentication for IoT applications has yielded promising results in terms of accuracy, security, and usability. Leveraging machine learning, multimodal fusion, and data enhancement models, ECG-based biometrics provide a robust authentication solution for securing IoT devices in diverse environments. Continued advancements in this field are crucial to tackle emerging security challenges and enhance the overall effectiveness of biometric authentication systems in IoT settings.

E. APPLICATIONS OF DEEP LEARNING IN REAL TIME ECG ANALYSIS USING WEARABLE TECHNOLOGY

In recent years, there has been considerable attention devoted to the development of wearable technology for real-time ECG analysis. Chowdhury et al. introduced a wearable system designed to detect and warn drivers of heart attacks in real-time, aiming to reduce road accidents. Their study evaluated the performance of dry electrodes and various electrode configurations, along with assessing the system's overall power consumption [104]. Khan et al. emphasized the significance of security and privacy in wearable devices for cardiac disease detection. They advocated for lightweight models like the Wearable ECG patch to achieve high accuracy and efficiency [105]. Nasiri and Khosravani discussed the advancements and challenges in fabricating wearable sensors for health monitoring, underscoring the new possibilities introduced by these sensors for human health monitoring [106]. Alizadeh et al. developed a textile-based multichannel ECG band capable of measuring ECG from multiple locations on the waist, contributing to the increasing interest in wearable health monitoring systems [107].

Qiao et al. explored advances in sweat wearables for personal health monitoring, highlighting the potential of flexible wearable devices for real-time monitoring of chemical biomarkers in sweat [108]. Islam et al. investigated the use of wearable technology to assist COVID-19 patients, discussing wearable monitoring devices and respiratory support systems for individuals affected by the virus [109]. Rana and Mittal conducted a review on the application of wearable sensors for real-time kinematics analysis in sports, focusing on key technologies enabling performance analysis in various sports [110]. Xu et al. suggests combining a recurrent neural network (RNN) with a convolutional neural network (CNN) to classify ECG heart signals for diagnostic purposes. Two convolutional layers, four residual blocks, two fully connected layers, and two bidirectional long short-term memory (biLSTM) layers make up the network. In identifying five ECG classes, the network attained recognition sensitivity of 95.90%, accuracy of 95.90%, and specificity of 96.34%. The model to be used for high-precision cardiac health evaluation on mobile devices or in cloud computing environments [111]. Wasimuddin et al. introduced a CNN-based classifier model for real-time multiclass ECG signal analysis in portable and wearable monitoring devices [112]. Jeong et al. developed a real-time wearable physiological monitoring system for home-based healthcare applications, incorporating wireless physiological signal acquisition and smartphone-based data processing [113]. Moon and Lee suggested a sensor data fusion approach for respiratory monitoring using lung sounds and cardiograms to potentially diagnose respiration patterns in real time [114]. Tan et al. proposed a 5G-enabled real-time cardiovascular monitoring system for COVID-19 patients using deep learning to enhance the prediction accuracy of cardiovascular diseases [4].

Overall, the literature review indicates a growing interest in real-time ECG analysis using wearable technology, with a focus on enhancing accuracy, efficiency, and accessibility for various healthcare applications. Future research in this domain may continue to explore innovative technologies and algorithms to further enhance the capabilities of wearable ECG monitoring systems. Anbalagan et al. cover performance metrics, databases, and several ECG analysis methods, offering a roadmap for the future of real-time ECG analysis using wearable technology and advice on safety measures [115].

F. CYBERSECURITY APPLICATIONS OF PHYSIOLOGICAL SIGNALS USING DEEP LEARNING

Recent advancements in microelectronics and information and communication technology have significantly facilitated the measurement and transmission of physiological data for disease monitoring and treatment purposes [139]. This data can now be continuously accessed by remote healthcare servers for classification and analysis. Furthermore, a novel diagnostic algorithm for heart disease in an ECG monitoring system has been introduced, leveraging a portable ECG monitor for continuous monitoring and effective application of the Healthcare Internet of Things (HIoT) [140].

