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A Review of Deep Learning Approaches Using ECG Signal Analysis

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***Abstract*—Electrocardiograms (ECGs) are non-stationary signals that are often used to assess heartbeat tuning and rate. In order to monitor cardiovascular health and identify diseases, electrocardiogram (ECG) signals are an essential diagnostic tool. This study offers a thorough examination of the core ideas, preprocessing strategies, and deep learning approaches used in ECG analysis. It begins by detailing the structure and components of ECG signals, common acquisition methods, and the major noise sources that affect signal quality. Preprocessing stages, including denoising, segmentation, feature extraction, and feature selection, are discussed with an emphasis on their role in improving classification accuracy. The paper also examines cutting-edge deep learning architectures that have demonstrated significant promise in automating ECG-based diagnoses, including Transformer models, Autoencoders, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN-RNN models. Practical applications such as arrhythmia detection, rhythm classification, sleep and stress monitoring, noise removal, and real-time analysis in wearable health devices are reviewed. The integration of such models into wearable technologies, exemplified by devices like ECG WATCH, indicates a significant shift towards real-time, personalized cardiac care.**

Keywords—Electrocardiogram (ECG), Signal Processing, Transformer, Autoencoder, ECG Denoising, Arrhythmia Detection, Wearable Health Devices, Cardiovascular Disease (CVD), Feature Extraction, Biomedical Signal Analysis.

I. INTRODUCTION

Cardiovascular diseases (CVDs) can be detected and classified using electrocardiography (ECG), a simple diagnostic method that captures the heart's electrical activity [1]. The WHO estimates that 85% of deaths globally from cardiovascular disease are caused by heart attacks, which accounted for around 31% of all deaths in 2016. The annual economic burden of CVD is significant, with estimates reaching €210 billion in Europe and $555 billion in the United States.

Globally, non- transmissible and non-infectious diseases are seeing an increase in mortality due to CVDs. Accurate diagnosis and prompt identification are essential for efficient clinical care and slowing the development of illness [2]. An essential diagnostic technique for detecting a variety of ECG analysis is used to identify cardiovascular abnormalities, including myocardial infarction, ischemic heart disease, arrhythmias, and cardiomyopathy. It reflects various electrophysiological properties such as cardiac excitability, conduction pathways, and myocardial recovery, offering insights into structural and functional abnormalities of the atria and ventricles [3]. Even while manual ECG signal interpretation can be clinically enlightening, it is a laborious and error-prone technique that is frequently made more difficult by inter-observer variability. Traditional diagnostic frameworks rely on a patient's clinical history and expert-driven feature extraction methods based on time, frequency, and wavelet-domain analyses. These conventional methodologies, while effective to an extent, often lack the scalability and precision required for modern healthcare systems.

In order to overcome these constraints, AI methods, specifically, ML and DL have become more popular for improving the precision of diagnoses and automating the interpretation of ECG signals. AI methodologies not only reduce healthcare costs and diagnostic delays but also improve patient outcomes through early illness identification and individualized therapeutic approaches [4]. In instance, DL methods have shown better capabilities than other techniques in capturing intricate patterns in physiological data without requiring manually generated features. These models enable end-to-end learning, leveraging layered architectures to identify subtle and non-linear relationships inherent in ECG data [5].

The use of DL algorithms for automated categorization of ECG and EEG data has been the subject of an increasing amount of study in recent years. Given their demonstrated performance and clinical relevance, this review aims to present a thorough examination of modern DL methods used in ECG signal analysis [6]. The paper will systematically examine architectural innovations, model performance metrics, and their implications for clinical integration, thereby promoting the development of automated and intelligent healthcare systems.

A. *Structure of the Paper*

This paper is organized in the following way: Section II covers the fundamentals of ECG signals. Section III discusses deep learning architectures used for ECG analysis. Section IV explores key applications in diagnostics and monitoring. Section V reviews relevant literature and comparative studies. Section VI concludes with key insights and outlines future research directions.

II. FUNDAMENTALS OF ECG SIGNALS

Signals from the biological processes the human body produces may be tracked collected and shown as time series. A wide variety of physiological events, each with unique properties, are distinguished by the signals produced by various systems [7][8][9]. An electrocardiogram (ECG) is used to measure the heartbeat, and an electroencephalogram

(EEG) is typically used to record brain waves. However, numerous physiological processes can be examined using alternative measurement methods, as the chemical content in tissues or fluids or those depicted by pictures.

