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Embedded Based Early Sepsis Detection in Non-Critical Care Units Using Edge AI

Nikeleshwaryaa S, Imran U, Jayasree R, Murugesan K
Department of Electronics and Communication Engineering, JNN Institute of Engineering, Chennai, Tamil Nadu, India

ABSTRACT - *A dysregulated immune response to infection causes sepsis, a potentially fatal illness that, if left untreated, can cause organ failure and a high death rate. The danger of delayed discovery is increased in non-critical care wards because they rely on occasional manual observation, while intensive care units are the primary locations for continuous monitoring equipment. This paper proposes an embedded early sepsis detection system with the use of NanoEdge AI Studio for the training of an anomaly detection model on the STM32 microcontroller. Biomedical sensors are used to continually measure physiological factors such as body temperature, oxygen saturation, respiration rate and heart rate. Real-time Edge AI inference without relying on the cloud is made possible by the direct deployment of a machine learning-based anomaly detection model created using NanoEdge AI Studio on the microcontroller.*

Keywords: *Sepsis Detection, Edge AI, NanoEdge AI Studio, Healthcare Monitoring, Anomaly Detection, Real-Time Monitoring.*

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I. INTRODUCTION

Early prediction of sepsis has gained interest in bio-medical machine learning due to the ability of early detection to minimize morbidity and mortality of the septic patient by sending an early warning signal to the clinicians before the severe clinical deterioration. Sepsis is a major worldwide health care problem and deadly condition affecting about 49 million people per year resulting in approximately 11 million deaths, representing 20 % of all deaths as per the Lancet and 2017 Global Sepsis Alliance Report [1]. In India, 70% of all health care expenditure is on hospital care and in intensive care units. The disease is attributed to 25–30% of all reported deaths, with over 50% of deaths occurring in ICUs [2]. These statistics indicate that there is a clear and immediate requirement for a reliable Early Detection of Sepsis system. Multiple researches have introduced machine learning models for sepsis prediction from historically collected clinical information like MIMIC database as well as ICU monitoring data [3 – 10]. The models analyze electronic health records and physiological time-series to find early warning signs and have obtained good classification performance by employing advanced statistical and temporal learning approaches [11]. Recurrent neural network-based model like DeepAISE, has been used to model the temporal correlations in the physiological recordings and, as most deep neural networks, they tend to be computationally intensive, requiring a centralized or cloud-based computational infrastructure [12]. Furthermore, the development of wearable and IoT-based monitoring systems for the continuous measurement of vital signs outside of ICU settings has been investigated. The i-CardiAx system combines multisensor wearable patches with shallow neural networks for physiological monitoring and basic classification [13]. However, its ability of real-time clinical risk assessment is limited. Frameworks such as FedSepsis use multimodal deep learning and federated learning among edge devices (Raspberry Pi, Jetson Nano, etc.,) to illustrate the power of distributed analytics [14].

Moreover, the following prior research in sepsis prediction are commendable for its progress: (1). Temporal learning models are solid references for representing time-varying physiological parameters and shaped the feature engineering in this study [3], [4], [11], [12]. (2). Wearable sensing frameworks show viable methods of power-efficient sensing and embedded inference thus making edge deployment generally tenable [13], [15]. (3). Distributed analytics and the fusion of heterogeneous data are promoted by federated and multimodal learning methods [14], [16]. Combining the knowledge from these research areas, this paper introduces a budget friendly embedded system for early sepsis identification for healthcare settings with continuous monitoring system capabilities.

The paper is organized as follows: Section II presents the system integration and modular composition of the proposed monitoring framework. Section III describes the acquisition and conditioning of physiological signals. Section IV focuses on temporal feature modeling and the analysis of physiological trends derived from the acquired signals. The design and development of the proposed Edge AI model is detailed in Section V. Section

VI outlines the hardware integration and software embedding of the system. The operational principle of the proposed framework, including hardware functionality, software processing, and interaction, is explained in Section VII. The experimental observations and discussion of the results obtained are presented in Section VIII. Finally, Section IX concludes the paper and highlights potential directions for future work. 2

II. SYSTEM INTEGRATION AND MODULAR COMPOSITION

The development of the embedded early sepsis detection system was driven by a single pragmatic requirement: applicability in a non-critical care setting. Whereas intensive care units are equipped with state-of-the art monitoring systems, that is not the case in surgical, intermediate and medical wards, where monitoring suffers from the lack of sophisticated instrumentation, monitoring has to be intermittent and the physiological alterations are not always revealed during scheduled exams. To fill this gap the architecture was deliberately engineered to function locally to the bed. The system does not rely on centralized processing remote servers or continuous Internet connectivity. Rather, the system only uses embedded hardware for acquiring analysing and issuing the alarm of the signals in real time.

