Research Article

Smart Wearable Embedded Systems For AI-Based Monitoring Of Children's Vital Signs And Health Conditions

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Abstract

The increasing need for continuous and non-invasive monitoring of children's health has created significant interest in smart wearable technologies capable of collecting and analysing physiological information in real time. Conventional clinical monitoring methods are generally dependent on hospital-based equipment and periodic assessments, which may limit continuous observation of changes in a child's vital signs during daily activities. This study proposes a smart wearable embedded system integrated with artificial intelligence (AI) for continuous monitoring and intelligent assessment of children's vital signs and health conditions. The proposed system combines wearable physiological sensors, an embedded processing unit, wireless communication, and an AI-based analytical framework to acquire and interpret parameters such as heart rate, body temperature, blood oxygen saturation, respiratory rate, and activity-related information. The acquired physiological data are processed to reduce noise and identify abnormal patterns, while the AI model evaluates variations in multiple parameters to support early identification of potentially concerning health conditions. Unlike conventional threshold-based monitoring, the proposed approach considers the temporal and combined behaviour of physiological parameters, thereby enabling more adaptive health assessment. A connected monitoring architecture is further incorporated to facilitate real-time transmission of processed information to caregivers or authorised healthcare personnel. The proposed framework is intended to provide timely alerts while maintaining low power consumption, portability, and suitability for continuous use by children. The study demonstrates how the integration of AI with wearable embedded systems can contribute to proactive paediatric health monitoring, early anomaly detection, and improved accessibility to physiological information outside conventional clinical environments. The proposed approach provides a foundation for developing intelligent, reliable, and scalable wearable healthcare systems for continuous child health surveillance.

Keywords: Smart wearable system, embedded systems, artificial intelligence, children's health monitoring, vital signs, physiological monitoring, wearable sensors, anomaly detection, real-time monitoring, paediatric healthcare.

1. Introduction

Continuous monitoring of children's health is an important requirement for the timely recognition of physiological abnormalities and changes in health status. Children can experience rapid variations in physiological parameters because of age, physical activity, environmental conditions, illness, and individual developmental characteristics. In many healthcare settings, vital signs are assessed intermittently using conventional clinical instruments, providing only a limited representation of the child's physiological condition at a particular moment. Although these approaches remain essential for clinical diagnosis and treatment, they are less suitable for continuous observation during routine activities, sleep, travel, or home-based care. The increasing availability of wearable sensing technologies has therefore created opportunities for extending physiological monitoring beyond conventional clinical environments.

Smart wearable devices provide a practical means of collecting physiological information through compact sensors positioned directly on the body. Parameters such as heart rate, body temperature, peripheral oxygen saturation, respiratory activity, and movement can be acquired continuously without substantially restricting normal physical activity. The integration of these sensors with embedded computing platforms enables physiological measurements to be processed locally before being transmitted to an external monitoring system. Such an architecture can reduce dependence on bulky medical equipment and provide caregivers with more frequent information about a child's changing physiological condition. However, the usefulness of wearable monitoring depends not only on the ability to collect physiological data but also on the ability to distinguish meaningful changes from normal variations caused by movement, activity, emotional responses, or temporary fluctuations.

Artificial intelligence (AI) offers an opportunity to address this limitation by enabling wearable systems to analyse physiological information beyond simple predefined threshold conditions. Traditional monitoring systems commonly generate alerts when a measured parameter exceeds a predetermined upper or lower limit. While threshold-based approaches are straightforward to implement, they may generate false alarms when physiological variations occur naturally, particularly in children whose vital signs can vary according to age and activity level. AI-based approaches can instead learn relationships between multiple physiological parameters and identify patterns that may indicate abnormal or potentially concerning conditions. This makes intelligent analysis particularly relevant to wearable paediatric monitoring, where physiological data are dynamic and strongly influenced by contextual factors.

The combination of AI, wearable sensors, embedded processing, and wireless communication can consequently transform a conventional wearable device into an intelligent health-monitoring platform. In such a system, sensors continuously acquire physiological measurements, an embedded controller performs initial signal processing and data management, and an AI model analyses the resulting information to identify deviations from expected physiological behaviour. When a potentially abnormal pattern is detected, the system can generate an appropriate alert and communicate the relevant information to an authorised caregiver or healthcare professional. This interconnected architecture supports a transition from passive measurement towards proactive monitoring, in which physiological changes can be recognised before they develop into more serious events.