A. *Structure and Components of ECG Signals*

Non-invasive electrodes might be used to detect and amplify tiny electrical impulses on the skin in order to get electrocardiogram (ECG) signals [10][11]. It was also investigated how temperature and environmental light affected pulse waves, and it was found that cold weather caused peripheral blood vessels to constrict, resulting in irregular blood flow. This finding might be utilized as a clinical diagnostic tool. Drivers' sleep state detection using ECG data can be replaced with a PPG sensor, which may be more cost-effective, according to research on the association between ECG and PPG data.

The P wave is a representation of conduction atrial depolarization. As a result of atrial depolarization, the Sino Atrial node influences the Atrio Ventricular node and the right atrium influences the left atrium [12]. Q waves, which are caused by ventricular depolarization, are followed by R waves, which are distinguished by a first positive deflection and an initial negative deflection. The S wave, which comes after the initial positive deflection, is the first negative deflection of the ventricular depolarization. The onset of ventricular repolarization precedes T-waves. The duration of the T wave is longer than that of the QRS complex. In Figure 1, the ECG cycle is displayed.

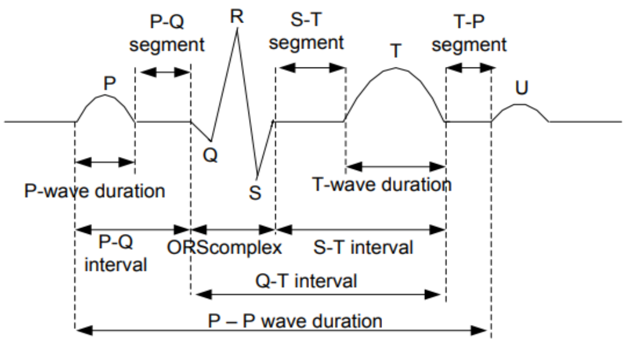

Fig. 1. ECG Cycle

B. *Signal Acquisition Methods and Common Noise Sources*

Computer-assisted medical diagnosis using ECG signals might look for unique patterns in the data in order to produce a straight diagnosis or specialized advice. A typical ECG collection equipment can be classified as 1-, 3-, 6-, or 12-lead, depending on how many leads it has. The 12-lead ECG, which is the most often utilized kind in clinical practice, simultaneously captures the potential changes of 12 sets of electrode patches connected to the body at standardised places. Hospitals often use the 12-lead ECG for professional diagnosis and treatment because it offers more precise information about heart activity than other types of ECG gathering equipment [13].

1) *Noise in Electrocardiogram (ECG):*

Normal ECG signals have a tiny amplitude and fluctuate over time, typically between 10 μV and 5 mV. They have frequencies ranging from 0.05 to 100 Hz, most of which are in the 0.05 to 35 Hz range. 1 mV is their typical value. To diagnose CVDs accurately and reliably, the majority of ECG analysis tools require comparatively noiseless ECG readings. Nevertheless, in reality, a number of disturbances and artefacts, ECG measurements are regularly disturbed by factors such baseline drift, electrode contact noise, PLI, and EMG noise, which distort and hinder feature extraction.

C. *Pre-processing Techniques*

There are some pre-processing techniques like denoising, segmentation, feature extraction and feature selection are discussing below and shown in Figure 2:

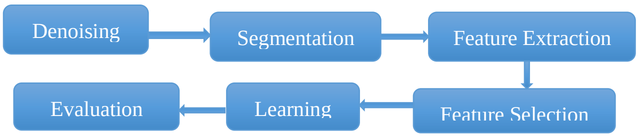

Fig. 2. ECG Analysis pipeline

1) *Denoising*

The primary causes of this noise include equipment or electronic devices, baseline change due to breathing, electrical activity of other bodily muscles, and inadequate electrode contact. Since the ECG is a non-stationary signal, noise cannot be effectively removed by standard filters; thus, a variety of approaches are employed to accomplish so. Many methods, including adaptive filtering, wavelet, and Savitzky-Golay filtering, are available for use in denoising signals [14][15] The ECG denoising literature makes mention to these techniques. Wavelets in denoising ECG signals are presented in several works, including. The wavelet is utilized in Gokhale to eliminate power line interference at 50/60 Hz from ECG data. Adaptive filtering is used in conjunction with ECG signals to eliminate noise, while the Savitzky-Golay filter is employed to smooth the ECG signals.

