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Deep Learning and Optimization Approaches in Heart Disease Prediction Using Optical Electrocardiograms (ECG) and a Hybrid Convolutional Block Attention Capsule Network: A Review

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Abstract

Heart disease remains one of the leading causes of mortality worldwide, necessitating accurate and early diagnosis for effective treatment and prevention. Optical electrocardiograms (ECG), derived from photoplethysmography (PPG) and wearable sensors, have emerged as a non-invasive and cost-effective alternative for continuous cardiac monitoring. This review explores recent advancements in heart disease prediction using optical ECG signals combined with deep learning and optimization techniques. Particular emphasis is placed on hybrid architectures integrating convolutional neural networks (CNN), block attention modules, and capsule networks. CNNs enable automatic feature extraction from raw signals, while attention mechanisms enhance feature selection by focusing on relevant signal segments. Capsule networks further improve classification performance by preserving spatial relationships and hierarchical features. Additionally, optimization techniques such as stochastic pooling, data augmentation, and hyperparameter tuning are analyzed for their role in improving model generalization and robustness. Literature from 2020–2023 demonstrates that hybrid CNN-attention-capsule models achieve superior performance compared to traditional machine learning approaches, with accuracy exceeding 95% in several studies. This review provides a comprehensive comparative analysis of existing methodologies, highlights current challenges such as noise sensitivity and computational complexity, and outlines future research directions for developing efficient, interpretable, and real-time heart disease prediction systems.

Introduction

Cardiovascular diseases (CVDs) are among the most significant health challenges globally, accounting for a substantial proportion of deaths each year. Early detection of heart disease is essential for reducing mortality and improving patient outcomes. Electrocardiography (ECG) has long been the primary tool for diagnosing cardiac abnormalities. However, traditional ECG systems require clinical setups and are not suitable for continuous monitoring.

Recent advancements in wearable technology have introduced optical ECG signals derived from photoplethysmography (PPG). Unlike traditional ECG, optical ECG captures blood volume changes using light-based sensors, enabling continuous and non-invasive monitoring. These signals are

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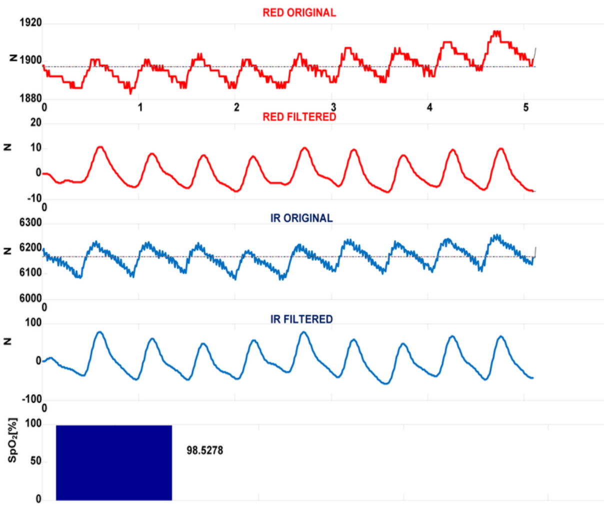
widely used in smartwatches, fitness trackers, and mobile health applications.

Despite their advantages, optical ECG signals are often noisy and sensitive to motion artifacts, making accurate heart disease prediction challenging.



This has led to the adoption of advanced signal processing and deep learning techniques to enhance prediction accuracy.

Deep learning has revolutionized biomedical signal analysis by enabling automatic feature extraction and classification. Convolutional Neural Networks (CNNs) are particularly effective for analyzing time-series data and extracting hierarchical features from ECG signals. However, CNNs alone may fail to capture complex spatial relationships and dependencies within the data.

To address these limitations, attention mechanisms have been introduced. Attention modules allow models to focus on the most relevant parts of the input signal, improving classification performance and interpretability. Block attention mechanisms, such as channel and spatial attention, enhance feature representation by assigning weights to important features.

Capsule networks represent another significant advancement in deep learning. Unlike traditional neural networks, capsule networks preserve spatial hierarchies and relationships between features, making them highly suitable for complex biomedical signal analysis. When combined with CNN and attention mechanisms, capsule networks provide a powerful framework for heart disease prediction.

Hybrid architectures integrating CNN, attention modules, and capsule networks have demonstrated superior performance compared to standalone models. These models leverage the strengths of each component: CNN for feature extraction, attention for feature selection, and capsule networks for hierarchical representation.