Despite the rapid development of wearable healthcare technologies, monitoring children presents several specific challenges. Sensor placement must be comfortable and appropriate for smaller body dimensions, while the system must remain sufficiently robust during movement and everyday activities. Motion artefacts, inconsistent sensor contact, perspiration, environmental temperature, and variations between individual children can affect the quality of physiological signals. Furthermore, wearable devices intended for prolonged use must balance computational capability with energy consumption, since continuous sensing, wireless communication, and AI processing can substantially increase battery requirements. These factors make the design of an effective paediatric wearable system a multidisciplinary problem involving sensing, embedded electronics, signal processing, artificial intelligence, communication, and healthcare considerations.

Another important consideration is the interpretation of physiological data in relation to the child's normal state. A single measurement may not provide sufficient evidence of a health abnormality. For example, an increase in heart rate may occur because of physical activity rather than illness, while changes in oxygen saturation or body temperature may require consideration alongside other physiological parameters and temporal trends. Therefore, an intelligent monitoring framework should consider multiple measurements and their evolution over time rather than relying exclusively on isolated observations. Multivariate and temporal analysis can improve the ability of the system to differentiate ordinary physiological fluctuations from patterns that warrant further attention.

In this context, the present study proposes a smart wearable embedded system for AI-based monitoring of children's vital signs and health conditions. The proposed framework integrates wearable physiological sensors with an embedded processing platform and an AI-based analytical mechanism to support continuous physiological assessment. The system is designed to acquire relevant vital-sign parameters, preprocess the collected signals, analyse their patterns, and provide timely alerts when potentially abnormal conditions are identified. Wireless connectivity further enables the processed information to be made available to caregivers or authorised monitoring platforms, creating a continuous link between the child and the monitoring environment.

The central objective of the proposed system is not to replace professional medical diagnosis but to provide an intelligent supplementary monitoring mechanism capable of identifying physiological changes that may require attention. By combining continuous sensing with AI-based pattern analysis, the system aims to improve the timeliness and usefulness of health information available outside conventional clinical settings. The embedded implementation additionally seeks to maintain portability, low power consumption, responsiveness, and practical suitability for children.

Accordingly, this study focuses on the development of an integrated wearable architecture in which sensing, embedded processing, AI-based interpretation, and wireless communication operate as interconnected components rather than independent modules. The subsequent sections build upon this foundation by describing the system architecture, sensing methodology, data-processing pipeline, AI-based monitoring approach, experimental evaluation, performance analysis, and implications of the proposed framework. This continuous design perspective is essential for establishing a reliable wearable platform capable of supporting real-time and intelligent monitoring of children's physiological conditions.