2) *Segmentation*

As part of the ECG analysis, QRS complexes, P, and T waves are detected, and their forms, amplitudes, relative locations, and other characteristics are then examined. Segmenting or delineating the detection of P and T wave onsets and offsets, as well as QRS complexes, is sometimes referred to as the ECG signal. The following factors make accurate ECG automated segmentation a challenging issue. The P wave, for instance, has a tiny amplitude and might be challenging to detect because of interference from muscle noise, electrode movement, etc. It is challenging to precisely identify the onsets and offsets of P and T waves since they might be biphasic. Some cardiac cycles might not include every typical segment; for instance, the P wave might not be present.

3) *Feature Extraction*

It is necessary to use a wave analysis technique to do feature extraction. Wave analysis methods often break down a wave into its constituent wavelets. DWT, auto-regressive methods, and the Fast Fourier Transform (FFT) are a few wave analysis techniques [16]. ECG signals often change from person to person; Waveform components like the P-wave, QRS complex, and T-wave are examples of those that will have different properties for different persons. Different heart diseases' ECG signals produce unique patterns in the time-frequency domain.

4) *Feature Selection*

A collection of pre-set features was used in the feature selection procedure. Either the best distinction across classes or the highest performance of a certain class of signals is utilized to choose features [17]. Consequently, a key component of classifying systems like NNs is feature selection. If-then clauses are typically used to build the classifying system for classification issues. These clauses specify the criteria of certain characteristics and the consequent rules.

The ECG analysis pipeline involves denoising raw signals, segmenting them, extracting and selecting relevant features, followed by model learning and evaluation to ensure accurate cardiac abnormality detection and classification. The ECG analysis pipeline is shown in Figure 2.

III. Deep Learning Architectures Applied to ECG Analysis

Cardiovascular disease diagnosis and monitoring depend heavily on ECG readings. The intricacy and unpredictable nature of ECG signals significantly impair their capacity to be accurately and efficiently classified. Conventional ML techniques might not adequately capture the complex patterns in ECG data and frequently call for substantial feature engineering. As DL has developed, a number of neural network topologies have shown potential for enhancing the accuracy and dependability of ECG categorization. DL, a computer-aided method that is highly effective in feature extraction, successfully classified ECG data. DL is achieved by constructing hierarchical ANN. The basic non-linear modules of each layer make DL possible, which is great for processing complicated non-linear inputs like ECG and EEG data. Tasks involving ECG signals are well-suited for DL techniques, particularly DNN, which can automatically develop hierarchical representations from raw data. CNNs, RNNs, Transformer, CAN and Hybrid CNN-RNN Models.

A. *Convolutional Neuronal Network*

One kind of feedforward neural network with a hierarchical structure is the convolutional neural network (CNN), shown in Figure 3. CNN proposes learning filters that, instead of the completely coupled layers observed in traditional neural networks, apply operations to every sub-region of the input. In terms of network architecture, a CNN usually has three layers: convolutional, pooling, and fully connected. CNN is used in many common deep learning networks [18]. In the convolutional layer, features are extracted from the input from the preceding layer by computing a convolution of every sub-region of the input using a filter kernel. Equation (1) displays the CNN formula for the jth Feature Map in the lth layer:

$$c_j^l = \theta\left(\sum_{i \in M_j} x_i^{l-1} * w_{ij}^l + b_j^l\right) \quad (1)$$

where M_j is the connection between c_j^l and Feature Map from the preceding layer, and θ is the activation function. The jth feature map's weight (or kernel) and the ith filter index are indicated by by w_{ij}^l, whereas the corresponding bias is denoted by b_j^l [19].

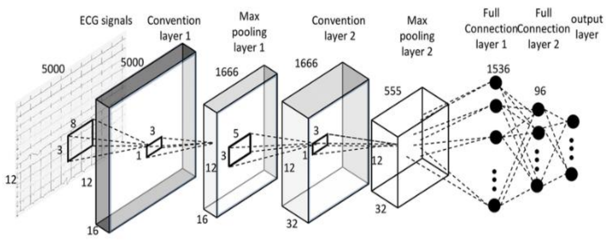

Fig. 3. CNN architecture for ECG analysis

B. *Recurrent Neuronal Network*

One sort of recursive neural network is the RNN, which is seen in Figure 4 and executes recursion in the direction of the sequence's progression. A chain connects each node, sometimes referred to as a memory cell. The capacity of RNN to generate output depends on its previous computation since each node in the network is arranged in a sequence where the neuron's output is utilized as its input.