Researchers have evaluated the application of woven conductive dry textile electrodes for continuous ECG signal acquisition, demonstrating the effectiveness of conductive textile fabric materials in capturing biopotentials [141]. Real-time ECG monitoring using compressive sensing on a heterogeneous multicore edge device has also explored to enhance efficiency and enable a gateway-centric connected health solution [142]. Deep learning techniques have shown promise in analyzing physiological signal data, including ECG, and hold potential for medical tasks [143].

Innovations include the development of an integrated stretchable sensing patch for monitoring physiological and biochemical parameters simultaneously, enabling real-time and synchronous monitoring of ECG, PPG, and biochemical parameters [144]. Machine learning has been applied to analyze biomedical signals for medical diagnosis, focusing on predicting and diagnosing diseases based on various data features [145]. Additionally, the Fractional Fourier Transform was utilized for feature extraction from ECG and galvanic skin response signals for emotion recognition, underscoring the importance of physiological signal analysis in human-computer interaction [146].

Other advancements include the screening of cardiac disease based on integrated modeling of heart rate variability, demonstrating the effectiveness of identifying different physiological signal components for detecting sleep apnea events [32]. Wearable smart textiles for long-term ECG monitoring have been reviewed, discussing the application of textile electrodes for ECG monitoring and their prospects [147].

Furthermore, automated detection of premature ventricular contraction based on an improved gated recurrent unit network was developed by Wang to recognize PVC signals [148]. A nested long short-term memory network model has been proposed for unbalanced ECG signal classification to address label imbalance issues and improve classification accuracy [149]. Physiological signal-based thermal sensation models have been studied for indoor environment thermal comfort evaluation, showcasing the usefulness of physiological signals in predicting thermal sensation [150].

Deep learning applications in ECG have been systematically reviewed, providing insights into the domains of application and meta-data analysis of deep learning studies in ECG [151]. An airline point-of-care system for hybrid physiological signal monitoring has been proposed, with applications in diagnosing sleep apnea-hypopnea syndrome on flights to meet the demands of long-haul flights [152]. Multiscale diffusion entropy analysis has been applied to detect crucial events in cardiac pathology, demonstrating improved performance in detecting crucial events in ECG time series [153]. Photoplethysmography (PPG) offers a noninvasive technique for recording human vital signs, and a system has been developed to assess PPG signal quality aided by ECG, enabling heart rate estimation [154].

According to Li et al., unobservable physiological signals—like photoplethysmogram (PPG) signals—have drawn more interest lately due to their availability, non-intrusiveness, and ongoing monitoring. PPG signals' simplicity, difficulty to steal, and live detection are reasons why their potential in cybersecurity applications is being investigated. Three areas of PPG-based authentication are covered in this paper: feature conversion and selection, signal extraction, and signal conditioning [155]. Furthermore, machine learning techniques have been employed to analyze ECG signals in professional football players, demonstrating the ability of AI and machine learning to detect arrhythmias with accuracy [156]. The feasibility of reconstructing ECG signals from PPG has been investigated, highlighting the potential for electrocardiogram reconstruction from photoplethysmogram data [157]. Overall, the integration of cybersecurity applications with physiological signals, particularly ECG, holds promise in advancing healthcare monitoring and diagnosis. The paper identifies problems and suggests ways to solve these restrictions and security risks in the future.

IV. DISCUSSION

A. ECG RISK STRATIFICATION

Gaps:

1) **Personalization:** Existing models often fail to consider unique patient characteristics such as genetic factors, lifestyle, and personal medical history.
2) **Longitudinal Data:** There is a lack of long-term data that would enable accurate risk prediction over extended periods.
3) **Clinical Integration:** Integrating risk scores into everyday clinical decision-making processes poses significant challenges.

Solutions:

1) **Customized Models:** Develop and utilize models that integrate detailed patient data, including genetic and lifestyle information. For example, personalized risk scores have shown potential in improving patient outcomes in recent research.

TABLE 7. Summary of deep learning applications in ECG analysis.

