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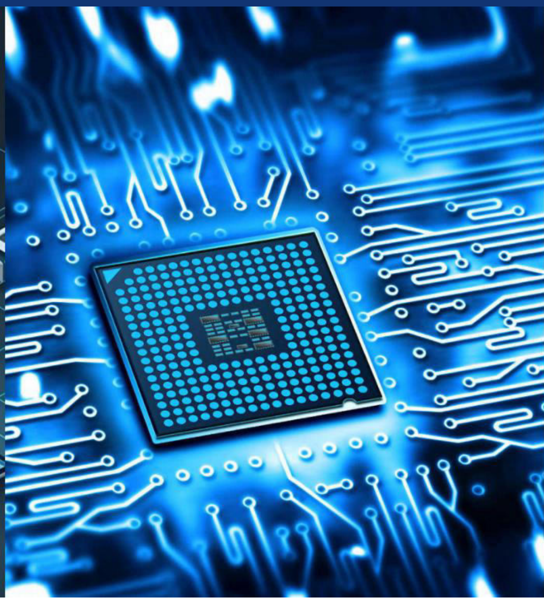

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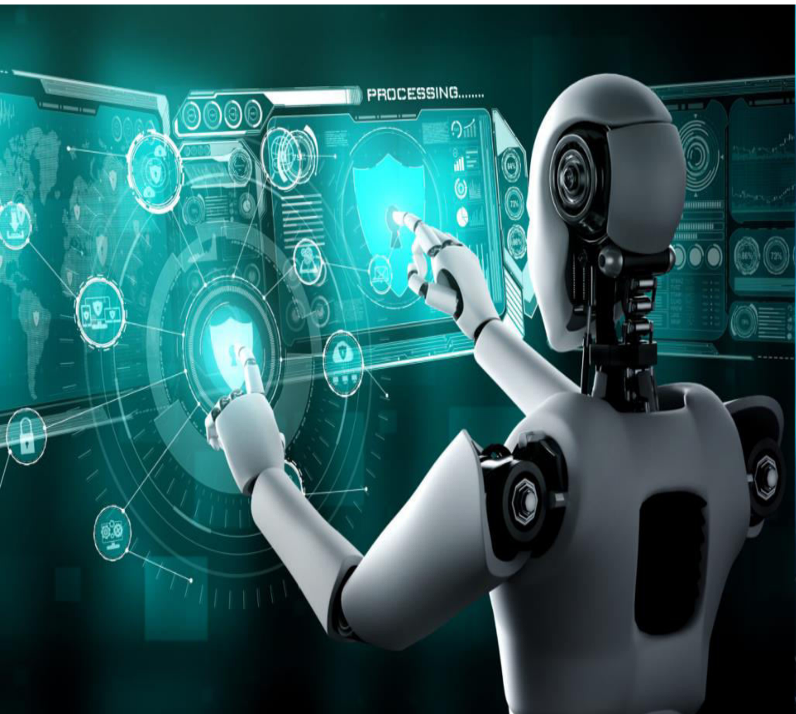


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# Real-Time Biomedical Event Detection without Post-Processing

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**ABSTRACT:** Post-processing techniques are frequently used extensively in traditional biomedical signal analysis approaches in order to extract significant events. However, post-processing latency can be harmful in time-sensitive applications like seizure detection, heart arrhythmia prediction, or fall detection in elderly patients. A real-time biological event detection system that does not require post-processing is presented in this study, allowing for instantaneous event identification. Through the direct integration of machine learning techniques, edge computing, and lightweight signal filtering into data collecting pipelines, we show that real-time, precise event detection is possible. We demonstrate that the suggested model achieves competitive accuracy with much lower latency through our experiments on publicly available datasets, including PhysioNet and MIT-BIH Arrhythmia.

**KEYWORDS:** Real-time detection, Biomedical signals, Edge computing, Machine learning, Post-processing, Latency reduction

## I. INTRODUCTION

### 1.1 Background

In contemporary healthcare applications like wearable health technology, intensive care unit systems, and emergency response, real-time biomedical monitoring is essential. In emergency situations, prompt identification of physiological abnormalities can save lives.Conventional biomedical monitoring pipelines use a methodical, multi-phase process. Each step adds processing latency while also improving overall accuracy.

