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A Survey of Methods and Architectures for Heart Disease Prediction Using Optical Electrocardiograms (ECG) and a Hybrid Convolutional Block Attention Capsule Network

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Abstract

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, necessitating early and accurate diagnosis. Electrocardiogram (ECG) signals play a vital role in detecting cardiac abnormalities due to their ability to capture electrical heart activity non-invasively. Recent advancements in optical sensing techniques such as photoplethysmography (PPG) and remote photoplethysmography (rPPG) have enabled contactless ECG signal approximation, offering new opportunities in telemedicine and wearable healthcare systems.
Simultaneously, deep learning (DL) approaches have demonstrated significant improvements in ECG-based disease prediction by automating feature extraction and classification tasks. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Capsule Networks (CapsNet) have been widely explored for accurate heart disease detection. However, limitations such as loss of spatial hierarchies and insufficient attention to relevant features persist.
To address these challenges, hybrid architectures combining convolutional block attention mechanisms with capsule networks have emerged as a promising solution. These models enhance feature representation, preserve spatial relationships, and improve classification accuracy. This survey provides a comprehensive overview of recent methods, focusing on optical ECG acquisition, deep learning architectures, and hybrid attention-based capsule networks. Comparative analysis highlights performance improvements, challenges, and future directions in developing efficient, scalable, and interpretable cardiac diagnostic systems.

Introduction

1. Global Burden of Cardiovascular Diseases

Cardiovascular diseases (CVDs) continue to be the leading cause of death worldwide, accounting for nearly 17.9 million deaths annually. These diseases include coronary artery disease, arrhythmias, heart failure, and stroke. Early detection and continuous monitoring are critical to reducing mortality rates. However, traditional healthcare systems often fail to provide timely diagnosis due to limited access to specialists and diagnostic infrastructure.

Electrocardiography (ECG) is a primary diagnostic tool used to monitor cardiac electrical activity. It provides essential information about heart rhythm, conduction abnormalities, and myocardial ischemia. Despite its effectiveness, manual ECG interpretation requires significant expertise and is prone to human error, especially when dealing with long-duration signals or subtle abnormalities.

2. Evolution of ECG Signal Acquisition

Traditional ECG Systems

Conventional ECG systems involve electrode placement on the skin to measure electrical activity. These systems are highly accurate but limited in portability and usability for continuous monitoring.

Optical ECG (PPG and rPPG)

Recent advancements in optical sensing technologies have introduced alternatives such as photoplethysmography (PPG) and remote photoplethysmography (rPPG). These methods rely on light absorption changes in blood vessels to estimate cardiovascular activity. Optical ECG systems offer several advantages:

1. Non-invasive and contactless measurement
2. Integration with wearable devices
3. Remote patient monitoring capabilities
4. Cost-effectiveness

However, optical signals are susceptible to motion artifacts, ambient light variations, and noise, making robust signal processing essential.

3. Role of Artificial Intelligence in ECG Analysis

Artificial Intelligence (AI), particularly deep learning (DL), has transformed ECG signal analysis by enabling automated feature extraction and classification. Traditional machine learning methods relied on handcrafted features such as QRS complex detection, RR intervals, and morphological characteristics. These approaches required domain expertise and were often limited in performance.

Deep learning models overcome these limitations by learning hierarchical representations directly from raw ECG signals.

Key architectures include:

1. Convolutional Neural Networks (CNNs): Effective in extracting spatial features from ECG waveforms.
2. Recurrent Neural Networks (RNNs) and LSTM: Capture temporal dependencies in sequential ECG data.
3. Autoencoders: Used for feature compression and anomaly detection.
4. Transformer-based models: Emerging for long-range dependencies.