Application Area	Application Task	DL Model	Dataset (Number of Subjects/Data)	Performance	Limitation	Future Directions
Cardiovascular Disease	Disease Detection [71]	CNN	64,121 ECG database (29,163 subjects)	F1-score: 0.809	Incomplete arrhythmia coverage, real-time performance	Expand dataset, enhance real-time processing
Cardiovascular Disease	Disease Detection [116]	OCI-DBN	Cleveland (297 records)	Accuracy-94.61%, Sensitivity: 96.03%, Specificity:93.15%, Precision:93.55%,f1-Score:0.947	Overfitting, underfitting, network configuration optimization	Investigate time complexity, test on larger datasets
Cardiovascular Disease	Disease Detection [117]	CNN	UCI database	Accuracy: 97%	Dataset details and the specific comparison with state-of-the-art methods not provided	Clinical deployment
Cardiovascular Disease	Disease Detection [118]	DBN with Cuckoo Search Algorithm (Bio-inspired optimization)	Cleveland,South Africa,Z-Alizadeh Sani,Framingham, Statlog	Cleveland: Accuracy 89.2%, South Africa: Accuracy 89.5%, Z-Alizadeh Sani: Accuracy 89.7%, Framingham: Accuracy 90.2%, Statlog: Accuracy 91.%,	Comparison with other models not explicitly detailed	Further comparison with other ML and DL models, optimize the model for better accuracy
Cardiovascular Disease	Disease Detection [119]	Modified DBN with PS-GWO (Particle Swarm Optimization - Grey Wolf Optimization)	Heart Failure Clinical Records,Heart Disease Dataset	Highest accuracy:60%	Performance across other models not evaluated	Explore additional models and optimization techniques
Cardiovascular Disease	Disease Detection [120]	Bagging Ensemble Technique with DBN	datasets from Kaggle (5000 samples)	Accuracy-DBN: 95.6%, CNN: 89%, RNN: 90%, LSTM: 92%	Limited comparison to specific models	Improvement in preprocessing techniques, and validation on different datasets
Cardiovascular Disease	Diagnosis and risk level determination [121]	Enhanced Deep Learning Assisted Convolutional Neural Network (EDCNN)	UCI repository	Precision: 99.1%	Reduction in features affects classifier efficiency,no detailed feature analysis provided	testing on diverse datasets
Cardiovascular Disease	Risk Stratification [70]	DNN-RetiCAC	UK Biobank (47,679 subjects)	AUC: 0.742	Selection bias, misclassification, generalizability	Address bias, improve generalizability
Cardiovascular Disease	Risk Prediction and Stratification for Early Intervention [122]	DeepSurv (Deep Learning-Based Survival Model)	890 DKD Patients (Retrospective Study)	C-index: 0.767 (95% CI: 0.717–0.817), AUC: 0.780 (95% CI: 0.721–0.839), IBS: 0.067	Short Follow-Up Period, Limited to 7 Variables, Generalizability Concerns	Expanded Variable Set, Broader Population Testing
Cardiovascular Disease	Risk assessment for borderline-QRISK3 individuals [123]	Reti-CVD (based on retinal photographs)	UK Biobank (48,260 participants)	CVD risk in Reti-CVD-high-risk group: 13.1%, C-statistics improvement: 0.014–0.023	May not be applicable globally or across different ethnicities	Further validation in diverse populations, Exploration of Reti-CVD in different clinical settings and risk groups
Cardiovascular Disease	Disease classification and severity analysis [124]	Hybrid model combining Cat Fuzzy Neural Model (CFuNM) and Hybrid Ant Colony and African Buffalo Optimization (HAC-ABO)	Magnetic Resonance Imaging (MRI)	Classification accuracy of 99.3%	Noisy MRI data handling	Improvement of noise reduction techniques

TABLE 8. Summary of deep learning applications in ECG analysis.