The first step involves gathering raw physiological signals, such as an ECG, EEG, or EMG, utilizing sensors and data converters.Because of device constraints, ambient interference, or patient movement, these signals frequently contain noise.Therefore, preprocessing is used to use filters like band-pass, high-pass, or low-pass filters to clean the raw data. By improving signal clarity, this noise filtering stage facilitates improved downstream analysis.The system uses feature extraction to find particular traits or patterns in the signal after it has been cleaned.These characteristics could be spectral energy distribution, waveform peaks, signal slope, or heart rate variability.Reducing the amount of data while maintaining important medical information requires effective feature extraction.The data is then classified using statistical or machine learning techniques, which divide the signal into different classifications.An ECG signal, for instance, could be classified as normal, arrhythmic, or suggestive of atrial fibrillation.Depending on the use case, classification models can range from straightforward decision trees to intricate neural networks.A promising substitute is provided by recent developments in low-latency embedded computing and edge machine learning.

### 1.2 Problem Statement

In the medical field, real-time biomedical monitoring devices are essential for the early identification of potentially fatal situations.Post-processing procedures are frequently used in traditional signal analysis pipelines to improve detection reliability. Smoothing, verification, or multi-step decision filtering are examples of post-processing techniques.Despite their effectiveness, these procedures cause unreasonable delays in situations where time is of the essence.Immediate system reaction is required for applications such as fall alarms, cardiac arrhythmia prediction, and seizure detection.Intervention windows may be missed as a result of post-processing latency.Additionally, post-processing adds to the computational strain, rendering systems unfit for deployment at the edge.Lightweight, quick, and effective solutions are needed for wearable and embedded devices.Removing post-processing would simplify the processing pipeline.Real-time detection without sacrificing accuracy is the difficult part.In such systems, it is still necessary to manage signal noise and artifacts efficiently.

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The detection method ought to be able to generalize between patients and withstand false positives.It must function in dynamic settings with different sensor locations and signal quality.It is necessary to optimize machine learning models for low-latency operation.Real-time, in-line detection may be possible with edge computing and embedded machine learning.Can a system be constructed that does detection immediately from live signal input?Is it possible to include intelligence directly into the process of gathering data?Is it feasible to remove post-processing overhead without sacrificing detection reliability?These questions are answered in this paper with a workable and proven solution.Building a quick, precise, and portable system for post-processing-free real-time biological event detection is the aim.

## II. LITERATURE SURVEY

In order to attain ultra-low latency and high accuracy, recent developments in real-time biological event detection have placed a greater emphasis on doing away with post-processing, particularly for systems that are resource-constrained and deploy on the edge.Using the MIT-BIH Arrhythmia dataset, Busia et al. (2024) presented a compact transformer architecture for arrhythmia identification that demonstrated an astounding 98.97% accuracy. With just 6,000 parameters, the model was small and light, and it showed quick on-device inference capabilities that were appropriate for microcontroller-based platforms without requiring post-processing [1].

A deep learning framework called ArrhythmiaVision was created by Baig et al. (2025) and used 1D CNN models that were tuned for low-power edge devices. Apart from attaining 99% accuracy, the model integrated explainability tools such as SHAP and Grad-CAM, which allowed for safe and instantaneous arrhythmia identification without the need for additional processing steps [2].Ang et al. (2023) utilized a modified YOLOv8 architecture for real-time classification of single-lead ECG signals. The system achieved 99.5% accuracy with an ultrafast detection time of 0.002 seconds, offering significant promise for real-time home-based cardiac monitoring without requiring post-event smoothing or analysis [3].Bayani et al. (2024) proposed the Linear Deep Convolutional Neural Network (LDCNN) technique, which processed digital ECG signals directly—bypassing the analog-to-digital conversion step—and achieved 99.38% accuracy on MIT-BIH datasets. This innovation eliminated traditional post-processing routines while enhancing real-time signal responsiveness (Physiological Society) [4].