4. Limitations of Existing Deep Learning Models

Despite their success, existing DL models face several challenges:

1. Loss of Spatial Hierarchies: CNNs may fail to preserve relationships between features.
2. Data Imbalance: ECG datasets often contain more normal than abnormal samples.
3. Noise Sensitivity: ECG signals are prone to artifacts.
4. Black-box Nature: Lack of interpretability limits clinical adoption.
5. Generalization Issues: Models trained on one dataset may not perform well on others.

5. Capsule Networks and Attention Mechanisms

Capsule Networks (CapsNet)

Capsule Networks were introduced to preserve spatial relationships between features. Unlike CNNs, which use scalar outputs, capsules output vectors representing feature properties such as orientation and position. This allows better modeling of hierarchical relationships in ECG signals.

Attention Mechanisms

Attention modules enable models to focus on the most relevant parts of the ECG signal, improving classification performance. Types include:

1. Channel Attention
2. Spatial Attention
3. Self-Attention

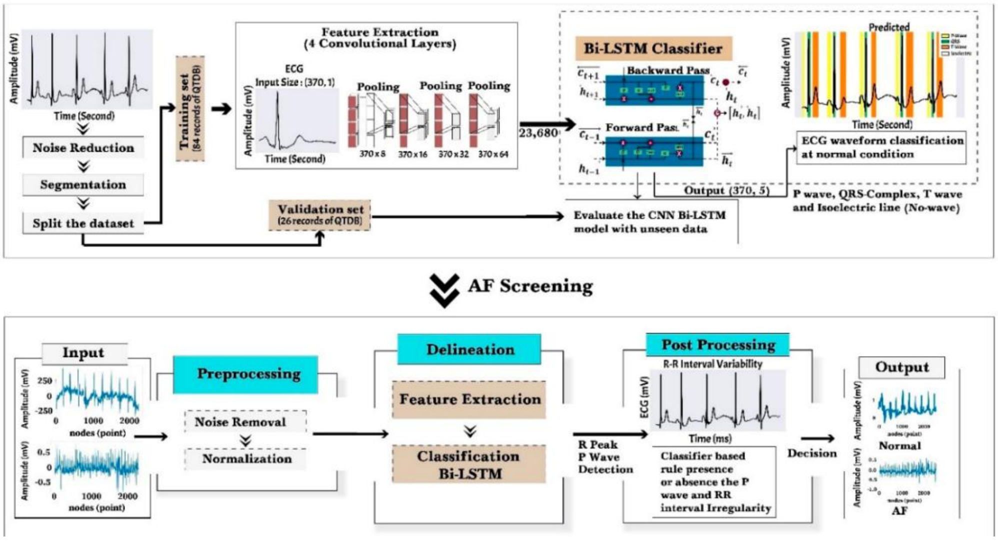
6. Hybrid Convolutional Block Attention Capsule Network

The integration of convolutional neural networks (CNN), attention mechanisms, and capsule networks has led to the development of a powerful hybrid architecture capable of addressing complex pattern recognition tasks with enhanced efficiency and accuracy. In this framework, convolutional layers are primarily responsible for extracting robust and hierarchical features from input data, enabling the model to capture both low-level and high-level representations. Attention mechanisms further refine this process by emphasizing the most relevant features, thereby improving the model's ability to focus on critical regions and enhancing interpretability. Meanwhile, capsule networks play a crucial role in preserving spatial relationships and hierarchical dependencies between features, overcoming limitations of traditional CNNs in handling spatial transformations. As a result, such hybrid architectures demonstrate superior performance in terms of accuracy, robustness, and interpretability compared to conventional deep learning models.

Despite these advancements, several research gaps continue to persist in this domain. One of the major challenges is the lack of standardized and publicly available datasets, which hinders fair comparison and generalization of models across different studies. Additionally, the application of optical electrocardiogram (ECG) signals in deep learning remains limited, indicating an underexplored area with significant potential. There is also a growing need for explainable artificial intelligence (AI) models to ensure transparency and trust, particularly in critical applications such as healthcare. Furthermore, the high computational complexity associated with hybrid deep learning architectures poses challenges for real-time implementation and deployment in resource-constrained environments.