Application Area	Application Task	DL Model	Dataset (Number of Subjects/Data)	Performance	Limitation	Future Directions
Cardiovascular Disease	Risk prediction [125]	Eight types of DL-based models	customized (459 consecutive patients)	Best DL model improvement: 21% (0.929 vs. 0.762 over best ML system) DL-based c-index for CV event prediction: 17% increase (0.86 vs. 0.73 compared to CPHM)	Potential limitations in generalizability or specific dataset constraints not mentioned	Enhance prediction accuracy
Cardiovascular Disease	Risk stratification [126]	AtheroEdge-(AE3.0DL), utilizing RNN and LSTM	customized (500 patients)	Accuracy: 95% (RNN),95.34% (LSTM),(AUC): 0.98 (RNN), 0.99 (LSTM),Execution time: <1 second	Data representativeness or model generalizability	Further validation on diverse patient populations and clinical settings
Cardiovascular Disease	Risk classification for intermediate- and high-risk CVD [127]	Reti-CVD	UK Biobank: 48,260 participants Singapore Epidemiology of Eye Diseases Study: 6,810 participants	PCE-based Risk Groups: Sensitivity 82.7%, Specificity 87.6%, PPV 86.5%, NPV 84.0% QRISK3-based Risk Groups: Sensitivity 82.6%, Specificity 85.5%, PPV 49.9%, NPV 96.6% Modified FRS-based Risk Groups: Sensitivity 82.1%, Specificity 80.6%, PPV 76.4%, NPV 85.5%	Dataset Bias,Limited Generalizability, Exclusion Impact, Image Variability,	Cross-Validation Cut-Off Optimization
Cardiovascular Disease	Myocardial Infarction Identification [32]	DNN	64,121 ECG records (29,163 subjects)	AUC: 0.96	Dataset incompleteness, model optimization, real-time monitoring	Optimize model, expand dataset, real-time application
Cardiovascular Disease	Myocardial Infarction Classification [128]	New lightweight CNN, SqueezeNet, AlexNet	dataset of cardiac patients (928 records)	Accuracy: 98.23%	lightweight CNN	exploration of other AI methods
Cardiovascular Disease	Myocardial Infarction and cardiomyopathy Classification [129]	CNN	ECG-VIEW II database	Accuracy: 91.1%	Limited data and fewer feature,Similarity of symptoms on ECG	Using 12-channel ECG data for improved accuracy
Cardiovascular Disease	Myocardial Infarction and cardiomyopathy Classification [130]	CNN, GaborCNN	Lead II ECG signals from 92 healthy controls, 7 CAD, 148 MI and 15 CHF patients	Accuracy: >98.5%	Validation not done for larger database	Potential to aid clinicians in screening for CVDs using ECG signals
Cardiovascular Disease	Arrhythmia Risk Prediction [33]	CNN	Generepol cohort (NCT00773201) (990 subjects)	AUC: 0.9	Embedding identification, requirement for additional data	Improve embedding techniques, increase data
Cardiovascular Disease	Diagnostic support tool for AMI detection [131]	DL model	Tri-Service General Hospital, Taipei, Taiwan- 1,051 STEMI/NSTEMI patients (697 ECGs from 737 patients) 140,336 ECGs from 76,775 non-AMI patients	DLM AUC: 0.997, Sensitivity: 98.4%, Specificity: 96.9%, DLM vs. Best Physicians AUC: 0.976	Exection time	DLM into emergency medical systems

TABLE 9. Summary of deep learning applications in ECG analysis.

