Poster Abstract: Real-Time Cardiovascular Disease Detection via Abnormal Electrocardiogram Cycles on Embedded Systems

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CCS CONCEPTS

• **Applied computing → Health informatics**.

KEYWORDS

Deep Learning, ECG Signal Processing, Real-time System

1 INTRODUCTION

Rapid response can effectively save lives from sudden cardiac death by detecting and recognizing heart conditions. Research highlights the effectiveness of rapid response in reducing preventable in-hospital cardiac arrests, showcasing the system's capability to enhance patient safety by continuously improving and speeding up physician responses [4]. However, over 356,000 Americans experience out-of-hospital cardiac arrests annually, with 60% to 80% died before reaching to hospitals [5]. Therefore, the research community explored a new rapid response paradigm for out-of-hospital use, which utilizes wearable sensing as the front end and performs comprehensive analysis based on deep neural networks (DNNs) at the cloud-based back end. Yet, this paradigm suffers from the limited reachability of communication services in remote or underserved areas.

Recent studies propose deploying DNNs on wearable devices for patient-side analysis to mitigate the communication barriers. To deploy DNN models, heart signals are optimized through compression, feature extraction, and selective transmission to reduce computational load. Models are modified via pruning, quantization, and lightweighting architectures to fit resource-constrained devices. While traditional resampling and optimization techniques applied to heart signals may inadvertently omit critical biomarkers, deploying complex deep neural network (DNN) models directly on wearable devices can introduce significant latency and reduce practicality for real-time use. This trade-off highlights the need for a balanced approach that minimizes data loss during signal processing and maintains model effectiveness and efficiency on resource-constrained wearable devices. Therefore, an approach that effectively bridges the gap between signal optimization and model simplification, ensuring the precise and resource-efficient processing of abnormal ECG cycles on wearable devices without compromising accuracy, is still in high demand.

In this study, we present an efficient cardiovascular disease detection paradigm. Our *key insight* is that we can achieve more efficient and accurate early detection and diagnosis of heart diseases by identifying specific abnormal ECG cycles at low cost and performing full analysis only on abnormal ECG cycles. Our method leverages an advanced neural network with knowledge distillation techniques to focus on singular ECG anomalies, significantly reducing computational complexity and enabling real-time patient condition monitoring. This approach shows a great potential in this field, emphasizing efficiency, accuracy, and the ability to deliver actionable insights in critical care scenarios outside of traditional hospital settings.

2 APPROACH

In this section, we introduce the proposed efficient approach that selectively analyzes sequences of ECG cycles indicative of potential abnormalities, rather than processing the entire waveform. By distinguishing between normal and abnormal ECG cycles through a lightweight foundation model, our methodology can reduce the computational overhead caused by analyzing normal ECG cycles, thereby improving the timeliness and accessibility of diagnostics through wearable technology.

As shown in Figure 1, the model design begins with the extraction of essential features from complete ECG recordings, including the Q-R-S complex and the peaks of P and T waves. We then segment the entire waveform from one R peak to the next, isolating individual ECG cycles. This process forms the basis for our model training phases, where we initially train a foundational model using ECG waveform from cycles without heart diseases. This foundational model helps in discerning normal and abnormal ECG cycles within waveform that indicate heart diseases, thereby aiding in pinpointing the specific elements that influence diagnosis, especially useful since abnormal heartbeats may not be present throughout the recordings.

Our research progresses by training a deep neural network tailored for diagnosing heart diseases from abnormal ECG cycles. This network employs an attention mechanism to focus on critical aspects of cardiac signals, integrating 1-dimensional Convolutional Neural Networks (CNNs) for spatial feature extraction and Long