As shown in Fig. 1, The architecture consists of four coordinated layers: Physiological Sensing Layer, Embedded Signal Processing Layer, Edge Intelligence Layer, Alert and Visualization Layer. Each layer performs a clearly defined function, ensuring modularity while maintaining low latency.

The sensing layer continuously acquires non-invasive physiological parameters. The processing layer cleans and structures the incoming data stream. The intelligence layer evaluates the processed signals using an embedded anomaly detection algorithm. Finally, the alert layer communicates risk in a simple, actionable format. Predictive accuracy was of course a prime goal of the designs, but operational robustness, interpretability and resource efficiency were all much higher ranked. The system needed to be robust over the time of long-term use, over changes in the signal, and under harsh memory and power restrictions.

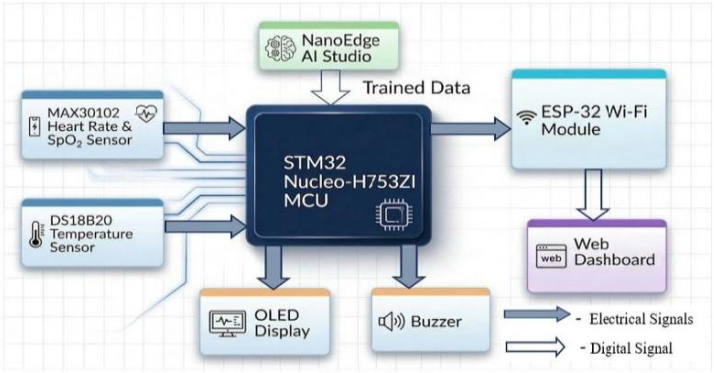


Fig 1. Block diagram of sepsis detection system

III. PHYSIOLOGICAL SIGNAL ACQUISITION AND CONDITIONING

Continuous physiological monitoring is more than just sensor to microcontroller communication in practical clinical situations disturbances in signals are present. Patient movement, sensor displacement, peripheral circulation variation, and ambient noise can cause a considerable amount of noise. Heart rate and oxygen saturation are extracted from photoplethysmographic signals. The variation in blood volume is detected through the light absorption properties. Although well integrated in clinical systems, embedded implementation of photoplethysmography monitoring systems mandates tight control of the timing of the system as well as the filtering of the incoming signal to allow the stability of the measurements. To maintain reliability, the system implements:

1. Adaptive smoothing filters to reduce motion artifacts
2. Outlier rejection mechanisms to eliminate sudden spikes
3. Stabilization intervals after sensor repositioning

While digital stability can be achieved in temperature measurement, the environment and lag during rapid physiological change can cause errors. The proposed approach is to keep track of the fluctuation over time. Raw data is not the final product, but the data is continuously changing stream requiring pre-processing. This allows the decision-making layer to receive the processed and meaningful data instead of unsteady raw data.

IV. TEMPORAL FEATURE MODELING AND PHYSIOLOGICAL TREND ANALYSIS

Initial sepsis generally does not appear as a very abnormal behaviour, but as a slow physiological trend. Detection of this slow deviation is at the core of the proposed method. The system does not use only single moment data and instead the analysis is done on short temporal windows. For each window the following parameters are assessed:

1. Rate of change in heart rate
2. Variability of oxygen saturation
3. Incremental rise in temperature
4. Cross-parameter deviation patterns

For instance, a slight rise in heart rate alone might not be alarming but in the context of rising temperature rate and slight oxygen fluctuation the overall physiological pattern start to to deviate from the baseline stability. The integrated algorithm turns raw sensor streams into structured feature vectors. These vectors account for both of the amount and the course of the change, allowing a early detection of instability. Physiological trend analysis is then performed on the extracted temporal features to understand the gradual deviation of vital signs from the normal physiological baseline. Instead of evaluating parameters independently, the system analyzes the combined evolution of heart rate, body temperature, and oxygen saturation over time. By tracking these interrelated physiological patterns across consecutive time windows, the algorithm identifies progressive trends such as sustained tachycardia, gradual temperature elevation, or fluctuating oxygen saturation levels. These coordinated physiological deviations form early indicators of systemic inflammatory response, enabling the system to detect potential sepsis development before severe clinical symptoms appear.