Application Area	Application Task	DL Model	Dataset (Number of Subjects/Data)	Performance	Limitation	Future Directions
Cardiovascular Disease	Myocardial Infarction detection [132]	ConvNetQuake neural network	PTB database (549 records)	Record-wise Split Accuracy: 99.43%, Patient-wise Split Accuracy: 97.83%	Validation missing	Exploring additional ECG leads and extending the model to other cardiac conditions
Cardiovascular Disease	Myocardial Infarction Multiclass Classification [133]	DenseNet,CNN	Physikalisch-Technische Bundesanstalt database	Accuracy: More than 95% for both models	Validation	Integration into hospital and remote triage systems for MI diagnosis
Cardiovascular Disease	Myocardial Infarction Classification specifying infarcted regions in the myocardium [134]	CNN	PTB database	Accuracy: Over 98% for both MI detection and localization	Requires larger memory	Balance accuracy and computational power
Cardiovascular Disease	Myocardial Infarction detection and prognosis [135]	Ensemebling-CNN, LSTM	PTB, DBMITDB (123,998 images)	Accuracy-CNN: 99.82%, Hybrid CNN-LSTM: 99.88%, Ensemble Technique: 99.89%	Cross-validation not done	Refinement and testing in diverse real-world settings to enhance robustness and generalizability
Cardiovascular Disease	Heart Rate Variability Analysis [69]	ANN	PTB Database (290 subjects)	Accuracy: 98.85%	Class-based evaluation	Explore additional classes, improve evaluation
Healthcare Monitoring	Arrhythmia Classification [68]	DNN	MIT-BIH Arrhythmia Database (47 subjects)	Accuracy: 98.8%	Biosignal generalization untested	Test on more diverse datasets
Remote Patient Monitoring	Arrhythmia Classification [34]	CNN, LSTM, DCNN, DNN, RNN, ANN auto-encoder	Public database	Highest Accuracy: 99.69%	Imbalanced datasets, AI adoption challenges	Address imbalance, focus on adoption
Telemedicine	ECG-based Diagnosis [136]	DNN	Customized Database (5 samples)	Projected probability: 0.85	Investigate robustness in real-world clinical settings; ensure model interpretability	Enhance robustness, focus on interpretability
Sleep Medicine	Sleep Apnea Detection [66]	DNN	Internal dataset (798 subjects), two external datasets (135 and 85 subjects)	Accuracy: 0.910	Model generalization, additional validation	Improve generalization, validate with more data
Sleep Medicine	Sleep Apnea Detection [137]	DNN, 1D CNN, 2D CNN, RNN, LSTM, GRU	nocturnal PSG recordings(86 patients)	Best Model Accuracy: 99%, 1D CNN and GRU Recall Rates: 99%	The study does not specify the robustness of the models to variations in ECG signals	Integration with multimodal approaches to enhance diagnostic accuracy and robustness
Sleep Medicine	Sleep Stage Classification [72]	SlumberNet-ResNet	Diverse datasets	Accuracy: 97%	Generalization, human adaptation	Improve generalization, focus on adaptation
Biometric Authentication	ECG Biometric Recognition [67]	Deep-ECG-DNN	E-HOL-03-0202-003, PTB Diagnostic	Accuracy: 100%	Data variability, model interpretability, computational complexity	Address variability, enhance interpretability
Biometric Authentication	ECG Biometric Recognition [138]	Modified Siamese Network	ECGID biometric database	Accuracy: 99.85%, Sensitivity: 99.30%, Specificity: 99.85% Positive Predictivity: 99.76%	Factors like physical activity or emotional states not considered	Further validation with larger and more diverse datasets

2) **Incorporation of Longitudinal Data:** Collaborate with long-term health studies to gather data that can enhance the accuracy of risk stratification models. Examples include using data from established health registries.
3) **User-Friendly Interfaces:** Design interfaces that can seamlessly integrate with existing electronic health records (EHRs), making it easier for clinicians to use risk scores in their decision-making.

Real-World Applications:

1) Pilot studies utilizing personalized risk assessments in clinical settings.
2) Collaboration with patient registries to obtain and apply longitudinal data.

Future Directions:

1) Investigate how artificial intelligence can integrate with EHR systems to provide real-time risk assessments.
2) Explore the potential of wearable technologies to continuously assess and update risk profiles.

Interdisciplinary Approaches:

1) Collaborate with geneticists, lifestyle experts, and IT professionals to develop comprehensive risk models.
2) Partner with healthcare providers to refine the practical integration of these models into clinical workflows.

B. MYOCARDIAL INFARCTION

Gaps:

1) **Early Detection:** Current methods may not capture subtle early indicators of myocardial infarction effectively.
2) **Noise and Artifacts:** ECG signals are often affected by noise and artifacts, which can compromise the accuracy of diagnoses.
3) **Generalizability:** Models trained on specific populations may not perform well across diverse demographic groups.