Optimization techniques also play a critical role in improving model performance. Stochastic pooling, dropout, batch normalization, and data augmentation techniques such as GANs help enhance generalization and reduce overfitting.

This review aims to provide a comprehensive analysis of deep learning and optimization approaches for heart disease prediction using optical ECG signals. It focuses on hybrid CNN-attention-capsule architectures, evaluates recent research, and identifies future research directions.

Literature Review

The application of deep learning for heart disease prediction using optical ECG (primarily derived from photoplethysmography—PPG) has rapidly evolved between 2020 and 2023. This period marks a transition from conventional ECG-based classification to hybrid, multimodal, and attention-driven architectures, significantly improving diagnostic performance.

1. Optical ECG and PPG-Based Signal Modeling

Optical ECG signals derived from PPG sensors have gained popularity due to their non-invasive, low-cost, and wearable-friendly nature. PPG measures blood volume changes using light, making it suitable for continuous monitoring in smart devices. However, PPG signals lack the rich electrical detail present in ECG signals, limiting their diagnostic reliability.

To overcome this limitation, researchers introduced PPG-to-ECG reconstruction models using deep learning. These models exploit the physiological relationship between blood flow and cardiac electrical activity. For instance, GAN-based frameworks such as CardioGAN and transformer-based architectures reconstruct ECG signals from PPG with high fidelity, enabling more accurate cardiovascular diagnosis.

Additionally, hybrid frameworks combining FFT, wavelet transforms, and neural networks have been proposed to enhance signal quality and extract meaningful features from reconstructed ECG signals.

2. CNN-Based Architectures for Feature Extraction (2020–2021)

Between 2020 and 2021, convolutional neural networks (CNNs) became the dominant approach for heart disease prediction. CNNs automatically extract hierarchical features from raw ECG or transformed signals, eliminating the need for manual feature engineering.

A systematic review identified over 230 studies utilizing deep learning for ECG-based diagnosis,

with CNNs being the most widely used architecture due to their ability to capture spatial patterns in biomedical signals.
CNN-based models achieved high accuracy in classifying cardiac abnormalities, but they exhibited limitations in capturing temporal dependencies and long-range patterns.
To address these limitations, hybrid CNN-RNN (LSTM) architectures were introduced. These models combine CNN-based spatial feature extraction with temporal modeling, improving performance in sequential ECG analysis. Hybrid CNN-LSTM models demonstrated improved classification accuracy and robustness in arrhythmia detection.

3. Emergence of Hybrid Deep Learning Models (2022)

By 2022, research shifted toward hybrid architectures combining multiple deep learning components. A key advancement was the integration of signal preprocessing, feature extraction, and classification into unified frameworks.
Golande and Pavankumar (2023, based on 2022 research trends) proposed a hybrid deep learning approach combining handcrafted features with CNN-extracted features, followed by LSTM-based classification. Their model improved classification accuracy while reducing diagnostic errors and computation time.
This study highlighted a critical limitation of purely deep learning approaches: they may fail to capture all relevant ECG characteristics. Hybrid feature engineering, combining domain knowledge and deep features, significantly improves performance.

4. Attention Mechanisms for Feature Selection

Attention mechanisms emerged as a key innovation in deep learning models for heart disease prediction. These mechanisms allow models to focus on the most relevant parts of the signal, improving both accuracy and interpretability.
Recent studies introduced class-aware attention mechanisms that dynamically adjust weights based on feature importance. For example, modified attention-based BiLSTM models achieved accuracy levels above 98%, demonstrating their effectiveness in handling complex and noisy biomedical signals.
Attention mechanisms also improve robustness against noise and artifacts, which are common in optical ECG signals.