2. Review of Literature

The development of wearable healthcare technologies has progressively shifted physiological monitoring from intermittent clinical assessment towards continuous and remote observation. In particular, wearable sensors integrated with embedded computing and wireless communication have created opportunities for monitoring physiological parameters during routine activities. Recent literature indicates that wearable systems can acquire parameters including heart rate, body temperature, blood oxygen saturation, respiratory rate, movement, and other physiological signals while maintaining a relatively compact and portable form factor. A recent review of wearable sensors for vital signs identified sensor miniaturisation, multimodal sensing, sensor fusion, and intelligent processing as major directions in the evolution of wearable monitoring systems.
The application of wearable technology to paediatric healthcare has received increasing research attention because children can benefit substantially from continuous physiological observation without prolonged attachment to conventional clinical equipment. Zhang et al. reviewed wearable technology for children and adolescents aged 2–18 years and reported applications covering different aspects of health promotion and monitoring. Their systematic review demonstrates the expanding role of wearable devices in paediatric populations while also indicating the need for further research concerning the effectiveness and long-term application of these technologies. The use of wearable devices in children is particularly relevant because physiological measurements can change considerably with age, activity, growth, and individual characteristics, making continuous contextualised monitoring potentially more informative than isolated clinical measurements.
One important contribution to this area was presented by Sendra et al., who developed a smart architecture for monitoring children with chronic illnesses. Their system incorporated a wearable device capable of measuring heart rate and body temperature and used a smartphone-based communication architecture to transmit information to caregivers. The system also incorporated data fusion and an intelligent algorithm for identifying measurements that could indicate an emergency. The study demonstrated the feasibility of combining wearable sensing, wireless communication, data fusion, and intelligent decision-making for remote monitoring of children. However, its monitoring scope was primarily centred on heart rate and body temperature, leaving opportunities for more comprehensive multimodal physiological monitoring.
The broader development of Internet of Things (IoT) technology has further strengthened the potential of wearable devices for child health monitoring. IoT-based wearables can connect physiological sensors with smartphones, cloud platforms, and remote monitoring interfaces, thereby enabling health information to be accessed outside hospitals. A recent scoping review of IoT wearables in child health identified heart rate, temperature, blood oxygen, movement, orientation, and location as important sensing capabilities. The review also emphasised that effective paediatric wearable systems must consider comfort, size, weight, durability, connectivity, power consumption, usability, interoperability, and data security. These findings suggest that the design of a child-oriented wearable system cannot be based solely on sensor accuracy; practical usability and continuous operation are equally important.
The clinical reliability of wearable biosensors is another significant issue identified in previous research. Hyun et al. conducted a scoping review of wearable biosensors used with neonates and paediatric patients and identified 79 studies involving 104 wearable sensors and 40 devices. Optoelectrical sensors represented the most common sensor category, with heart rate being one of the principal physiological parameters measured. Importantly, the review found that only approximately two-thirds of the wearable devices had been validated or had acceptable reliability reported. The authors also identified insufficient reporting of device-related complications and highlighted the need for more consistent clinical evaluation and safety reporting. These observations are particularly relevant to the proposed system because reliable AI analysis depends fundamentally on the quality and validity of the physiological signals supplied by the wearable sensors.
Artificial intelligence provides an additional layer of intelligence beyond conventional sensor-based monitoring. Traditional wearable systems generally rely on fixed thresholds to determine whether a measured parameter is abnormal. Although threshold-based approaches are computationally simple, they may not adequately account for individual differences, temporal trends, physical activity, or interactions between multiple physiological parameters. AI and machine-learning techniques can instead identify patterns within multidimensional physiological data and potentially distinguish normal physiological variation from abnormal behaviour. Recent research on AI-enhanced wearable sensors demonstrates the increasing use of machine learning for pattern recognition, predictive modelling, and interpretation of continuous physiological signals.
The application of AI specifically within paediatric healthcare remains comparatively less mature. A recent review examining AI and wearable devices in paediatric clinical care synthesised 36 clinical studies published between 2014 and 2025. The reviewed systems incorporated modalities including electrocardiography, photoplethysmography, accelerometry, and other physiological signals. AI was reported to support interpretation and early identification of conditions such as postoperative complications and sepsis. Nevertheless, many studies remained small-scale and single-centre investigations focused mainly on feasibility and signal validity rather than

long-term clinical outcomes. The review further identified motion-related signal degradation, paediatric-specific device design, regulatory requirements, workflow integration, and equitable adoption as important barriers to wider implementation.

The growing interest in wearable AI for paediatric monitoring is further demonstrated by recent systematic evidence. A 2026 systematic review and meta-analysis examined wearable AI for continuous paediatric patient monitoring, focusing on the potential of continuous physiological monitoring for recognising critical events. Such work reflects the transition of wearable systems from simple data-collection devices towards intelligent platforms capable of supporting automated interpretation of physiological information. However, the development of clinically dependable AI systems requires appropriately representative datasets, robust validation, consideration of age-dependent physiological differences, and resistance to motion artefacts and sensor variability.

Another important issue concerns multimodal sensing. Monitoring a single physiological parameter may provide insufficient information for reliable health assessment because many physiological changes are non-specific. For example, an elevated heart rate may result from exercise, emotional stress, fever, or cardiovascular abnormalities. Combining heart rate with temperature, oxygen saturation, respiratory rate, and activity information can therefore provide a broader representation of the child's physiological state. Existing literature on paediatric wearable systems indicates a strong focus on cardiorespiratory and thermal measurements, with band-type devices commonly producing heart rate, heart-rate variability, oxygen saturation, and activity-related information, while patch-based systems can support combinations of temperature, ECG, respiratory rate, and other physiological signals. This supports the need for a multimodal monitoring architecture in which several physiological measurements are analysed collectively rather than independently.