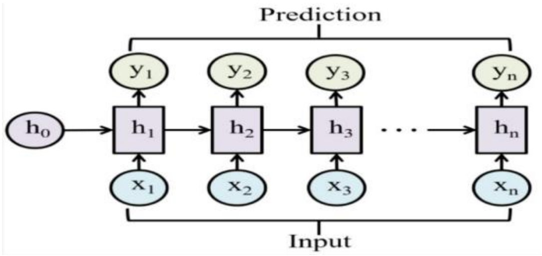

Fig. 4. Basic RNN architecture [20]

C. *Hybrid Deep Learning Model*

Several research take into account the possibility of combining several DL models into one DL network for ECG classification, as shown in Figure 5. It combines the CNN and RNN to provide an encoder-decoder architecture, which may be used for tasks such as heartbeat categorization [21]. CNN is utilized to extract features, while RNNs are utilized to convert those features into the appropriate categories. There are more instances of CNNs being used in conjunction with LSTM and BiLSTM, where CNNs are set up for feature extraction in front of LSTM/BiLSTM modules.

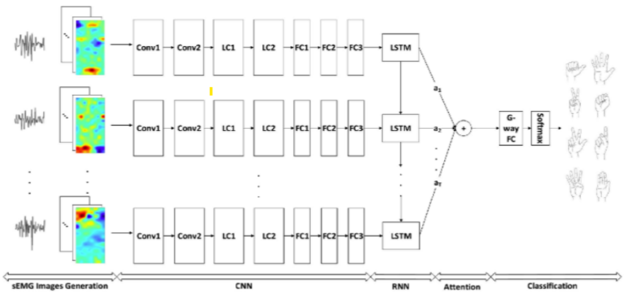

Fig. 5. Hybrid CNN-RNN Architecture

D. *Transformer*

The ability of the attention mechanism to learn how to give important characteristics larger learning weights has led to its increased prominence in current DL research circles. With just completely linked layers and attention mechanisms, the transformer is an encoder–decoder structure. Despite being originally developed for NLP, its use has spread to other domains due to its better performance than RNN/LSTM. Figure 6 depicts the transformer's construction.

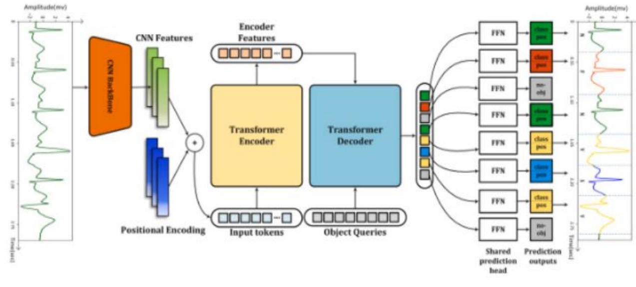

Fig. 6. Transformer Architecture

E. *Deep Convolution Auto-Encoded Network (ACN)*

In order to replicate the input signal as closely as possible, At the input layer, the 1D-auto-encoder convolution can encode data, and at the output layer, it can reconstruct it. This is achieved by teaching the neural network to alter the input data in a way that preserves important information during encoding. By determining the most pertinent factors in the ECG signal, A feature extraction method may be automatically generated by the machine by following this approach [22]. The input vector $x \in [0,1]\ d$ of the auto-encoder is translated to a hidden representation $y \in [0,1]\ d$ between input-output mappings. The formula for auto-encoder is shown in equation (2) and Figure 7.

$$y = fa\,(x) = ReLu(Wx + b) \tag{2}$$

$$ReLu = \begin{cases} 0, if\ x < 0 \\ x, otherwise \end{cases}$$

In this case, $ReLu$ ($Rectifed\ Linear\ Unit$) = max (0, x), where W is a Weight Matrix of d X d, b is a Bias Vector, and ReLu is the activation function. This time, the replicated vector$z \in [0,1]d$ is transferred back to the concealed output y.