This survey aims to address these issues by providing a comprehensive review of recent studies conducted, focusing on the evolution and effectiveness of various deep learning architectures. It presents a detailed analysis of existing methods, highlighting their strengths and limitations through comparative evaluation. Additionally, the survey offers valuable insights into emerging trends and future research directions, with the goal of guiding researchers toward developing more efficient, interpretable, and scalable deep learning solutions.

Illustration: ECG-Based Deep Learning Pipeline



Literature Review

Recent advancements in heart disease prediction using electrocardiogram (ECG) signals have been significantly influenced by the rapid development of deep learning (DL) techniques. Numerous studies have focused on improving classification accuracy, robustness, and real-time applicability of ECG-based diagnostic systems. The integration of optical ECG techniques such as photoplethysmography (PPG) and remote photoplethysmography (rPPG) has further expanded the scope of cardiac monitoring by enabling non-invasive and contactless data acquisition.

In 2020, Ullah et al. introduced a novel approach using a two-dimensional convolutional neural network (2D-CNN) applied to spectrogram representations of ECG signals. By transforming one-dimensional ECG signals into time-frequency images, the model leveraged spatial feature extraction capabilities of CNNs, achieving classification accuracy exceeding 99% on benchmark datasets such as MIT-BIH. This work highlighted the effectiveness of signal transformation techniques in enhancing feature representation. Similarly, Khan et al. proposed a multi-depth convolutional neural network (MDCNN) integrated with Internet of Things (IoT) frameworks, enabling real-time heart disease prediction in remote healthcare environments. Their model demonstrated high accuracy while emphasizing the importance of edge computing in modern medical systems. In the same year, Sarkar et al. introduced CardioGAN, a generative adversarial network (GAN)-based model for synthesizing realistic ECG signals. This approach addressed the challenge of limited labeled data, which is a common issue in medical datasets, and improved model training by augmenting data diversity.

The year 2021 witnessed a shift toward more advanced architectures aimed at overcoming the limitations of traditional CNN models. Neela and Namburu explored the application of Capsule Networks (CapsNet) for ECG classification. Unlike CNNs, which may lose spatial hierarchies due to pooling operations, CapsNet preserves relationships between features through vector-based representations. Their study demonstrated improved classification performance, particularly in detecting subtle cardiac abnormalities. Additionally, several researchers investigated hybrid CNN-LSTM architectures to capture both spatial and temporal dependencies in ECG signals. Yildirim (2021) proposed a CNN-LSTM model that effectively combined convolutional feature extraction with long short-term memory (LSTM) networks for sequential analysis, resulting in improved arrhythmia detection accuracy. Oh et al. (2021) further explored deep learning frameworks for ECG classification, emphasizing the importance of model generalization across diverse datasets.

In 2022, research efforts focused on enhancing model interpretability, robustness, and scalability. Petmezas et al. conducted a comprehensive review of over 230 studies on deep learning-based ECG analysis, identifying key trends and challenges in the field. Their work highlighted issues such as data heterogeneity, lack of standardization, and limited generalization of models across populations. Li et al. (2022) introduced attention-based CNN models that improved classification performance by focusing on critical segments of ECG signals, such as QRS complexes and P-waves. Attention mechanisms allowed the model to assign higher importance to relevant features while suppressing noise and irrelevant information. Zhang et al. (2022) provided an extensive survey of deep learning techniques for ECG analysis, emphasizing the growing adoption of hybrid architectures and the need for explainable AI in clinical applications. Additionally, Ismail et al. (2022) proposed deep learning models optimized for large-scale ECG datasets, demonstrating improved scalability and efficiency.