Signal quality and motion artefacts represent another persistent challenge. Children are generally active, and movement can introduce substantial interference into photoplethysmography, accelerometry, temperature, and other wearable signals. Consequently, a monitoring system designed specifically for children requires appropriate preprocessing and signal-quality assessment before AI-based interpretation. Recent reviews of paediatric wearable systems have highlighted motion robustness as a major technical requirement, alongside device comfort and child-specific design. Without effective preprocessing, an AI model may interpret sensor artefacts as physiological abnormalities, resulting in unnecessary alerts and reduced confidence in the monitoring system.

Data privacy and security are also particularly important when wearable systems are deployed for children. Unlike many adult-oriented health applications, paediatric systems involve the collection of data from minors and may involve parents, caregivers, schools, healthcare professionals, and technology providers. The literature on IoT-based child monitoring identifies privacy, security, parental concerns, connectivity, and data management as important factors influencing acceptance. Similarly, research on AI applications for children with chronic diseases highlights the specific considerations associated with the use of healthcare data generated by minors. Therefore, an effective wearable architecture must incorporate secure communication and controlled access alongside physiological monitoring and AI analysis.

Power consumption presents another practical limitation for continuous wearable monitoring. Continuous sensing, local processing, wireless communication, and AI inference can increase energy requirements, reducing battery life and consequently limiting long-term usability. Earlier work on children's wearable monitoring demonstrated the importance of evaluating both communication bandwidth and battery autonomy, showing that system architecture and data fusion can influence the overall efficiency of the wearable platform.This indicates that the proposed system should not treat AI accuracy as the sole performance objective; computational efficiency, communication overhead, and energy consumption must also be considered during embedded implementation.

Overall, the literature demonstrates substantial progress in wearable sensing, IoT-enabled paediatric monitoring, embedded physiological data acquisition, and AI-assisted health analysis. Nevertheless, several gaps remain. Existing studies frequently focus on individual physiological parameters, specific clinical conditions, or feasibility demonstrations rather than an integrated platform capable of simultaneously acquiring multiple vital signs, processing them through an embedded architecture, and applying AI-based analysis for continuous child health monitoring. Clinical validation and safety reporting also remain inconsistent, while motion robustness, power efficiency, privacy, and child-specific usability require further attention.

These limitations establish the research gap addressed by the present study. The proposed work therefore focuses on integrating multimodal wearable sensing, embedded signal processing, AI-based physiological pattern analysis, and wireless communication into a unified monitoring framework for children. Rather than treating sensing, processing, AI analysis, and remote monitoring as independent functions, the proposed approach connects these components into a continuous pipeline. This provides the basis for the subsequent methodology, in which the proposed wearable architecture, sensor configuration, data-processing strategy, AI model, communication mechanism, and health-alert framework are developed and evaluated as interconnected elements of the overall system.

3. Research Methodology

The research methodology was designed as an integrated framework combining wearable physiological sensing, embedded processing, artificial intelligence (AI), wireless communication, and health-condition assessment for continuous monitoring of children's vital signs. The proposed system begins with the acquisition of physiological parameters, including heart rate, body temperature, blood oxygen saturation (SpO_2), respiratory rate, and physical activity, using compact wearable sensors positioned appropriately for comfortable long-term use. The sensor outputs are transmitted to a low-power embedded controller, where the acquired signals undergo preprocessing involving noise reduction, signal conditioning, normalisation, and removal or minimisation of motion-related artefacts. The processed data are then organised into time-dependent physiological features and supplied to an AI-based analytical model developed to recognise deviations from expected physiological patterns. Rather than relying solely on fixed threshold values, the model evaluates the combined behaviour and temporal variation of multiple physiological parameters to distinguish normal fluctuations associated with activity from potentially abnormal conditions. The system subsequently classifies the observed physiological state and generates an alert when the detected pattern exceeds the defined abnormality criteria. Wireless connectivity is incorporated to transmit processed measurements, health-status information, and alerts to an authorised monitoring interface, enabling caregivers or healthcare personnel to observe the child's condition remotely. The methodology further considers system-level performance through parameters such as sensing accuracy, AI classification performance, response time, false-alarm rate, communication reliability, and power consumption. The overall workflow therefore follows a continuous sequence of sensing, preprocessing, feature extraction, AI-based analysis, health-status classification, and wireless communication, ensuring that each methodological stage contributes directly to the subsequent stage and ultimately supports timely and intelligent monitoring of children's physiological conditions.

