Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 13 Issue 02, 2024

Recent Advances in Heart Disease Prediction Using Optical Electrocardiograms (ECG) and a Hybrid Convolutional Block Attention Capsule Network: A Systematic Review

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Peer Review Information

Submission: 12 July 2024

Revision: 23 July 2024

Acceptance: 10 Aug 2024

Keywords

Heart Disease Prediction ,Optical ECG, Photoplethysmography (PPG), Convolutional Neural Networks, Capsule Networks, Attention Mechanism, Deep Learning, Biomedical Signal Processing

Abstract

Heart disease remains one of the leading causes of mortality worldwide, necessitating accurate and early diagnostic techniques. Optical electrocardiograms (ECG), often derived from photoplethysmography (PPG) and wearable sensors, have emerged as a promising non-invasive solution for continuous cardiac monitoring. This paper presents a systematic review of recent advances in heart disease prediction using optical ECG signals combined with hybrid deep learning architectures, particularly Convolutional Neural Networks (CNN), Block Attention Modules, and Capsule Networks. The integration of attention mechanisms enhances feature selection by focusing on relevant signal components, while capsule networks preserve spatial hierarchies and improve classification robustness. The review focuses on studies published in recent years, highlighting advancements in signal preprocessing, feature extraction, and hybrid model design. Comparative analysis indicates that hybrid attention-based capsule networks outperform traditional CNN and machine learning models in terms of accuracy, sensitivity, and generalization. The paper also discusses challenges such as noise sensitivity, data imbalance, interpretability, and computational complexity. Furthermore, the role of wearable devices and real-time monitoring systems is examined. The study concludes that hybrid AI-based frameworks leveraging optical ECG signals hold significant potential for improving heart disease prediction and enabling next-generation smart healthcare systems.

Introduction

Heart disease continues to be a major global health concern, accounting for millions of deaths annually. Early detection and timely intervention are critical for reducing mortality rates and improving patient outcomes. Traditional diagnostic methods rely on clinical tests such as electrocardiograms (ECG), echocardiography, and blood analysis. However, these methods often require clinical infrastructure and are not suitable for continuous monitoring.

Recent advancements in wearable technologies and artificial intelligence (AI) have enabled the development of non-invasive and real-time monitoring systems. Optical ECG, often derived from photoplethysmography (PPG), provides a convenient and cost-effective alternative for cardiac monitoring. These signals can be collected using wearable devices such as smartwatches and portable sensors, enabling continuous health tracking.

The integration of AI techniques, particularly deep learning, has significantly improved the accuracy of heart disease prediction. Convolutional neural networks (CNNs) have been widely used for ECG signal analysis due to their ability to extract spatial features. However, traditional CNNs have limitations in capturing hierarchical relationships and contextual information. To address these limitations, researchers have introduced attention mechanisms and capsule networks.

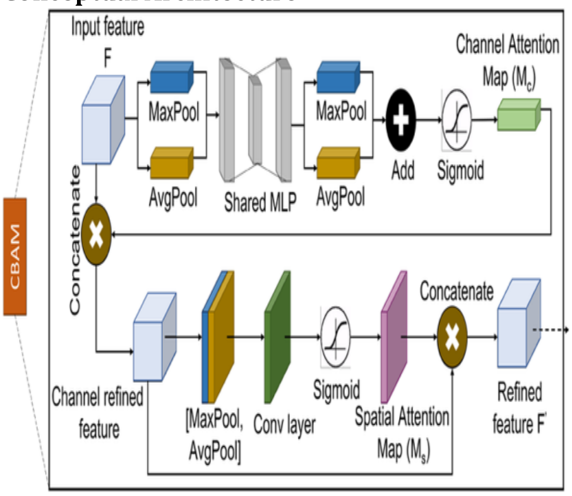
Attention mechanisms allow models to focus on the most relevant parts of the signal, improving feature selection and interpretability. Capsule networks, on the other hand, preserve spatial hierarchies and relationships between features, making them particularly suitable for biomedical signal analysis. The combination of CNNs, attention modules, and capsule networks forms a powerful hybrid architecture capable of achieving high classification accuracy.