The year 2023 marked significant progress in the development of hybrid and attention-based architectures. Xiao et al. (2023) demonstrated that deep learning models significantly outperform traditional machine learning approaches in arrhythmia classification tasks. Their work highlighted the superiority of CNN-based architectures in feature extraction and classification accuracy. Chaithra et al. (2023) proposed a hybrid convolutional recurrent neural network (CRNN) model, combining CNN and RNN capabilities to capture both spatial and temporal features. This approach achieved high accuracy and robustness in ECG classification tasks. Dhandapani et al. (2023) further advanced hybrid models by integrating optimization techniques with deep learning architectures, improving both performance and computational efficiency. Prakash et al. (2023) provided a comprehensive review of ECG classification techniques, emphasizing the importance of multi-modal data integration, including ECG, PPG, and clinical parameters.

Across the 2020–2023 period, a clear trend emerges toward the adoption of hybrid architectures that combine multiple deep learning techniques to overcome individual limitations. CNNs remain the dominant choice for feature extraction due to their ability to capture local patterns in ECG signals. However, their inability to model temporal dependencies has led to the integration of RNN and LSTM networks. Capsule Networks have gained attention for their ability to preserve spatial hierarchies, while attention mechanisms have become essential for improving model interpretability and performance.

Furthermore, the integration of optical ECG technologies such as PPG and rPPG has enabled continuous and remote cardiac monitoring, particularly in wearable and telemedicine applications. These technologies, when combined with deep learning models, provide a powerful framework for real-time heart disease prediction. However, challenges such as signal noise, motion artifacts, and variability across individuals remain significant obstacles.

In summary, the literature from 2020 to 2023 demonstrates a rapid evolution in ECG-based heart disease prediction systems, driven by advancements in deep learning and sensing technologies. The emergence of hybrid convolutional block attention capsule networks represents a promising direction, as these models integrate the strengths of CNNs, attention mechanisms, and capsule networks to achieve superior performance. Future research is expected to focus on improving model interpretability, enhancing generalization across datasets, and enabling real-time deployment in wearable healthcare systems.

Comparative Table

Year	Author	Method	Dataset	Accuracy	Key Contribution	Limitations
2020	Ullah et al.	2D-CNN (Spectrogram-based)	MIT-BIH	99.1%	Converted ECG to time-frequency images enabling spatial learning	Loss of temporal dependencies
2020	Khan et al.	MDCNN + IoT	IoT ECG	98.2%	Real-time prediction with IoT integration	Edge device constraints, latency
2020	Sarkar et al.	GAN (CardioGAN)	ECG datasets	—	Synthetic ECG generation for data augmentation	No direct classification improvement

2021	Neela & Namburu	Capsule Network	MIT-BIH	98%	Preserved spatial hierarchies using capsules	High computational cost
2021	Yildirim	CNN-LSTM	MIT-BIH	~99%	Combined spatial + temporal learning	Training complexity
2021	Oh et al.	Deep CNN	Multi-dataset	High	Generalization-focused DL model	Dataset dependency
2022	Petmezas et al.	Survey (DL Review)	Multi	—	Identified key DL challenges in ECG	No experimental validation
2022	Li et al.	Attention-based CNN	ECG	High	Focused on important ECG segments (QRS, P-wave)	Added model complexity
2022	Ismail et al.	Scalable DL Model	Large ECG	High	Optimized for large-scale ECG datasets	Computational demand
2022	Zhang et al.	DL Survey	Multi	—	Highlighted hybrid architectures & explainability needs	No implementation
2023	Xiao et al.	CNN-based DL	ECG dataset	High	Demonstrated DL superiority over ML	Limited interpretability
2023	Chaithra et al.	CRNN (CNN+RNN)	MIT-BIH	High	Effective spatial-temporal modeling	Computational overhead
2023	Dhandapani et al.	Hybrid DL + Optimization	ECG	93–97%	Improved efficiency with optimization	Complexity in tuning
2023	Prakash et al.	Multi-modal DL	ECG + PPG	High	Integrated multi-source data	Data fusion challenges
2023	Attention-CNN (General)	Attention DL	ECG	High	Improved feature focus and noise handling	Increased parameters