V. EDGE AI MODEL DEVELOPMENT

Since the embedded hardware and the logistical difficulties of gathering big labeled clinical datasets were taken into account the core of the system is anomaly detection instead of supervised classification. The development was divided in four main steps:

A. Baseline Pattern Learning

Initially, physiological data representing stable conditions were collected. These data sequences were used to train the embedded model to recognize patterns associated with normal physiological behavior.

B. Model Generation and Optimization

The anomaly detection model was generated using embedded machine learning tools designed for microcontroller deployment. Memory footprint was carefully evaluated to ensure compatibility with on-board flash and RAM constraints.

C. Threshold Calibration

For every new time window, an anomaly score is calculated. The threshold is established in order to decide if the deviation is big enough to send a warning and this threshold was experimentally optimized for favoring the sensitivity or the specificity.

D. Real-Time Deployment

Once deployed on the microcontroller, the model performs inference continuously. Each cycle includes data acquisition, feature extraction, anomaly scoring, and decision logic execution.

The entire process operates within milliseconds, enabling near-instantaneous risk identification.

VI. HARDWARE INTEGRATION AND SOFTWARE EMBEDDING

The hardware platform was chosen in order to meet the compromise between computational performance and energy efficiency. The microcontroller, in fact, has to guarantee the real-time operation of signal processing algorithms, also considering that the system has to be low power. Sensor modules have to be interfaced through standard communication protocols in order to guarantee the transfer of the signals without errors. The Wi-Fi module, on the other hand, is included only for visualization and has not to be involved in the risk calculation. Power regulation circuits have been added to guarantee the power supply stability. The overall hardware setup of the proposed system is illustrated in Fig. 2.

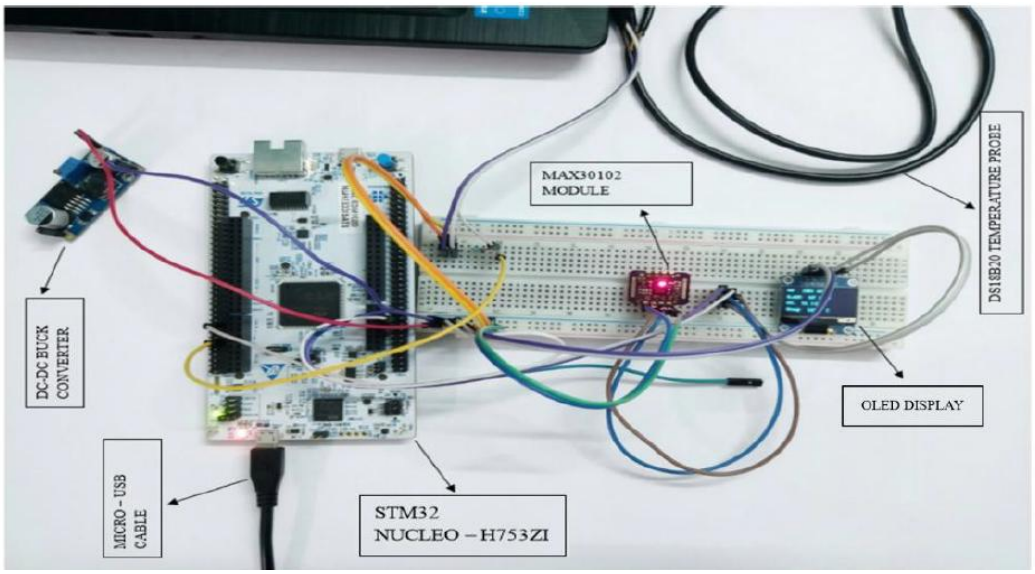


Fig. 2. Hardware setup of the proposed system

From a software point of view, the embedded system has been designed and developed using various software tools to achieve signal acquisition, embedded intelligence, and wireless communication. For instance, the primary firmware for the microcontroller has been designed and developed using STM32CubeIDE. This software tool has been used to configure the microcontroller, acquire sensor data in real-time, and process signals. For the implementation of the Edge AI model, the software tool used is NanoEdge AI Studio. This software tool has been used to develop lightweight machine learning libraries that can run on the microcontroller to achieve real-time anomaly detection and pattern recognition of physiological signals. Furthermore, the Arduino software tool has been used to develop the firmware for the ESP32 module, which has been used to achieve wireless communication and IoT-based monitoring. 4

VII. WORKING PRINCIPLE

The suggested embedded system for early sepsis detection functions on the synchronized collaboration of sensing equipment embedded processing and intelligent software codes. Individual part within the whole system is doing a task but it is the overall the integration of all those parts which presents an efficient solution. The physical hardware is responsible for sensing physiologic signals from patient and software layer is used to processing the signals and to detect the deviated pattern which may lead to premature physiological distress.