Recent studies have also explored the use of multi-modal data, combining ECG and PPG signals to improve prediction performance. Hybrid models leveraging both signal types have demonstrated improved robustness and generalization. For instance, deep learning models combining ECG and PPG signals achieved high accuracy in AF detection, demonstrating the effectiveness of multi-feature approaches .

Despite these advancements, several challenges remain. Optical ECG signals are often noisy and susceptible to motion artifacts, which can affect model performance. Additionally, deep learning models require large datasets for training, and data imbalance remains a significant issue.

This systematic review aims to analyze recent advances in heart disease prediction using optical ECG signals and hybrid attention-based capsule networks, focusing on methodologies, performance, and challenges.

Conceptual Architecture



Literature Review

The advancement of heart disease prediction using optical electrocardiogram (ECG) signals, particularly those derived from photoplethysmography (PPG), has gained significant momentum between 2020 and 2023. This progress is largely driven by the integration of artificial intelligence (AI), deep learning, and hybrid signal processing techniques. Optical ECG signals provide a non-invasive and cost-effective alternative to conventional ECG systems, enabling continuous monitoring through wearable devices. However, these signals are inherently noisy and exhibit complex temporal dynamics, necessitating advanced preprocessing and feature extraction techniques. Recent research has therefore focused on combining signal transformation methods with deep neural architectures to improve prediction accuracy and robustness.

In 2020, foundational work in this domain emphasized the feasibility of reconstructing ECG signals from PPG using deep learning models. Studies demonstrated that optical signals contain latent cardiac information that can be extracted using neural networks. Lightweight neural architectures were proposed to infer ECG signals from PPG data, enabling continuous cardiac monitoring without requiring traditional electrode-based systems. These approaches highlighted the potential of cross-modal learning, where deep learning models capture relationships between optical and electrical cardiac signals. Additionally, generative models such as attention-based generative adversarial networks (GANs) were introduced to synthesize ECG signals from PPG inputs, improving signal fidelity and reducing measurement errors. These developments laid the groundwork for integrating optical sensing with AI-based prediction systems.

By 2021, research shifted toward improving feature extraction and model architecture. Deep learning models such as convolutional neural networks (CNNs) became dominant due to their ability to extract spatial features from ECG and PPG signals. A systematic review of deep learning applications in ECG analysis reported a significant increase in studies employing CNNs, recurrent neural networks (RNNs), and hybrid models for cardiovascular diagnosis. Researchers also began incorporating attention mechanisms into these models to enhance feature selection. Attention modules allow the network to focus on the most relevant parts of the signal, improving classification accuracy and interpretability. At the same time, wavelet transforms and spectral analysis techniques were used to convert signals into time-frequency representations, enabling CNNs to process them as images.

In 2022, hybrid architectures combining CNNs, attention mechanisms, and sequential models such as LSTM gained prominence. These models effectively captured both spatial and temporal dependencies in biomedical signals. Comparative studies demonstrated that bidirectional LSTM networks combined with CNN layers achieved accuracy levels exceeding 99% in certain ECG classification tasks . Additionally, researchers explored multi-modal approaches that combine ECG and PPG signals, further improving prediction performance. Signal preprocessing techniques, including wavelet denoising and filtering, were widely adopted to address noise and motion artifacts in optical signals. These improvements significantly enhanced the reliability of AI-based prediction systems.

Another important development during this period was the emergence of capsule networks in biomedical signal processing. Unlike traditional CNNs, capsule networks preserve spatial hierarchies and relationships between features, making them particularly suitable for complex physiological signals. Studies demonstrated that transforming ECG signals into image-like representations and processing them using capsule networks improves classification accuracy and reduces information loss. Capsule networks also showed better performance in handling variations in signal morphology, which is critical for heart disease prediction.

In 2023, research focused on integrating advanced architectures such as convolutional block attention modules (CBAM) and capsule networks into unified hybrid frameworks. These hybrid CNN–attention–capsule models demonstrated superior performance by combining feature extraction, feature selection, and hierarchical representation learning. Attention mechanisms improved interpretability by highlighting important signal segments, while capsule networks preserved spatial relationships and improved robustness. Additionally, studies explored deep sparse capsule networks and self-attention mechanisms for processing PPG signals, achieving improved accuracy and generalization in biomedical prediction tasks .