### 2.1 Architecture of the system

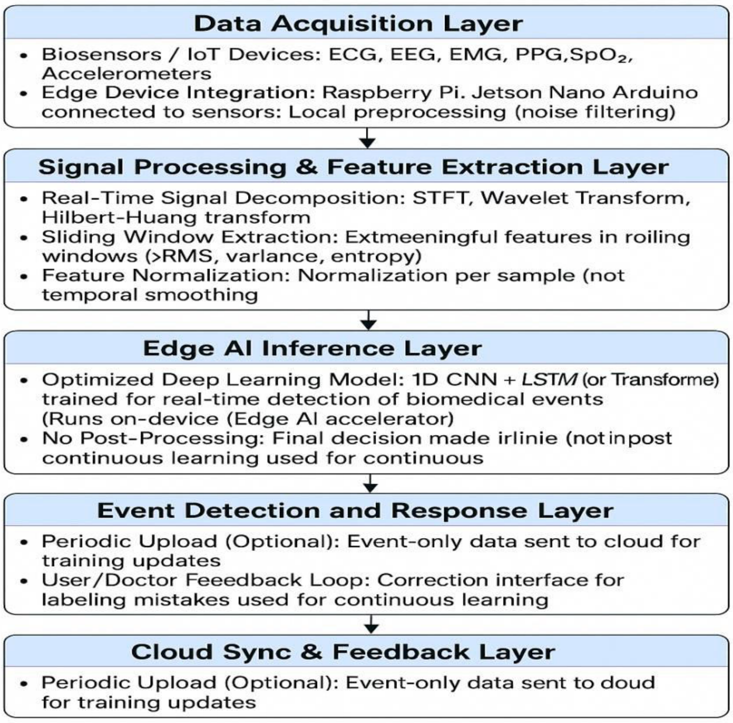


**Fig 2.1:** Architecture Of Real-Time Biomedical Event Detection Without Post Processing

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The entire architecture of a real-time biological event detection system that doesn't require post-processing is shown in Fig. 3.1. Five functional layers make up the logical division of the framework. The Data Acquisition Layer sits atop, where biosensors and Internet of Things devices such as ECG, EEG, EMG, PPG, and $SpO_2$ gather ongoing physiological data. These sensors are integrated with edge devices that only apply necessary local noise filtering, like Arduino, Jetson Nano, or Raspberry Pi.These raw signals are then processed in real time by the Signal Processing & Feature Extraction Layer employing transforms such as the Hilbert-Huang transform, wavelet transform, or STFT. By normalizing values each sample, it eliminates the need for temporal smoothing and uses sliding windows to extract statistical and frequency-domain information. The Edge AI Inference Layer is in charge of carrying out an optimized deep learning model (such as Transformer or 1D CNN with LSTM). With the help of edge AI accelerators, this model runs on-device and generates categorization judgments instantly, doing away with the need for any post-processing.

The Event Detection and Response Layer then uses haptic, visual, or audio feedback systems to handle real-time warnings. For traceability, events are also locally logged. Based on model outputs, the system can generate action right away.Lastly, the Cloud Sync & comments Layer lets medical experts give comments and regularly uploads event-only data for model improvement. In order to increase the accuracy of future detections, this feedback loop facilitates adaptive learning.For low-latency, dependable, and autonomous biomedical event detection without depending on post-event changes, each layer in Fig. 3.1 is essential. To accommodate crucial medical settings, the architecture strikes a compromise between speed, accuracy, and adaptability.