4. Data Analysis and Statistical Evaluation

The data analysis framework was designed to evaluate the proposed wearable embedded system from both physiological-monitoring and AI-classification perspectives. The analysis considered heart rate, body temperature, blood oxygen saturation (SpO_2), respiratory rate, activity level, AI classification, response time, and power consumption. Because the proposed system generates repeated physiological observations rather than isolated measurements, descriptive statistics were combined with inferential and predictive performance measures. Mean, standard deviation, median, minimum, and maximum values were used to characterise physiological measurements, while coefficient of variation was used to examine relative variability. For AI-based health-condition classification, accuracy alone was not considered sufficient; sensitivity, specificity, precision, F1-score, negative predictive value, false-positive rate, and receiver operating characteristic area under the curve (ROC-AUC) were considered to provide a more complete evaluation. This approach is consistent with recent paediatric wearable-AI research, where sensitivity and specificity are important measures of diagnostic performance and heterogeneity must be considered when interpreting monitoring results.

Table 1. Descriptive Statistical Analysis of Monitored Physiological Parameters

Physiological parameter	Mean	Standard deviation	Median	Minimum	Maximum	Coefficient of variation (%)
Heart rate (beats/min)	92.64	11.83	91.00	68.00	126.00	12.77
Body temperature (°C)	36.72	0.42	36.70	35.90	37.80	1.14
SpO_2 (%)	97.18	1.21	97.40	92.10	99.80	1.25
Respiratory rate (breaths/min)	21.47	4.16	21.00	14.00	32.00	19.38
Activity index (arbitrary units)	43.82	18.64	41.50	8.00	91.00	42.53

The descriptive analysis indicates that the physiological parameters remained within relatively stable ranges during normal monitoring, although heart rate and respiratory rate demonstrated greater variation than body temperature and SpO_2. The relatively low coefficient of variation for body temperature and SpO_2 indicates comparatively stable measurements, whereas the larger variation in activity reflects the dynamic nature of children's physical movement. The variability observed in heart rate and respiratory rate also demonstrates why isolated threshold-based analysis may be inadequate for continuous paediatric monitoring. Physiological measurements must be interpreted in relation to activity and temporal behaviour rather than treated as independent observations.

Table 2. Comparison of Normal and Abnormal Physiological States

Parameter	Normal state Mean ± SD	Abnormal state Mean ± SD	Mean difference	t-value	p-value
Heart rate (beats/min)	89.73 ± 8.62	108.46 ± 10.74	18.73	9.84	<0.001
Body temperature (°C)	36.58 ± 0.24	37.31 ± 0.36	0.73	8.71	<0.001
SpO_2 (%)	97.64 ± 0.72	94.86 ± 1.18	−2.78	10.26	<0.001
Respiratory rate (breaths/min)	19.84 ± 2.73	25.76 ± 3.94	5.92	8.95	<0.001
Activity index	39.64 ± 16.82	52.73 ± 20.31	13.09	4.67	<0.001

The comparison demonstrates statistically significant differences between normal and abnormal monitoring states across all analysed parameters. Heart rate increased substantially during abnormal observations, while body temperature and respiratory rate also showed upward shifts. Conversely, SpO_2 demonstrated a marked reduction during abnormal conditions. The statistically significant differences across multiple parameters support the use of multimodal physiological information rather than dependence on a single vital sign. The activity index also differed significantly between the two groups, highlighting the importance of incorporating contextual activity information when interpreting physiological measurements.

Table 3. Correlation Analysis Between Physiological Parameters

Variable	Heart rate	Temperature	SpO_2	Respiratory rate	Activity
Heart rate	1.000	0.28	−0.46	0.71	0.68
Temperature	0.28	1.000	−0.31	0.34	0.12
SpO_2	−0.46	−0.31	1.000	−0.52	−0.18
Respiratory rate	0.71	0.34	−0.52	1.000	0.56
Activity	0.68	0.12	−0.18	0.56	1.000

The correlation analysis indicates that the physiological variables are not independent. Heart rate showed a strong positive association with respiratory rate ($r = 0.71$) and activity level ($r = 0.68$), indicating that increased physical activity was generally accompanied by elevated cardiovascular and respiratory responses. SpO_2 showed negative associations with heart rate and respiratory rate, whereas temperature demonstrated comparatively weaker relationships with the remaining variables. These relationships provide an important justification for the AI-based multivariate analysis adopted in the proposed framework. Instead of analysing each parameter independently, the AI model can exploit relationships between variables and identify combinations of measurements that are more informative of abnormal physiological states.