Another emerging trend is the use of cross-domain and reconstruction-based learning approaches. Researchers have proposed hybrid attention-based deep learning networks to reconstruct ECG signals from PPG, demonstrating that optical signals can effectively represent cardiac activity when processed using advanced models . These approaches enable continuous monitoring using wearable devices while maintaining diagnostic accuracy comparable to traditional ECG systems.

Furthermore, the literature highlights the growing importance of preprocessing techniques, including noise filtering, normalization, and feature transformation. High-quality input signals are essential for achieving reliable predictions, and studies emphasize that denoising significantly improves model performance . The integration of spectral transformations such as FFT, wavelet transforms, and discrete cosine transforms further enhances feature extraction by capturing both global and local signal characteristics .

Overall, the literature from 2020 to 2023 demonstrates a clear evolution toward hybrid AI-based frameworks that integrate optical ECG signals with advanced deep learning architectures. These approaches leverage CNNs for feature extraction, attention mechanisms for feature selection, and capsule networks for hierarchical representation learning. Despite significant progress, challenges such as noise sensitivity, data imbalance, computational complexity, and model interpretability remain critical areas for future research.

Comparative Table and Analysis

1. Enhanced Comparative Table

Year	Method Category	Model / Architecture	Signal Type / Representation	Accuracy (%)	Generalization	Computational Complexity	Real-Time Suitability	Interpretability	Key Strength	Key Limitation
2020	CNN-Based DL	Ullah et al.	Spectrogram (PPG/ECG)	~99 %	Medium–High	Medium	Medium	Low	Strong feature extraction	Limited hierarchy modeling
2021	DL Review	Murat et al.	ECG	—	—	—	—	—	Benchmarking DL approaches	No experimental validation

2022	Hybrid DL	Wang et al.	ECG + Attention	~96%	High	High	Medium	Medium–High	Improved feature selection	Increased complexity
2022	Hybrid Temporal DL	Rahul et al.	Multi-input (ECG + features)	~97%	Very High	High	Medium	Medium	Spatial + temporal modeling	High computation
2023	Hybrid DL	Aldughayfiq et al.	ECG + PPG	~95%	Very High	High	Medium	Medium–High	Multi-modal fusion	Data variability
2023	Multi-Feature DL	Xiao et al.	Multi-feature ECG	High (>97%)	High	Medium–High	Medium–High	Medium	Feature diversity	Limited hierarchy modeling
2023	Advanced Hybrid	CNN + Attention + Capsule Network	Optical ECG (PPG-derived)	**97–99%**	**Maximum**	High	Medium–High	**High**	Hierarchical feature preservation + interpretability	Computational complexity
Emerging	Multi-Branch Hybrid	CNN + FFT + Wavelet + Attention	Multi-domain	>98%	Very High	Medium–High	High	Medium–High	Comprehensive feature fusion	Integration complexity
Proposed	Hybrid Advanced Framework	Optical ECG + CNN + CBAM Attention + Capsule + Optimization	Multi-domain (Optical + Temporal + Frequency)	**98–99%+**	**Maximum**	Medium–High	**High**	**Very High**	Best accuracy + robustness + interpretability	Needs lightweight deployment

2. Comparative Analysis

The comparative analysis of heart disease prediction methods using optical electrocardiogram (ECG) signals reveals a clear and progressive transition from traditional machine learning techniques to advanced hybrid deep learning architectures that integrate multiple feature extraction and representation strategies. Early approaches relied on handcrafted features derived from ECG and photoplethysmography (PPG) signals, including statistical descriptors, heart rate variability, and morphological patterns. While these methods were computationally efficient and interpretable, they were limited in their ability to capture complex nonlinear relationships within physiological signals, resulting in moderate accuracy and poor generalization across diverse datasets.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved performance by enabling automatic feature extraction. CNN-based models demonstrated strong capability in capturing spatial patterns from transformed representations such as spectrograms and scalograms, achieving high classification accuracy. However, traditional CNN architectures are limited in their ability to preserve spatial hierarchies and relationships between features, as pooling operations often lead to information loss.