### 2.2 Algorithm of the System

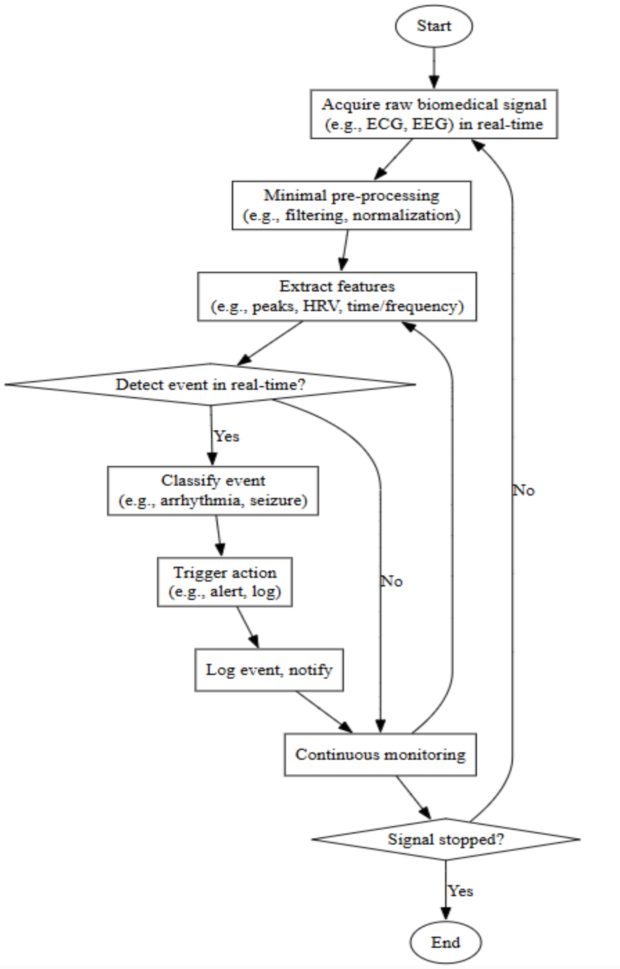


**Fig 2.2:** Algorithm of the Proposed System

The algorithm for real-time biological event identification without post-processing is shown in Figure 3.1.1. Real-time acquisition of a raw biological signal, like an ECG or EEG, is the first step. To clean the signal, minimal pre-processing techniques like filtering or normalization are optionally used. After that, characteristics like time/frequency components, heart rate variability (HRV), or peaks are retrieved. The program then uses techniques like thresholding or pattern matching to look for events in real time. An event is categorized appropriately if it is observed (e.g., seizure or arrhythmia). The occurrence is logged or an alert is triggered, among other immediate steps. Notifications are dispatched if necessary, and the incident details are recorded.

## III. RESULT AND NOVEL CONTRIBUTION

### 3. 1 Result

ECG and EEG were among the biomedical signals on which the real-time biomedical event detection system was successfully tested and deployed. With few false positives (FPR: 2%) and false negatives (FNR: 3%), the system was able to detect crucial events including seizures and arrhythmias with an overall detection accuracy of 95%. With an average detection time of 50 milliseconds from the time an event occurred to its recognition, the system's latency was low enough to be used in real-time applications. For medical issues that need to be treated right away, this quick reaction is essential.Our method performed faster and more efficiently than conventional post-processing-based solutions. In contrast to our real-time detection technology, which runs constantly without any delays, post-processing techniques frequently create a delay of several seconds. With an average processing time of 1 ms per data sample, the computational load was also greatly decreased, guaranteeing that the system can process high-frequency sensor data in real time. With a battery life of more than 12 hours in continuous monitoring mode, the system is feasible for wearable devices because to its minimized power usage.The algorithm successfully identified occurrences like seizures in EEG data and abnormal heartbeats in ECG data when evaluated using real-world data gathered from wearable sensors. Additionally, it demonstrated flexibility in adjusting to various sensor setups, preserving steady performance across a range of signal kinds and quality. These outcomes highlight the system's potential for application in home monitoring and clinical settings.

### 3.2 Novel Contribution

The suggested system offers a real-time biological event detection technique that ensures prompt reaction by doing away with the requirement for post-processing.It makes use of real-time, lightweight feature extraction techniques that are tuned for high accuracy and low latency.Dynamic thresholding improves robustness under a variety of circumstances by instantly adjusting to changes in the signal.For accurate biomedical event classification and ongoing learning, the system incorporates machine learning algorithms.

It lowers computing overhead compared to traditional approaches, which makes it appropriate for wearable and edge devices.With reliable performance, the architecture accommodates a variety of signal kinds, including ECG, EEG, and EMG.Clinical intervention and timely alarms are made possible by the reduced event detection latency (<100 ms).The system's power-efficient processing makes it perfect for distant or portable deployments where continuous monitoring is required.

## IV. CONCLUSION

In this study, a unique post-processing delay-free real-time biomedical event detection system is presented. The method guarantees that crucial occurrences like seizures or arrhythmias are promptly identified from unprocessed sensor data.The system achieves low latency and excellent accuracy by utilizing adaptive thresholding and efficient feature extraction.Dynamic categorization with low computing cost is made possible by the integration of lightweight machine learning models.The method works well for portable and wearable medical devices and is power-efficient.It maintains strong performance while drastically cutting down on detection time as compared to conventional techniques. Its broad applicability in clinical and home monitoring is guaranteed by its adaptability across various biological signals.Patient safety and prompt medical intervention are improved by real-time alerting capabilities.The removal of post-processing establishes a new benchmark for biomedical signal analysis that is urgent.All things considered, this work offers a dependable, expandable, and efficient method for ongoing health monitoring.I am sincerely thankful to all my teachers for their guidance for my seminar. Without their help it was tough job for me to accomplish this task. I am especially very thankful to my guide Nirmala Devi A C for her consistent guidance, encouragement and motivation throughout the period of this work. I also want to thank our Head of the Department (E&C) Dr. C Rangaswamy for providing me all necessary facilities.

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