A. OPERATION OF HARDWARE COMPONENTS

Physiological sensors constitute the main contact between the patient and the monitoring system and are able to constantly extract signals, representative of the patient's physiology, known as vital signals. The optical pulse oximetry sensor is used to determine heart rate and peripheral oxygen saturation by employing photoplethysmography where the sensor emits light which transmits through the skin and interacts with the blood vessels under the skin. The blood volume changes in each cardiac cycle cause the variation of the light absorption and the backscattered light. The variations are detected by the sensor and transformed to an electrical signal which is processed into the pulse waveform of the patient. The wave data are used to determine the patient's heart rate and oxygen saturation levels according to the wave frequency and amplitude. The temperature sensing part is used to determine the body temperature of the patient.

The temperature sensing element consists of a firming digital thermal sensor. The thermal sensor contains an internal thermistor element which alters its electrical resistance based on the temperature. Because temperature changes can be slow during infection or systemic inflammation, the sensor repeatedly refreshes the temperature readings at set time intervals to reveal minor changes in time. The signals of all sensors are transmitted to the embedded microcontroller by digital communication protocols. The system's core controller is realized by the microcontroller. It takes sensor information, buffers this information and controls all operations. The microcontroller is also responsible for managing the additional elements such as the display, the communication module, and the alarm system apart from obtaining the data. The display module is a visual interface for caregivers and medical practitioners. It reports real-time physiological measurements so the user can directly see current vital signs from the device. By visual feedback the patient's state can be immediately evaluated without the need of external sensing equipment. The alarm system has a buzzer or other audible alarm that sounds if irregular

physiological signals are recognized. Its function is to attract the immediate attention of staff of the risk of a patient's deterioration so that they can act accordingly. ESP32 integrated for sending of monitoring data to a web dashboard or local monitoring station. This module enables remote real-time monitoring of patient vitals and also facilitates storage of the monitored data but the central processing of physiological signals is done locally on the embedded device.

B. SOFTWARE AND SIGNAL PROCESSING

All signal processing and decision activities are handled by the systems software layer. The code executing on the microcontroller is implemented as a perpetually executing supervisory cycle that continuously executes data collection, data processing, data analyzing and alarm generation. At each monitoring cycle start, the program acquires the new sensor measurements from the physiological sensors. The original signals can be contaminated by noise introduced by motion artifacts, dislocation of sensors or interferences from the environment. To do this, the program initially utilizes filtering methods (smoothing) for the stabilization of the responses and elimination of the irregular responses. Post filtering the program arranges the sensor data into time-based data windows. Rather than considering individual measurements in isolation the system looks at the way in which the physiological parameters change over time. By this method, the algorithm will be able to detect slow deviations that are not clearly visible from the individual measurements. The subsequent step is feature extraction in which significant features are extracted from the preprocessed signals. For instance, the program computes the heart rate of change, the fluctuation of oxygen saturation, and the progression of temperature increase. Such features are more descriptive of the patient's condition than the pure sensor data. After grabbing those features, the algorithm checks if your current physiological data looks too different from what it considers normal. The model compares the new readings with baseline values and calculates an anomaly score. The process of decision-making in the proposed system occurs through a continuously iterative process of evaluation. For each temporal feature window, an anomaly score is determined to measure the extent of deviation of the present physiological pattern from patterns that have been encountered in the training process. The alert process in the system involves a two-stage process of evaluation, where preliminary anomaly detection occurs, followed by confirmation of the anomaly through successive deviation windows. This helps in eliminating false alarms that may result from transient changes in the physiological state. Once the abnormal state is confirmed, the system activates different alert modalities, including an audible alert, a visual alert, and an update to the dashboard. It should be noted that the alert generated by the system represents a state of potential risk but not a medical diagnosis.