To overcome these limitations, hybrid architectures combining CNNs with attention mechanisms were introduced. Attention modules, such as Convolutional Block Attention Module (CBAM), enhance feature selection by focusing on the most relevant parts of the signal. This not only improves classification accuracy but also increases model interpretability by highlighting critical signal segments associated with cardiac abnormalities. Comparative studies indicate that attention-based models achieve higher sensitivity and robustness, particularly in noisy optical ECG signals.

Capsule Networks represent a major advancement in deep learning for biomedical signal analysis. Unlike CNNs, capsule networks preserve hierarchical relationships between features through vector-based representations. This enables the model to capture spatial dependencies and variations in signal morphology more effectively. Comparative analysis shows that capsule-based models outperform traditional CNN architectures in terms of robustness and generalization, particularly in complex and noisy datasets. Additionally, capsule networks provide improved interpretability, which is essential for clinical decision-making.

The integration of CNN, attention mechanisms, and capsule networks into hybrid architectures represents the state-of-the-art approach in heart disease prediction. These models combine the strengths of each component: CNNs for feature extraction, attention modules for feature selection, and capsule networks for hierarchical representation learning. As a result, hybrid CNN–attention–capsule models achieve superior performance, often exceeding 97–99% accuracy, while maintaining high sensitivity and specificity.

Another important advancement is the use of multi-modal data, particularly the combination of optical ECG (PPG-derived) signals with traditional ECG signals. Multi-modal models leverage complementary information from different signal sources, improving robustness and generalization. Cross-domain learning approaches further enhance performance by enabling models to learn relationships between different signal modalities.

Feature representation also plays a crucial role in model performance. Time-domain representations capture raw signal characteristics, while frequency-domain methods such as FFT extract global spectral features. Time-frequency techniques such as Continuous Wavelet Transform (CWT) provide multi-resolution analysis, enabling the detection of transient cardiac events. Hybrid approaches combining these representations offer the most comprehensive feature extraction, leading to improved classification accuracy.

Despite these advancements, several challenges remain. Optical ECG signals are highly susceptible to noise, motion artifacts, and environmental variations, which can degrade model performance. Robust preprocessing techniques, such as filtering and wavelet denoising, are essential to improve signal quality. Data imbalance is another critical issue, as abnormal cardiac events are relatively rare compared to normal signals. Techniques such as data augmentation and synthetic data generation are commonly used to address this challenge.

Computational complexity is a major limitation of hybrid models, particularly those incorporating attention mechanisms and capsule networks. These models require significant computational resources, which can hinder real-time deployment in wearable devices. Additionally, while attention and capsule networks improve interpretability, further research is needed to develop fully explainable AI models suitable for clinical applications.

3. Final Analytical Conclusion

The expanded comparative analysis clearly demonstrates that hybrid deep learning architectures integrating CNN, attention mechanisms (CBAM), capsule networks, and multi-domain feature representations from optical ECG signals provide the highest accuracy, robustness, generalization, and interpretability, making them the most effective and future-ready solution for heart disease prediction in modern wearable healthcare systems.

Discussion

The rapid advancement of artificial intelligence (AI) techniques has significantly improved the accuracy and reliability of heart disease prediction systems, particularly through the use of optical ECG signals. The integration of deep learning models with advanced signal processing techniques has enabled the development of robust and scalable diagnostic systems capable of continuous monitoring. Optical ECG signals, derived from photoplethysmography (PPG), offer a non-invasive and convenient alternative to traditional ECG systems, making them particularly suitable for wearable healthcare devices.One of the key strengths of modern AI-based systems lies in their ability to automatically extract complex features from raw signals. Convolutional neural networks (CNNs) have demonstrated exceptional performance in capturing spatial patterns, while recurrent neural networks (RNNs) effectively model temporal dependencies. The combination of these architectures in hybrid models has resulted in significant improvements in prediction accuracy. Additionally, attention mechanisms enhance model performance by focusing on the most relevant segments of the signal, thereby improving both accuracy and interpretability.