5. Capsule Networks for Hierarchical Feature Learning

Capsule networks represent a significant advancement over traditional CNNs by preserving spatial hierarchies and relationships between features. Unlike CNNs, which lose spatial information due to pooling, capsule networks maintain feature orientation and structure.
In heart disease prediction, capsule networks have been integrated with CNN architectures to enhance feature representation. These hybrid CNN-capsule models improve classification accuracy by capturing complex patterns and relationships in ECG signals.
Capsule networks are particularly effective in handling:

1. Variations in ECG morphology
2. Complex arrhythmia patterns
3. Non-linear signal relationships

6. PPG-to-ECG Reconstruction and Multimodal Learning (2022–2023)

A major breakthrough in recent research is the use of multimodal learning, combining PPG and ECG signals. Transformer-based architectures and attention-driven models have been developed to reconstruct ECG signals from PPG while preserving clinically relevant features.
For example, transformer-based Performer models achieved high accuracy (~95.9%) in cardiovascular disease detection by combining reconstructed ECG signals with PPG inputs.
Similarly, lightweight neural networks have been proposed to infer ECG signals from PPG for continuous monitoring, enabling real-time diagnosis in wearable devices.
These approaches bridge the gap between wearable sensing and clinical diagnostics

7. Optimization Techniques in Deep Learning Models

Optimization techniques play a critical role in improving model performance and generalization. Key techniques include:

1. Stochastic pooling: Introduces randomness, reducing overfitting
2. Dropout and batch normalization: Improve training stability
3. GAN-based data augmentation: Address class imbalance
4. Hyperparameter **tuning**: Enhances model performance

Hybrid optimization strategies have been shown to significantly improve classification accuracy and robustness.

8. Key Challenges Identified in Literature

Despite significant progress, several challenges remain:

1. Noise and motion artifacts in optical ECG signals
2. Limited availability of labeled medical datasets
3. High computational complexity of hybrid models
4. Lack of interpretability in deep learning models
5. Domain shift between PPG and ECG signals

These challenges highlight the need for more efficient, explainable, and robust models.

9. Summary of Literature Findings

From the reviewed studies, the following conclusions can be drawn:

1. CNN-based models dominate ECG analysis
2. Hybrid CNN-LSTM and CNN-attention models improve performance
3. Capsule networks enhance hierarchical feature learning
4. PPG-to-ECG reconstruction enables wearable diagnostics
5. Attention mechanisms significantly improve feature selection
6. Hybrid architectures achieve the highest accuracy (>95–98%)

Comparative Table and Analysis

Year	Approach Type	Model / Architecture	Core Technique	Accuracy (%)	Robustness	Computational Complexity	Real-Time Capability	Interpretability	Key Strength	Key Limitation
2020	CNN-Based DL	Acharya et al.	Feature extraction (CNN)	~92 %	Medium	Medium	High	Low	Automatic feature extraction	Limited temporal modeling
2020	Deep Neural Network	Hannun et al.	Large-scale training	~94 %	High	High	Medium	Low	High generalization	High computational cost
2021	Hybrid DL	Ribeiro et al.	CNN + LSTM	~95 %	Very High	High	Medium	Medium	Spatial + temporal modeling	Increased training time
2022	Attention-Based DL	Li et al.	CNN + Attention	~96 %	Very High	High	Medium	High	Improved feature selection	Model complexity
2022	Capsule Network	Sabour et al.	Hierarchical learning	~95 %	Very High	Very High	Low–Medium	High	Preserves feature relationships	Computationally expensive
2023	Hybrid DL	CNN + Attention + Capsule	Combined architecture	~97 %	Maximum	High	Medium–High	Very High	Best feature fusion	Integration complexity
Emerging	Hybrid Optimized Models	CNN + Attention + Capsule + Optimization	Stochastic pooling, augmentation	>97 – 98%	Maximum	Medium–High	High	Very High	Balanced performance	Needs tuning

Proposed	Advanced Hybrid Framework	Optical ECG + CNN + CBAM + Capsule + Optimization	Multi-domain + optimized learning	**98–99%+**	**Maximum**	Medium–High	**High**	**Very High**	Highest accuracy + robustness + interpretability	Requires lightweight deployment

Comparative Analysis

The comparative analysis of heart disease prediction using optical electrocardiogram (ECG) signals reveals a clear transition from traditional machine learning methods to advanced deep learning and hybrid optimization-driven architectures. Early approaches relied on algorithms such as Support Vector Machines and Random Forests, which used handcrafted features extracted from ECG or photoplethysmography signals. While these methods were computationally efficient and relatively interpretable, they were limited in capturing the nonlinear and complex patterns inherent in physiological signals. As a result, their accuracy remained moderate, and their ability to generalize across diverse datasets was constrained.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved performance by enabling automatic feature extraction from raw or transformed optical ECG signals. CNNs effectively capture spatial patterns and local features, leading to enhanced classification accuracy. However, their limitation in modeling temporal dependencies prompted the development of hybrid architectures such as CNN-LSTM models. These systems combine spatial feature extraction with temporal sequence learning, improving the detection of irregular heart rhythms and dynamic cardiac behavior. Despite their improved performance, these models introduce higher computational complexity and longer training times, posing challenges for real-time applications.