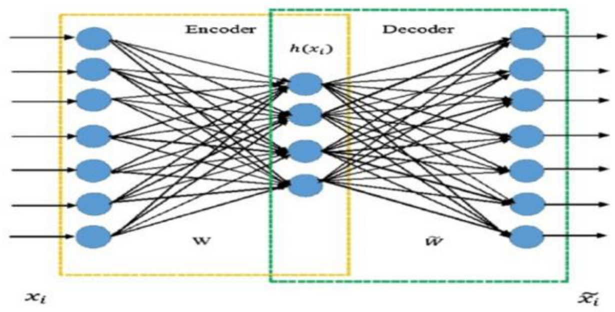

Fig. 7. Autoencoder architecture

IV. Applications of Deep Learning in ECG-Based Diagnostics

This section will cover the most significant ECG analysis applications in the area of study throughout the last many years. will describe the latest advancements in ECG analysis.

A. *Arrhythmia Detection*

Arrhythmias are a collective term for a variety of irregular heartbeats. Because ECG is easy to use and non-invasive, doctors can use it to find these anomalies. Automatic heartbeat categorization and arrhythmia identification methods based on electrocardiogram (ECG) data have been the primary focus of computational approaches to ECG analysis [23]. The two primary types of arrhythmias are as follows. The first kind, known as morphological arrhythmias, is distinguished by a series of irregular heartbeats. The automated identification of morphological arrhythmia types is the main topic of this part, but the difficulty of identifying the various ECG rhythm types is covered separately in the next section.

B. *Rhythm Detection and Classification*

A series of irregular heartbeats is a characteristic of rhythmic arrhythmias [24]. The most popular databases of atrial fibrillation (AF) recordings are MIT-BIH AF, and AF is the most prevalent kind. The latest generation of public ECG datasets in recent years, including the PTB-XL database, the 10,000-patient arrhythmia database from Shaoxing People's Hospital, and the 2018 China Physiological Signal Challenge Dataset, encompass a wide spectrum of rhythms in addition to atrial fibrillation. These consist of heart blockages, bradycardia, and different types of tachycardia.

C. *Noise Removal*

The clinical ECG signal is acquired noninvasively by employing high-gain amplifiers to enhance the biopotential signals that are collected from surface electrodes applied to the skin. Additionally, a conducting gel is put between the electrode surfaces and the skin to maintain appropriate conductivity and lower the skin-contact impedance. When the ECG signals are being acquired, they may become polluted by other sounds [25]. An electrocardiogram (ECG) signal could be contaminated by power line interference, muscular activity, and unstable electrodes caused by improper skin adhesion.

D. *Stress and Sleep Monitoring*

A healthy lifestyle depends on getting enough excellent sleep. The most prevalent medical disorder that impairs the quality of sleep is sleep apnoea [26][27] It results in disordered breathing during sleep and is caused by repeated blockage of airflow. Approximately 1 billion individuals worldwide suffer from sleep apnoea, according to a recent survey. There are 425 million persons with moderate-to-severe obstructive sleep apnoea (OSA) and 936 million with mild to severe OSA between the ages of 30 and 69. Researchers have shown that sleep apnoea increases the risk of heart disease by three times, accidents by seven times, and strokes by four times.

E. *Real-Time Analysis in Wearable Health Devices*

The market for components that can interact with smartphones and tablet computers is expanding as these devices have become increasingly widespread. The built-in hardware of smartphones actually functions effectively as a recording tool, network uplink, and user interface; however, it is unable to provide the wide range of sensors and devices for electrical components that are already available on the market (such as temperature, humidity, pressure, infrared, and more).

1) *The ECG WATCH*

An unobtrusive, wireless device known as the ECG WATCH. Its primary function is to facilitate cardiac monitoring by means of the easy acquisition and presentation of a 10-second single-lead electrocardiogram (ECG) on a personal computer or mobile app [28]. A cardiologist may also be given access to the obtained ECG, after which they can review it and determine whether the patient requires a more thorough assessment. Figure 8 shows an example of an email exchange between a doctor's office and a patient's mobile app.

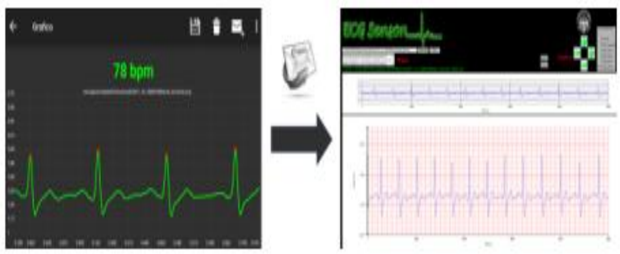

Fig. 8. Communication between the patient mobile app and the doctor via email

V. Literature of Review

This literature review explores DL techniques for ECG analysis, focusing on classification, segmentation, real-time monitoring, hardware integration, and diagnostic accuracy improvement.