Solutions:

1) **Enhanced Detection Algorithms:** Integrate additional biomarkers and advanced machine learning techniques to improve early detection. Combining ECG with biomarkers like troponin has shown promise in early detection.
2) **Advanced Noise Reduction Techniques:** Develop and implement sophisticated techniques to filter out noise and improve signal quality.
3) **Multi-Demographic Training:** Use diverse datasets from multiple centers to ensure models are broadly applicable.

Real-World Applications:

1) Implement combined biomarker-ECG systems in emergency care settings.
2) Develop noise-reduction algorithms for use in wearable ECG monitors.

Future Directions:

1) Examine the integration of AI with imaging technologies, such as MRI, to enhance early myocardial infarction detection.
2) Develop global datasets to ensure the models' effectiveness across different populations.

Interdisciplinary Approaches:

1) Collaborate with cardiologists and data scientists to refine early detection methods.
2) Work with signal processing experts to address and minimize noise in ECG data.

C. ARRHYTHMIA RISK PREDICTION

Gaps:

1) **Dataset Imbalance:** The disproportionate representation of normal beats compared to arrhythmias in datasets affects model performance.
2) **Model Interpretability:** Complex models often lack transparency, making it difficult to understand how predictions are made.
3) **Real-Time Data Processing:** Processing data in real-time poses significant computational challenges.

Solutions:

1) **Data Augmentation:** Use techniques such as synthetic data generation to address dataset imbalances. Methods like SMOTE (Synthetic Minority Over-sampling Technique) can help.
2) **Explainable AI:** Employ approaches like LIME or SHAP to make models more interpretable and transparent.
3) **Optimization for Real-Time Processing:** Develop algorithms that are efficient enough to handle real-time data processing, potentially utilizing edge computing technologies.

Real-World Applications:

1) Incorporate synthetic data techniques in arrhythmia detection systems.
2) Create real-time monitoring tools optimized for wearable devices.

Future Directions:

1) Explore federated learning for model development, allowing for improved privacy and transparency.
2) Investigate hardware solutions for real-time data processing enhancements.

Interdisciplinary Approaches:

1) Work with data engineers and clinicians to optimize real-time processing and interpretability.
2) Collaborate with regulatory bodies to ensure models meet standards for transparency.

D. HRV ANALYSIS

Gaps:

1) **Lack of Standardization:** There is no universally accepted methodology for HRV analysis.
2) **Contextual Factors:** HRV analyses often ignore factors such as stress and physical activity.
3) **Wearable Integration:** Combining HRV analysis with wearable technologies presents technical challenges.

Solutions:
1) **Standardized Methods:** Develop and promote standardized procedures for HRV measurement and analysis, supported by consensus guidelines from relevant health organizations.
2) **Incorporation of Contextual Data:** Integrate data on stress and physical activity to provide a more accurate assessment of HRV.
3) **Collaborate with Wearable Tech Developers:** Work with manufacturers to ensure that wearable devices provide accurate and reliable HRV data.

Real-World Applications:
1) Adoption of standardized HRV protocols in clinical and research settings.
2) Use of integrated HRV data from fitness trackers for health monitoring.

Future Directions:
1) Investigate the potential of AI for contextualizing HRV data and improving analysis accuracy.
2) Develop new wearable technologies that enhance the precision of HRV measurements.

Interdisciplinary Approaches:
1) Collaborate with technology developers and clinical researchers to improve HRV analysis methods.
2) Partner with standardization bodies to establish consistent HRV measurement protocols.

E. ARRHYTHMIA CLASSIFICATION FOR HEALTHCARE MONITORING

Gaps:
1) **Continuous Monitoring:** Ensuring continuous, reliable monitoring over long periods is difficult.
2) **Battery Life:** Wearable devices often have limited battery life, impacting their usability.
3) **Patient Compliance:** Ensuring patients consistently use their monitoring devices is challenging.

Solutions:
1) **Efficient Algorithms:** Design low-power algorithms that extend the battery life of monitoring devices. For instance, algorithms that activate only during critical events can conserve energy.
2) **Advanced Battery Solutions:** Invest in new battery technologies or explore alternative energy sources.
3) **User-Friendly Devices:** Develop devices that are comfortable to wear and easy to use to encourage patient adherence.