C. INTEGRATED HARDWARE – SOFTWARE INTERACTION

Even when every part of hardware or software handles a separate job, smooth operation relies heavily on constant communication across levels. Right after sensors capture live bodily signals, those inputs move toward the processing core. Inside the device, programmed code reshapes raw data into clearer forms through filtering steps. As soon as digital information gets cleaned up, automated logic checks for signs that could point to worsening medical conditions. Only once analysis finishes does the loop restart - driven by fresh measurements gathered directly from the person being watched. Features pulled from data feed into the anomaly detector, judging if vital signs stay close to typical ranges. When shifts arise beyond usual trends, alarms trigger without delay while screen outputs refresh automatically. Early signals emerge through linked processes - giving medical staff time 5

to act ahead of decline. Sensors paired with on-board logic support constant tracking, instant evaluation, followed by swift warnings inside a small computing frame. Working together, circuits and code turn the unit into a timely tracker spotting hidden changes tied to sepsis danger.

VIII. OBSERVATION AND DISCUSSION

Early recognition of abnormal physiological parameters is critical in recognizing the onset of sepsis. Clinical screening models, such as those advocated by the Surviving Sepsis Campaign, have emphasized that abnormal vital sign parameters, such as body temperature, heart rate, respiratory rate, and oxygen saturation, are critical indicators of infection. Abnormal trends in these physiological parameters, such as those that result from sepsis, can thus be recognized by monitoring these parameters. The physiological parameters, their ranges, and abnormal values used as a reference guide for sepsis screening are presented in Table 1.

Table 1: Standard physiological indicators for early sepsis screening

Physiological Parameter	Normal Range	Possible Sepsis Indicator
Body Temperature	36.5 – 37.5 °C	> 38 °C (fever) or < 36 °C (hypothermia)
Heart Rate (HR)	60 – 100 bpm	> 90 bpm (tachycardia)
Respiratory Rate (RR)	12 – 20 breaths/min	> 22 breaths/min (tachypnea)
Oxygen Saturation (SpO_2)	95 – 100 %	< 94 % (possible respiratory compromise)

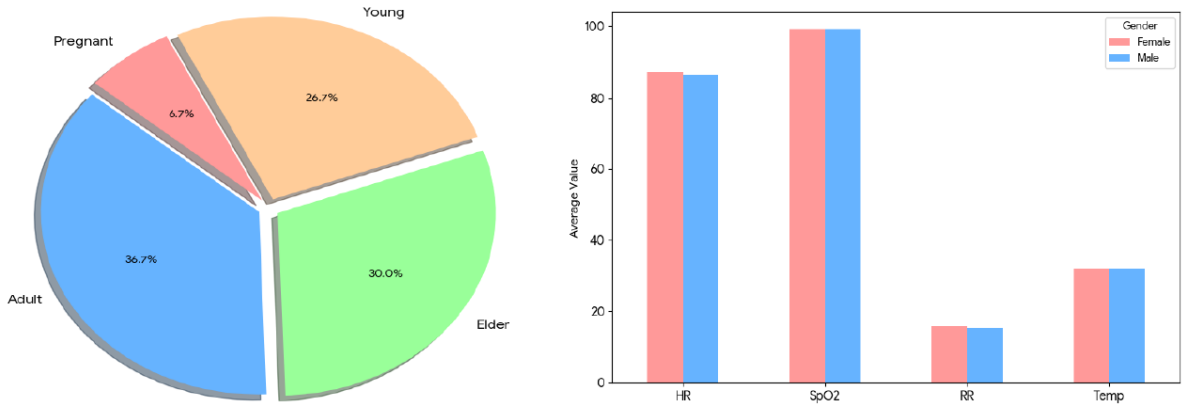
Physiological thresholds established in Table 1 are widely used in clinical monitoring and early warning systems for the diagnosis of potential sepsis conditions. Any variations from these values indicate abnormal physiological responses, which may be expected during systemic infections. In this study, these values were used as a reference to compare the physiological data collected from the proposed monitoring system on the 30 participants.