G et al. (2025) A novel DL technique has been put out that combines. a deep CNN that uses a BLSTM block. The processed data is analyzed through a four-layer DL model, consisting of a BLSTM block and two layers that are fully connected. In this project, the first step involves an analysis process that utilizes a wavelet transform for ECG signal pre-processing, which removes noise and enhances signal clarity. Peak extraction and segmentation performed. Two datasets signal, one for RR interval (dataset A) and one for the sequence of heartbeats in terms of waves P-QRS-T, then after the fully connected layer, it detects if the signal is AF or not AF [29].

Kumar et al. (2025) EEG and ECG signals are electrographic measures of brain and heart activity, respectively and can indicate neurological states and mental task states. In order to differentiate between task-oriented and relaxing cognitive states, provided in this study an improved method using a collection of unique temporal characteristics, including energy, Shannon energy, entropy, and temporal energy, with cutting-edge ML classifiers. In addition, investigate DL techniques like LSTM networks and CNNs due to their capacity to recognize complex characteristics in EEG and ECG rhythms. Used a publicly available dataset from physionet.org, consisting of 36 (male and female) subjects with 21 channels (20 EEG plus 1 ECG) [30].

Yang and Zheng (2024) proposes an ECG signal classification algorithm based on deep learning, combined with the corresponding circuit design, to achieve efficient and accurate ECG signal analysis. ECG signals are first described, and then they are taken from They were divided into eight categories using the MIT-BIH database. Based on this, a one-dimensional CNN is developed to do both diagnosis and classification in order to increase classification accuracy and comprehensively evaluate the properties. Through experiments on public data sets, the ability of the proposed algorithm in ECG signal recognition is verified when the network is fully converged, and the classification accuracy [31].

Tiwary et al. (2023) cardiovascular diseases (CVDs) have developed into a broad category of chronic illnesses that pose serious risks to human health. By applying electrodes to the patient's skin, the ECG equipment can monitor the occurrence of recurrent cardiac contractions and relaxations. ECG signals typically consist of a number of wave types, including T, P, and QRS complex waves. The structural and statistical features of these ECG waves can be used to trace the symptoms associated with any heart condition. DL has been effectively applied to medical diagnostics in recent years, and it uses ECG data to automatically identify faulty cardiac function [32].

Satheeskumaran et al. (2023), An IoT and cloud-based healthcare system is created to measure the risk of heart illness by extracting properties of electrocardiogram (ECG) signals and analyzing them. Cloud computing enables IoT-based healthcare devices to require very little local signal processing. However, when employing a cloud architecture for signal processing and real-time monitoring, several concerns regarding service quality arise [33].

Choudhary (2023) examined HRV and HR signals from a variety of people, including those with cardiac issues, varying ages, and sexes. Statistical indicators are used to help spot variations. A database of their lab's electrocardiogram (ECG) and photoplethysmogram (PPG) readings is also created throughout this procedure. The PPG's peaks are also detected, and a comparison of the PPG's HR and the ECG's shows that the PPG may be utilized in place of HRV detection [34]

Haleem and Pecchia (2022) an attention-based architecture network called Conv-BiLSTM uses local beat characteristics and temporal sequencing to correlate ECG beats across many locations. The performance of their ECG segmentation tool has been compared to the most sophisticated techniques in terms of ECG segmentation and fiducial point identification accuracy [35].

Kumar et al. (2022) as environmental factors including dietary habits, work cultures, and lifestyles change, the occurrence of stroke-related disorders is increasing every day. According to a recent WHO study, stroke ranks as the second most common cause of death, after cardiovascular disease. One of the most important criteria for both patients and medical personnel was the early detection of stroke-related disorders. When used appropriately, DL techniques are among those that can be used to diagnose stroke illness. This study proposed a medical framework approach to detect abnormalities in ECG data linked to stroke disorders. Left ventricular hypertrophy is one of many stroke risk factors that can only be detected using an ECG [36].

Table I presents a summary of the literature review, highlighting each study’s focus, approach, key findings, challenges, and proposed future directions.