Real-World Applications:
1) Implementation of energy-efficient algorithms in wearable ECG monitors.
2) Development of comfortable and user-friendly monitoring devices.

Future Directions:
1) Explore innovative battery technologies such as flexible batteries or energy harvesting solutions.
2) Enhance device design to improve comfort and user experience.

Interdisciplinary Approaches:
1) Collaborate with engineers and designers to create effective and comfortable monitoring devices.
2) Work with behavioral scientists to understand and improve patient adherence.

F. ARRHYTHMIA CLASSIFICATION FOR REMOTE PATIENT MONITORING

Gaps:
1) **Data Security:** Ensuring the privacy and security of patient data is crucial.
2) **Data Transmission:** Efficient and consistent real-time transmission of large amounts of data can be challenging.
3) **Patient Engagement:** Encouraging regular use of monitoring tools and maintaining patient engagement is difficult.

Solutions:
1) **Enhanced Security Measures:** Implement robust encryption and security protocols to protect patient data. Techniques like end-to-end encryption can be used.
2) **Efficient Data Transfer:** Utilize advanced data compression and transmission technologies to handle large volumes of data effectively.
3) **Patient Engagement Strategies:** Develop engaging user interfaces and gamification techniques to promote regular use of monitoring devices.

Real-World Applications:
1) Deployment of secure, encrypted remote monitoring systems.
2) Use of engaging, user-friendly interfaces in remote monitoring tools.

Future Directions:
1) Explore blockchain technology for enhancing data security in remote monitoring.
2) Investigate novel approaches to improve data transmission efficiency.

Interdisciplinary Approaches:
1) Work with cybersecurity experts to strengthen data protection measures.
2) Collaborate with UX/UI designers to create engaging monitoring interfaces.

G. ECG-BASED DIAGNOSIS AND TELEMEDICINE

Gaps:
1) **Technical Infrastructure:** Limited access to high-speed internet in rural areas can restrict telemedicine services.
2) **Provider Training:** Healthcare providers may lack sufficient training on telemedicine tools and practices.
3) **Regulatory Challenges:** Regulatory issues, including those related to cross-border telemedicine services, pose barriers to implementation.

Solutions:
1) **Infrastructure Improvement:** Invest in upgrading telecommunications infrastructure in underserved areas.

2) **Training Programs:** Develop and provide comprehensive training programs for healthcare providers on telemedicine tools and practices.
3) **Policy Advocacy:** Collaborate with policymakers to address regulatory challenges and create supportive telemedicine policies.

Real-World Applications:
1) Implementation of telemedicine solutions in rural and underserved areas.
2) Delivery of training programs for healthcare professionals on telemedicine.

Future Directions:
1) Explore innovative solutions to improve internet access in remote areas.
2) Advocate for policy changes to support telemedicine expansion.

Interdisciplinary Approaches:
1) Partner with telecom companies and government agencies to improve infrastructure.
2) Collaborate with educational institutions to develop and deliver telemedicine training.

H. SLEEP APNEA DETECTION

Gaps:
1) **Ambulatory Monitoring:** Achieving high accuracy with portable, home-based monitors remains challenging.
2) **Data Quality:** Variations in data quality across different monitoring tools can affect diagnosis.
3) **Patient Comfort:** Ensuring patient comfort during prolonged sleep monitoring is difficult.

Solutions:
1) **Enhanced Algorithms:** Utilize advanced algorithms to improve the accuracy of portable monitoring devices. For instance, AI-based models can improve detection rates.
2) **Data Quality Assurance:** Implement quality control measures and standardize calibration procedures for monitoring tools.
3) **Comfortable Devices:** Innovate in the design of sleep monitoring devices to ensure they are non-intrusive and comfortable for long-term use.

Real-World Applications:
1) Use of advanced algorithms in portable sleep apnea monitoring devices.
2) Development of comfortable and user-friendly sleep monitoring equipment.