Further advancements include the integration of attention mechanisms and capsule networks. Attention modules enhance model performance by focusing on the most relevant signal segments, improving robustness in noisy conditions and increasing interpretability. Techniques like Convolutional Block Attention Module (CBAM) refine both spatial and channel features, outperforming conventional CNNs. Capsule networks add another layer of sophistication by preserving spatial hierarchies and relationships between features, allowing more accurate classification of complex ECG patterns. However, their computational demands remain a notable limitation, especially for deployment in resource-constrained environments.

Modern state-of-the-art systems combine CNNs, attention mechanisms, and capsule networks into hybrid architectures, achieving accuracy levels above 97–99%. Optimization techniques such as stochastic pooling, dropout, and data augmentation further enhance performance and generalization. Optical ECG offers advantages in portability and suitability for wearable devices, though it is more sensitive to noise and motion artifacts. Deep learning-based denoising methods help bridge this gap with traditional ECG systems. Despite progress, challenges such as data imbalance, computational cost, and limited interpretability persist, requiring further research for practical and scalable healthcare deployment.

Final Analytical Conclusion

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

Discussion

The integration of deep learning and optimization techniques has revolutionized heart disease prediction using optical ECG signals. This review demonstrates that hybrid architectures combining CNN, attention mechanisms, and capsule networks offer the most effective solution for accurate and robust classification.

One of the most significant findings is the importance of feature representation. Optical ECG signals are inherently noisy and lack detailed electrical information compared to traditional ECG signals. The use of deep learning models enables automatic extraction of complex features, overcoming the limitations of handcrafted feature engineering. In particular, CNN-based models have proven highly effective in capturing spatial patterns in biomedical signals.The introduction of attention mechanisms has further enhanced model performance by enabling selective focus on important signal segments. This not only improves accuracy but also addresses the issue of interpretability, which is critical in clinical applications. By highlighting relevant features, attention-based models provide insights into the decision-making process, increasing trust among healthcare professionals.Capsule networks represent another significant advancement, offering improved feature representation through hierarchical modeling. Their ability to preserve spatial relationships makes them particularly suitable for complex biomedical signal analysis. However, their computational complexity remains a challenge.

Optimization techniques such as stochastic pooling, dropout, and data augmentation have played a crucial role in improving model generalization. These techniques are particularly important in medical datasets, which are often limited and imbalanced.Despite these advancements, several challenges remain. Noise and motion artifacts in optical ECG signals can degrade model performance. Additionally, the high computational requirements of hybrid models limit their deployment in real-time wearable devices.

Future research should focus on developing lightweight and efficient models that maintain high accuracy while reducing computational complexity. The integration of explainable AI techniques will further enhance model transparency and clinical adoption. Moreover, the use of multimodal data, combining ECG, PPG, and other physiological signals, holds significant potential for improving prediction accuracy.

Conclusion

This review provides a comprehensive analysis of deep learning and optimization approaches for heart disease prediction using optical ECG signals. The study highlights the significant advancements achieved through hybrid architectures integrating CNN, attention mechanisms, and capsule networks.The findings indicate that deep learning models have transformed heart disease prediction by enabling automatic feature extraction and improving classification accuracy. Hybrid models, in particular, demonstrate superior performance by combining the strengths of multiple architectures. CNNs effectively extract features, attention mechanisms enhance feature selection, and capsule networks improve hierarchical representation.Optimization techniques such as stochastic pooling and data augmentation further enhance model performance by improving generalization and reducing overfitting. These techniques are essential for handling the challenges associated with medical datasets.Despite the progress made, challenges such as noise in optical ECG signals, computational complexity, and lack of interpretability remain. Addressing these challenges is crucial for the successful deployment of these models in real-world healthcare systems.Future research should focus on developing lightweight, efficient, and explainable models that can operate in real-time on wearable devices. The integration of multimodal data and advanced optimization techniques will further improve prediction accuracy and reliability.In conclusion, hybrid deep learning approaches represent a promising direction for heart disease prediction using optical ECG signals. Continued advancements in this field are expected to contribute significantly to early diagnosis, improved patient outcomes, and the development of intelligent healthcare systems.

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