TABLE I. COMPARATIVE ANALYSIS OF ECG SIGNAL ANALYSIS USING DEEP LEARNING

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
G et al. (2025)	AF detection using ECG signals	4-layer DL model combining CNN with Bidirectional LSTM; Wavelet preprocessing, segmentation, and peak extraction	Achieved effective AF detection using features from RR intervals and P-QRS-T waves	Complex architecture may increase computational cost	Real-time deployment with reduced latency and computational complexity
Kumar et al. (2025)	EEG and ECG for cognitive state classification	Novel temporal features with ML classifiers and DL models (CNN, LSTM); Physio net EEG+ECG dataset used	Identified cognitive states (task vs relaxing) with high accuracy	Fusion of EEG and ECG increases data dimensionality and complexity	Explore transformer-based architectures for improved temporal dependency learning
Yang and Zheng (2024)	ECG classification using DL and circuit design	1D CNN for 8-category ECG classification from MIT-BIH dataset	Achieved high accuracy with simplified 1D CNN; efficient hardware implementation suggested	Hardware-software optimization balance needed	Expansion to real-time embedded systems and wearable devices
Tiwary et al. (2023)	CVD detection via ECG signal	Use of DL for automatic detection from morphological and statistical ECG features	Demonstrated effectiveness of DL in detecting heart abnormalities	Requires large, annotated ECG datasets for model training	Development of lightweight models for low-resource settings

Satheeskumaran et al. (2023)	IoT-cloud based ECG analysis	IoT devices for acquisition; cloud for ML-based heart disease risk assessment	Enables remote health monitoring and risk prediction	QoS issues in cloud-based real-time systems	Hybrid edge-cloud frameworks for better latency and reliability
Choudhary, (2023)	HR and HRV from ECG and PPG	Statistical indices and comparison between ECG and PPG-based HR/HRV detection	Demonstrated PPG as a viable substitute for HRV detection	PPG signal quality is sensitive to noise and motion	Advanced signal denoising and adaptive filtering for PPG analysis
Haleem and Pecchia (2022)	ECG segmentation	Conv-BiLSTM with attention on beat features and temporal sequencing	Achieved state-of-the-art segmentation and fiducial point detection	Model complexity affects training and deployment time	Optimizing model size for real-time ECG interpretation
Kumar et al. (2022)	Stroke diagnosis from ECG	DL framework targeting stroke-related ECG abnormalities	Detected left ventricular hypertrophy and other stroke-related ECG patterns	ECG signal variation across individuals	Multi-modal analysis combining ECG with MRI/CT for stroke detection

VI. Conclusion and Future Work

Electrocardiogram (ECG) signal analysis has become a cornerstone in modern healthcare for diagnosing and monitoring cardiovascular diseases (CVDs). This paper has presented a comprehensive overview of the fundamental principles of ECG signals, their acquisition, pre-processing techniques, and DL-based analytical architectures. Although they possess a wealth of diagnostic potential, the structural elements of ECG signals, such as P, QRS, and T waves, are noisy and require advanced denoising and segmentation methods. To enhance accuracy and robustness, advanced pre-processing methods like wavelet denoising, adaptive filtering, and Savitzky-Golay smoothing have been employed. Moreover, DL models, namely CNNs, RNNs, Transformers, and hybrid architectures, have proven exceptionally effective in automatic feature extraction and classification tasks. Applications including arrhythmia detection, rhythm classification, sleep apnea monitoring, and stress analysis demonstrate the growing utility of AI-enhanced ECG interpretation. The development of wearable devices like ECG WATCH illustrates the integration of real-time ECG monitoring into consumer-grade health solutions, offering non-invasive, mobile, and continuous cardiac health tracking. Such innovations promise personalized medicine, faster diagnostics, and wider healthcare accessibility.

Future Work will focus on enhancing model generalization across diverse patient populations by training on multi-center, multi-ethnic datasets. Additionally, integrating explainable AI (XAI) into ECG analysis systems could provide interpretability in clinical decisions, thereby increasing trust among medical professionals. The integration of edge AI for real-time inference on wearable devices and the incorporation of multimodal data (e.g., ECG + PPG + EEG) will be crucial for holistic health monitoring. Finally, regulatory compliance, data privacy, and robust security mechanisms must be embedded into future wearable ECG systems to ensure ethical and secure deployment in healthcare ecosystems.

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