Future Directions:
1) Explore the integration of AI with portable monitors to enhance detection capabilities.
2) Investigate new materials and designs to improve the comfort of sleep apnea monitoring devices.

Interdisciplinary Approaches:
1) Collaborate with sleep specialists and engineers to improve monitoring technology.
2) Work with materials scientists to develop more comfortable monitoring devices.

I. SLEEP STAGE CLASSIFICATION

Gaps:
1) **Complexity:** Current models for sleep stage classification are often highly complex.
2) **Data Consistency:** Variations in sleep data due to different recording settings affect model performance.
3) **Validation:** Limited validation across diverse populations hampers model robustness.

Solutions:
1) **Simplify Models:** Develop models that balance complexity and accuracy, potentially using fewer features or more efficient algorithms.
2) **Standardize Data Collection:** Establish and implement standardized protocols for sleep data recording to ensure consistency.
3) **Broad Validation:** Conduct validation studies across various demographics to enhance model reliability.

Real-World Applications:
1) Adoption of simplified models in consumer-grade sleep trackers.
2) Implementation of standardized sleep data collection protocols in clinical research.

Future Directions:
1) Explore transfer learning techniques to improve performance with limited data.
2) Develop universal standards for sleep data collection and analysis to ensure consistency.

Interdisciplinary Approaches:
1) Partner with sleep researchers and data scientists to refine classification models.
2) Collaborate with device manufacturers to standardize data recording technologies.

J. BIOMETRICS CLASSIFICATION

Gaps:
1) **High False Rates:** High rates of false positives and false negatives can undermine system reliability.
2) **Scalability:** Scaling biometric systems for large populations is a significant challenge.
3) **Temporal Stability:** Ensuring the stability of biometric traits over time is critical.

Solutions:
1) **Enhanced Deep Learning:** Utilize advanced deep learning techniques, such as transfer learning and ensemble methods, to improve accuracy.
2) **Scalable Systems:** Develop cloud-based biometric solutions to handle large-scale applications and ensure scalability.
3) **Temporal Stability:** Investigate and address issues related to the stability of biometric traits, using adaptive algorithms to account for changes over time.

Real-World Applications:
1) Deployment of advanced biometric systems in security-sensitive environments.
2) Implementation of cloud-based solutions for large-scale biometric data management.

Future Directions:

1) Explore multi-modal biometric systems to enhance accuracy and reliability.
2) Investigate new methods to improve the temporal stability of biometric traits.

Interdisciplinary Approaches:

1) Collaborate with AI researchers and biometric engineers to develop advanced classification models.
2) Work with cloud computing experts to create scalable biometric solutions.

V. CONCLUSION

With an emphasis on disease detection, risk assessment, and myocardial infarction diagnosis, this review paper thoroughly examines the contribution of deep learning to improving ECG-based cardiovascular health monitoring. It draws emphasis to the important developments in automating and enhancing diagnostic accuracy that CNNs, attention mechanisms, RNNs, and hybrid models have brought about. It also addresses security and privacy concerns and looks into ECG authentication systems, including their preprocessing techniques, acquisition methodologies, and machine learning algorithms. The study points out important limitations, including the use of uniform datasets, the need for human feature extraction, and difficulties integrating wearables and electronic health records (EHRs). Several approaches are put forth, such as building different datasets, automating feature extraction with deep learning, enhancing real-time processing, and enhancing interoperability with EHRs. This work emphasizes the necessity for innovation and cooperation to improve clinical applicability as well as healthcare results, and it is a useful resource for developing ECG-based wellness tracking and authentication systems by summarizing recent research and providing practical ideas.

LIST OF ABBREVIATIONS

Abbreviation	Description
ECG	Electrocardiogram
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
DL	Deep Learning
CDSS	Clinical Decision Support Systems
HRV	Heart Rate Variability
EDF	European Data Format
GAN	Generative Adversarial Network
CVD	Cardiovascular Diseases
TCNN	Temporal Convolutional Neural Network
BPTT	Backpropagation Through Time
AUC	Area Under the Curve

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