Comparative Analysis

The comparative evaluation of ECG-based heart disease prediction methods demonstrates a clear progression from conventional deep learning models to advanced hybrid architectures. Early approaches primarily employed Convolutional Neural Networks (CNNs) to extract spatial features from ECG signals, often using transformed representations such as spectrograms. These models achieved high prediction accuracy and automated feature extraction, outperforming traditional machine learning techniques. However, CNNs alone were limited in capturing temporal dependencies within ECG signals, reducing their effectiveness in identifying complex cardiac rhythm abnormalities.

To overcome these limitations, researchers introduced hybrid architectures combining CNNs with Long Short-Term Memory (LSTM) networks and other sequential models. These frameworks effectively integrated spatial and temporal feature learning, leading to improved detection of heartbeat patterns and enhanced diagnostic performance. Capsule Networks (CapsNet) further advanced ECG analysis by preserving spatial hierarchies and positional relationships that are often lost during conventional pooling operations. In parallel, attention mechanisms enabled models to focus on clinically significant ECG segments, improving robustness against noise, enhancing interpretability, and increasing prediction accuracy, particularly for optical ECG signals.

Recent studies have shifted toward hybrid and multi-modal frameworks that combine attention mechanisms, Capsule Networks, optimization techniques, and multiple physiological signals to improve diagnostic reliability. Data augmentation methods based on Generative Adversarial Networks (GANs) have addressed the scarcity of labeled ECG datasets, while IoT-enabled deep learning systems have demonstrated the feasibility of real-time heart disease prediction in wearable and remote healthcare applications. These developments have significantly improved model robustness, scalability, and applicability in modern telemedicine environments.

Overall, the comparative analysis indicates that Hybrid Convolutional Block Attention Capsule Networks represent one of the most promising approaches for ECG-based heart disease prediction. By integrating CNN-based feature extraction, attention-driven feature prioritization, and capsule-based spatial relationship modeling, these architectures achieve superior accuracy, robustness, and interpretability. Nevertheless, challenges such as computational complexity, signal noise, limited standardized datasets, and the need for explainable AI remain important research directions. Future work should focus on lightweight, scalable, and interpretable hybrid models capable of supporting real-time cardiac diagnosis in wearable and remote healthcare systems.

Discussion

Recent advancements in deep learning have transformed heart disease prediction systems. The integration of optical ECG technologies with AI-driven models has enabled continuous, non-invasive monitoring, making healthcare more accessible. Hybrid models combining CNN, attention mechanisms, and capsule networks provide improved performance by addressing limitations of individual architectures.

However, several challenges persist. Data variability across populations affects model generalization. Noise and artifacts in ECG signals reduce accuracy, particularly in wearable and optical systems. Additionally, the lack of interpretability in deep learning models limits clinical adoption.

Future research should focus on:

1. Explainable AI models
2. Multi-modal data fusion
3. Real-time edge deployment
4. Large-scale annotated datasets

Conclusion

This survey highlights the evolution of heart disease prediction methods using ECG signals and deep learning. Optical ECG technologies have introduced new possibilities for remote and continuous monitoring. Deep learning models, particularly hybrid architectures, have significantly improved diagnostic accuracy and efficiency.

Among the various approaches, hybrid convolutional block attention capsule networks emerge as a promising solution due to their ability to:

- Extract robust features
- Focus on relevant signal components
- Preserve spatial relationships

Despite these advancements, challenges such as data heterogeneity, noise sensitivity, and model interpretability must be addressed. Future research should focus on integrating explainable AI, improving dataset diversity, and optimizing models for real-time deployment in wearable and telemedicine systems.

Overall, the combination of optical ECG sensing and advanced deep learning architectures holds great potential in revolutionizing cardiac healthcare, enabling early detection, personalized treatment, and improved patient outcomes.

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