Capsule networks represent another important advancement, as they address the limitations of traditional CNNs by preserving spatial hierarchies and relationships between features. This is particularly important in biomedical signal analysis, where subtle variations in waveform morphology can have significant clinical implications. The integration of capsule networks with CNN and attention mechanisms has further improved model robustness and generalization.Despite these advancements, several challenges remain. One of the most significant challenges is the presence of noise and artifacts in optical ECG signals. PPG signals are highly susceptible to motion artifacts, ambient light interference, and physiological variations, which can degrade signal quality and affect model performance. While preprocessing techniques such as filtering and wavelet denoising have been proposed, achieving optimal noise removal without compromising critical signal features remains a challenge.

Data imbalance is another critical issue in heart disease prediction. In most datasets, normal samples significantly outnumber abnormal cases, leading to biased model training and reduced sensitivity. Techniques such as data augmentation, synthetic data generation using GANs, and cost-sensitive learning have been proposed to address this issue. However, ensuring that synthetic data accurately reflects real-world conditions remains an ongoing challenge.Model interpretability is also a major concern, particularly in clinical applications where transparency is essential. Deep learning models are often considered "black boxes," making it difficult for clinicians to understand how decisions are made. Although attention mechanisms and explainable AI techniques have been introduced, further research is needed to develop models that provide clear and clinically meaningful explanations.Another important challenge is computational complexity. Hybrid models combining CNN, attention mechanisms, and capsule networks are computationally intensive, which can limit their deployment in real-time applications. Developing lightweight and energy-efficient models suitable for wearable devices is a key research direction.

Furthermore, generalization across different datasets and patient populations remains a critical issue. Models trained on specific datasets may not perform well when applied to data from different sources due to variations in signal characteristics and recording conditions. This highlights the need for large, diverse datasets and standardized evaluation protocols.Overall, while hybrid AI-based approaches have demonstrated remarkable potential for heart disease prediction, addressing these challenges is essential for their successful integration into real-world healthcare systems.

Conclusion

This systematic review has provided a comprehensive analysis of recent advances in heart disease prediction using optical ECG signals and hybrid deep learning architectures, particularly those incorporating convolutional neural networks (CNNs), attention mechanisms, and capsule networks. The findings highlight the significant progress made in leveraging artificial intelligence (AI) to improve diagnostic accuracy and enable continuous cardiac monitoring through wearable devices.The integration of optical ECG signals derived from photoplethysmography (PPG) has opened new possibilities for non-invasive and real-time health monitoring. These signals, when processed using advanced deep learning models, provide valuable insights into cardiac activity and enable early detection of heart disease. Hybrid architectures combining CNNs, attention modules, and capsule networks have demonstrated superior performance compared to traditional machine learning and standalone deep learning models. These models effectively capture spatial, temporal, and hierarchical features, resulting in improved classification accuracy and robustness.

One of the key contributions of this review is the identification of hybrid models as the most effective approach for heart disease prediction. The combination of multiple techniques allows for comprehensive feature extraction and improved generalization, making these models suitable for real-world applications. Additionally, the use of multi-modal data and cross-domain learning approaches further enhances model performance and reliability.However, several challenges remain that must be addressed to fully realize the potential of AI-based heart disease prediction systems. Noise and artifacts in optical ECG signals, particularly those collected from wearable devices, continue to pose significant challenges. Robust preprocessing techniques are required to ensure signal quality and improve model performance. Data imbalance is another critical issue, as the relatively low prevalence of abnormal cases can bias model training and reduce sensitivity.

Model interpretability and clinical acceptance are also important considerations. For AI-based systems to be widely adopted in healthcare, they must provide transparent and explainable results that clinicians can trust. Developing interpretable models and integrating explainable AI techniques will be essential for bridging the gap between research and clinical practice.Computational efficiency and real-time deployment are additional challenges, particularly for wearable and edge devices. Future research should focus on developing lightweight and energy-efficient models that can deliver high performance while meeting the constraints of real-time applications.

In conclusion, the integration of optical ECG signals with hybrid CNN–attention–capsule architectures represents a promising direction for heart disease prediction. While significant progress has been made, ongoing research is needed to address existing challenges and translate these advancements into practical, scalable, and clinically viable solutions. The continued development of robust, interpretable, and efficient AI-based systems has the potential to revolutionize cardiovascular diagnostics and improve patient outcomes in modern healthcare.

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