For the evaluation of the proposed system's performance, physiological data were collected from 30 subjects using the developed monitoring system. The system monitored four vital signs continuously: heart rate (HR), respiratory rate (RR), oxygen saturation levels (SpO_2), and body temperature. The collected data were then analyzed and compared against the reference values provided in Table 1 to detect anomalies that may represent abnormal physiological states. The collected physiological data from the subjects are presented in Table 2. 6

Table 2: Observed physiological data from 30 subjects

Subject	Age	Gender	Category	HR (bpm)	SpO_2 (%)	RR (bpm)	Temp (°C)
S1	22	Male	Young	78	99.4	14	37.4
S2	25	Male	Young	82	99.1	15	37.6
S3	27	Male	Young	75	98.9	13	36.5
S4	29	Male	Young	84	99.7	14	37.8
S5	24	Male	Young	79	99.2	15	37.7
S6	32	Male	Adult	86	98.7	16	36.0
S7	35	Male	Adult	88	99.3	15	36.9
S8	38	Male	Adult	83	99.5	14	37.8
S9	41	Male	Adult	90	98.8	16	36.1
S10	45	Male	Adult	87	99.1	15	37.0
S11	53	Male	Elder	92	98.6	16	36.2
S12	57	Male	Elder	89	99.0	17	37.3
S13	61	Male	Elder	102	98.7	16	37.4
S14	66	Male	Elder	93	98.5	17	36.5
S15	23	Female	Young	76	99.6	14	37.5
S16	26	Female	Young	80	99.2	13	36.6
S17	28	Female	Young	74	99.4	14	37.4
S18	30	Female	Adult	81	99.1	15	36.7
S19	33	Female	Adult	85	99.0	15	37.2
S20	36	Female	Adult	83	98.9	16	36.9
S21	39	Female	Adult	86	99.3	15	37.0
S22	42	Female	Adult	88	99.1	16	37.1
S23	48	Female	Adult	84	98.8	15	38.0
S24	52	Female	Elder	90	98.7	16	36.2
S25	56	Female	Elder	87	98.9	17	37.3
S26	60	Female	Elder	91	98.6	17	37.4
S27	65	Female	Elder	92	98.5	16	37.5
S28	68	Female	Elder	94	98.4	17	36.6
S29	29	Female	Pregnant	112	99.0	17	36.2
S30	31	Female	Pregnant	91	98.8	18	37.3

From the physiological data collected from the 30 participants, the majority had physiological data within the normal range, though there were minor variations in physiological data such as heart rate and body temperature in some of the participants. This shows the capability of the proposed monitoring system in collecting physiological data in real-time, including the ability to detect anomalous patterns in the data, which could be useful in the early surveillance of physiological changes that could be indicative of the onset of sepsis or other systemic infections.



(a) (b)

Fig. 3. (a) Distribution of subjects by category. (b) Vital sign comparison between male and female participants

The demographic composition of the participants is represented in Fig. 3(a), which indicates that the data set is composed of people classified as young, adult, elderly, and pregnant. This classification ensures that the monitoring system is evaluated based on different populations. Fig. 3(b) indicates the comparison of mean physiological parameters for male and female participants. The results indicate minimal differences in physiological parameters for both genders, as all parameters are within normal physiological ranges. 7