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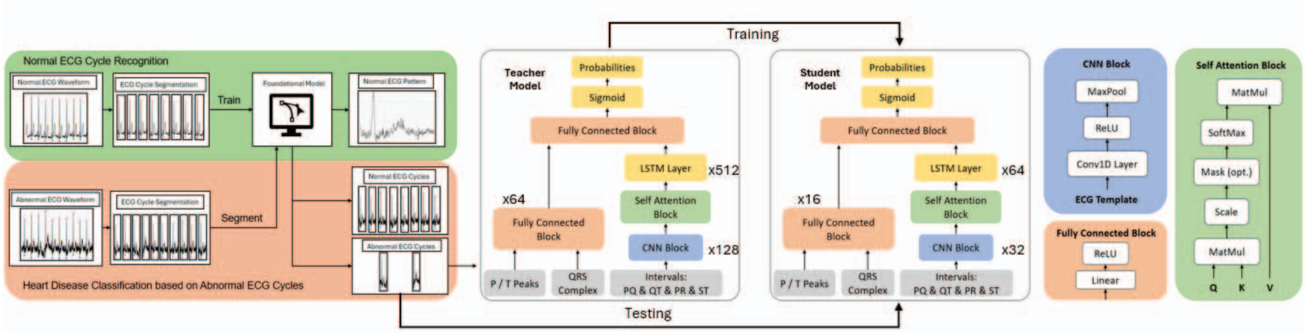

Figure 1: The two-stage framework of the proposed efficient cardiovascular disease detection. Computational overhead is reduced by only conducting analysis on abnormal ECG cycles selected by the lightweight foundation model.

Short-Term Memory (LSTM) networks for analyzing temporal sequences, thus capturing the nuances of ECG signals comprehensively. It processes key ECG features, such as the Q-R-S complex and the peaks of P and T waves, through fully connected layers. Additionally, it analyzes intervals like PQ, QT, PR, and ST using specialized CNN-LSTM blocks equipped with self-attention, treating these as sequential data to grasp their temporal relationships better.

Employing a knowledge distillation approach, we maintain the same architecture for both teacher and student models but reduce the complexity of the student model by scaling down its parameters. This method calculates a composite loss function that merges traditional classification loss against hard labels with distillation loss, ensuring the student model's predictions conform to the soft labels generated by the teacher model, thereby refining its performance with a more streamlined structure. Eventually, the student model will be tested on Raspberry Pi 4 to showcase its performance on balancing the accuracy and inference speed.

Table 1: Preliminary Results

Model	Leads	Size(mb)	Score*	Latency*
MHA ResNet	12	33.7	0.64	2.1
MHA ResNet	6	28.3	0.62	1.5
MHA ResNet	4	27.4	0.63	1.3
MHA ResNet	3	26.1	0.63	1.1
MHA ResNet	2	25.7	0.62	0.9
XGBoost	1	120.5	0.48	0.32
Ours(teacher)	1	11.1	**0.64**	0.48
Ours(student)	1	**3.3**	0.63	**0.31**

*Score: Reflects a metric that awards partial credit for misdiagnoses leading to similar treatments or outcomes, aiming for a balance between accuracy and patient safety.
*Latency: Measured in seconds, indicates the time taken by the model to return a diagnosis, emphasizing the importance of speed in clinical settings.

3 PRELIMINARY RESULTS

In our preliminary experiments with the PhysioNet 2021 Challenge dataset [3], concentrating on single-lead ECG (lead II) data and using a Raspberry Pi 4 to simulate wearable device limitations, our self-attention CNN-LSTM models, both teacher and student versions, outperformed traditional models like eXtreme Gradient Boosting (XGBoost) [1] and Multi-head Attention Residual Neural Network (MHA-ResNet) [2] in terms of both accuracy and efficiency. These results underscore our model's potential for effective integration into wearable devices for remote heart disease monitoring, balancing computational demands with high diagnostic precision. The promising outcomes suggest our approach can significantly enhance early detection and management of heart conditions, potentially transforming wearable health technology and patient care in settings with limited resources.

4 FUTURE WORK

In future work, we aim to enhance our model's diagnostic accuracy by incorporating additional physiological signals and employing federated learning for privacy-preserving data analysis. This strategy will not only improve the model's generalizability across diverse populations but also bolster real-time monitoring capabilities on wearable devices, making heart health management more accessible and efficient for users worldwide.

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