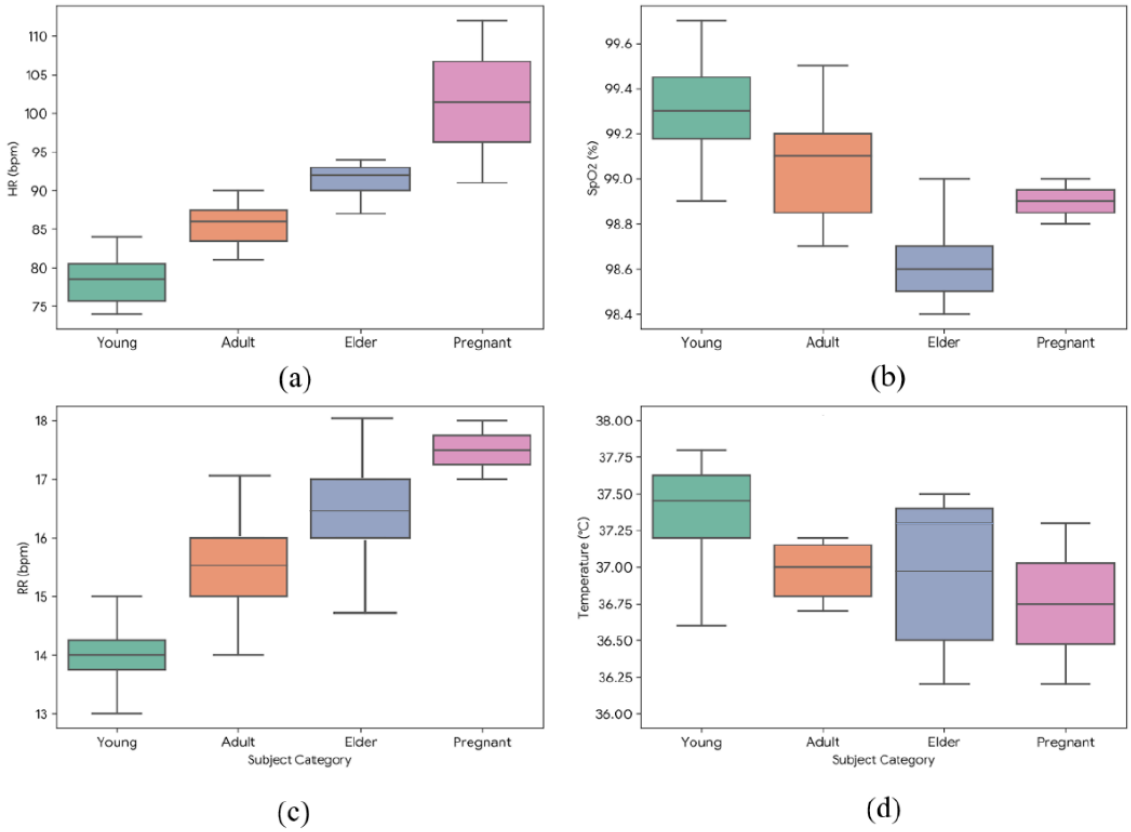


Fig. 4. Distribution of physiological parameters across subject categories: (a) heart rate distribution, (b) oxygen saturation distribution, (c) respiration rate distribution, and (d) body temperature distribution.

Fig. 4 illustrates the distribution of physiological parameters in different subject categories. Fig. 4(a) shows the heart rate distribution. There is a gradual increase across the subject categories, but it stays within normal physiological limits. Fig. 4(b) presents the oxygen saturation distribution. It indicates stable SpO_2 values across all categories, with only minor changes. Fig. 4(c) represents the respiration rate distribution. Slight differences occur between subject groups, but they remain within expected ranges. Fig. 4(d) displays the body

temperature distribution, which also stays within normal physiological limits across the various categories. Overall, the results suggest that the monitoring system can reliably measure and represent physiological parameters across different subject groups. 8

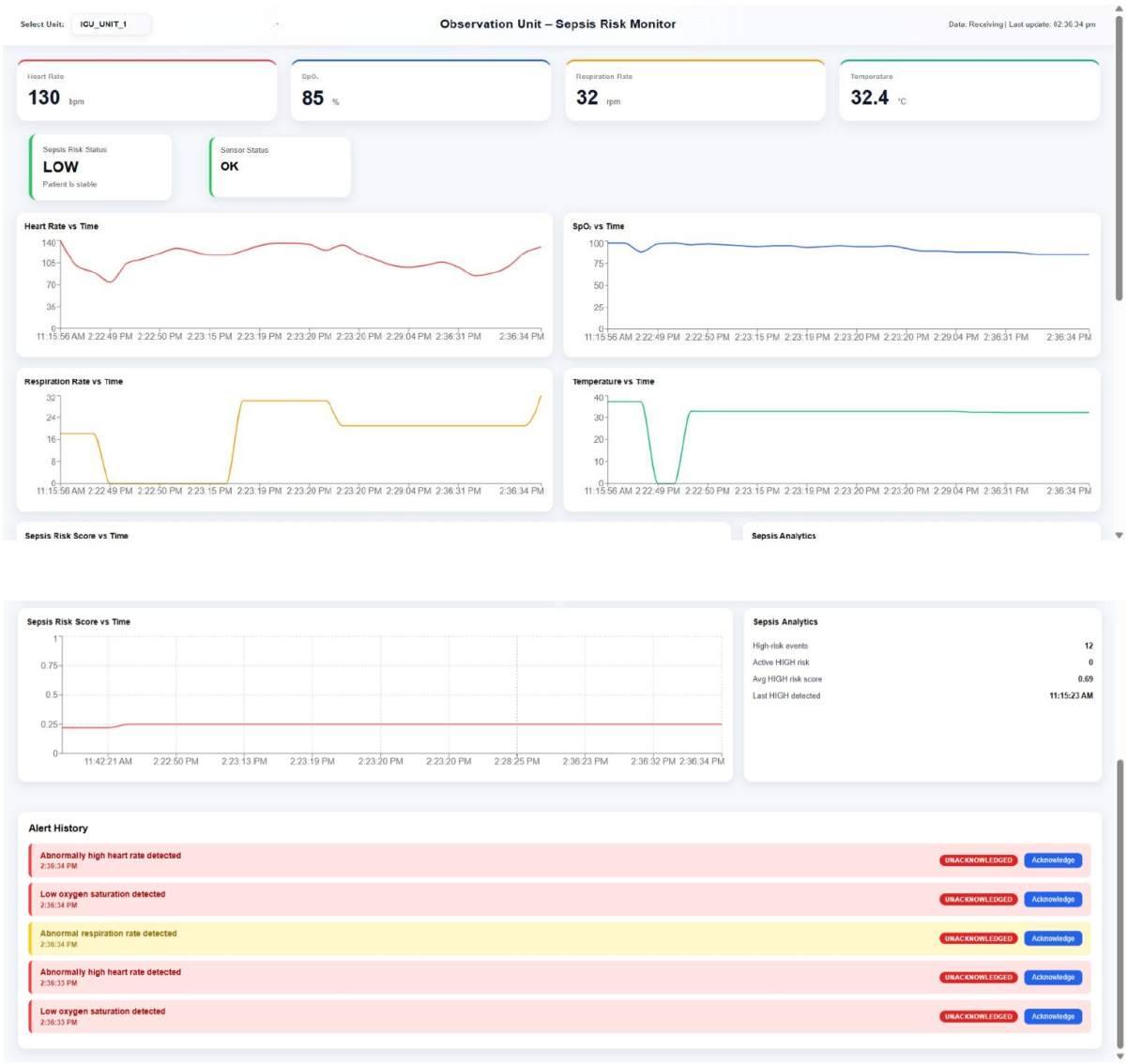


Fig. 5. Web-based dashboard for real-time physiological parameter monitoring.

The web-based dashboard in Fig. 5 is used as a visual interface for viewing the physiological parameters measured by the developed system. The parameters include heart rate, respiration rate, oxygen saturation, and body temperature. The alert history section displays detected abnormalities in the physiological parameters. Alerts marked as "Unacknowledged" indicate that the abnormal condition has been detected but has not yet been reviewed by the clinician, whereas the "Acknowledge" button allows the clinician to confirm that the alert has been noticed and reviewed. Based on the analysis of the web-based dashboard, it is clear that the parameters measured by the system are updated in real time and presented in an understandable manner.

The observations obtained from the collected physiological dataset demonstrate that the developed monitoring system is capable of reliably measuring key vital parameters across different demographic groups. The recorded values of heart rate, respiration rate, oxygen saturation, and body temperature remained within the expected physiological ranges for healthy individuals, indicating the stability and accuracy of the sensing framework. The distribution analysis further shows that minor variations in physiological parameters occur across subject categories, which reflects natural biological differences rather than measurement inconsistencies. These results highlight the capability of the system to capture real-time physiological trends that are essential for monitoring potential health abnormalities. By integrating continuous physiological sensing with Edge AI processing, the developed system enables efficient standalone monitoring without dependence on centralized infrastructure. Such a system can support early identification of abnormal physiological patterns that may indicate the onset of critical conditions such as sepsis.

VIII. CONCLUSION AND FUTURE DIRECTIONS

The current work offers a fully embedded edge-intelligent approach for the early detection of sepsis risk within non-critical care hospital settings. By leveraging real-time physiological sensing with a lightweight anomaly detection approach deployed on the microcontroller hardware itself, this work offers an autonomous early warning system for use within a general ward setting. The emphasis on computational efficiency, system autonomy, and physiological interpretability offers this work as a key engineering contribution to addressing a critical healthcare need. By avoiding the need for infrastructure-intensive prediction-based approaches, this work shows that a key early detection need can be addressed through optimized embedded design. However, the proposed system is limited in the number of physiological parameters used, as well as the physiological baseline of the individual. In addition, the use of non-invasive sensors may lead to inaccurate measurements owing to external factors, as the proposed system is meant for early risk detection, not diagnosis. Future work may involve the aggregation of the results in a multi-patient centralized dashboard, the adaptation of the baselines, the integration with the electronic hospital systems, the miniaturization of the wearable sensors, and the expansion of the physiological parameters. Additionally, large-scale deployment will need to be supported by a series of clinical trials. 9

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