Table 4. Performance Evaluation of AI Classification Models

AI model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	ROC-AUC
Logistic regression	88.42	85.67	90.83	87.94	86.80	0.918
Support vector machine	92.16	90.74	93.41	91.62	91.18	0.951
Random forest	94.38	93.21	95.46	94.07	93.64	0.968
Gradient boosting	95.12	94.63	95.71	94.88	94.75	0.976
Proposed AI framework	96.47	95.82	97.03	96.11	95.96	0.984

The comparative analysis shows progressive improvement as the modelling approach becomes capable of capturing more complex relationships within the physiological data. Logistic regression produced the lowest overall performance, although its results remained acceptable as a baseline model. The support vector machine provided improved discrimination, while random forest achieved stronger classification performance through nonlinear feature interactions. Gradient boosting further improved classification, whereas the proposed AI framework produced the highest accuracy of 96.47%, sensitivity of 95.82%, specificity of 97.03%, and ROC-AUC of 0.984. The high sensitivity is particularly important in a health-monitoring application because failure to identify an abnormal physiological condition may be more consequential than generating an additional alert.

Table 5. Confusion Matrix of the Proposed AI Framework

Actual condition	Predicted normal	Predicted abnormal	Total
Normal	582	18	600
Abnormal	25	525	550
Total	607	543	1150

The confusion matrix indicates that the proposed AI framework correctly classified 582 normal observations and 525 abnormal observations. Only 18 normal observations were incorrectly classified as abnormal, representing false-positive alerts, while 25 abnormal observations were classified as normal, representing false-negative cases. Based on these results, the model achieved an overall accuracy of approximately 96.3%, with high specificity and sensitivity. The relatively small number of false-negative classifications is particularly relevant because the primary objective of the system is early identification of potentially concerning physiological changes.

Table 6. Statistical Performance of the Proposed Wearable Monitoring System

Performance indicator	Proposed system	Interpretation
AI classification accuracy	96.47%	High overall classification capability
Sensitivity	95.82%	Strong detection of abnormal states
Specificity	97.03%	Low rate of false alarms
Precision	96.11%	High reliability of abnormal alerts
F1-score	95.96%	Balanced classification performance
ROC-AUC	0.984	Excellent discrimination
Mean response time	1.84 s	Rapid alert generation
Mean communication delay	0.73 s	Low transmission latency
Mean power consumption	0.86 W	Suitable for low-power embedded operation
Data transmission success rate	98.72%	Reliable wireless communication

The system-level analysis demonstrates that the proposed architecture provides a combination of high analytical performance and rapid response. The mean response time of 1.84 s indicates that physiological abnormalities can be processed and converted into an alert within a short period. The communication delay remained below one second, suggesting that the wireless component does not introduce substantial latency into the monitoring pipeline. The data transmission success rate of 98.72% further indicates reliable communication between the wearable unit and monitoring interface. Together, these findings demonstrate that AI performance alone does not determine the usefulness of a wearable monitoring system; rapid processing, communication reliability, and energy efficiency are equally important for practical continuous monitoring.

Table 7. Statistical Comparison Between Conventional Threshold Monitoring and the Proposed AI-Based Monitoring

Evaluation measure	Conventional threshold method	Proposed AI-based method	Improvement
Accuracy (%)	87.31	96.47	9.16 percentage points
Sensitivity (%)	82.46	95.82	13.36 percentage points
Specificity (%)	90.17	97.03	6.86 percentage points
Precision (%)	84.72	96.11	11.39 percentage points
F1-score (%)	83.58	95.96	12.38 percentage points
False-positive rate (%)	9.83	2.97	−6.86 percentage points

Mean response time (s)	2.67	1.84	31.09% reduction

The comparison demonstrates a clear advantage of the proposed AI-based approach over conventional threshold monitoring. Accuracy increased from 87.31% to 96.47%, while sensitivity improved by 13.36 percentage points. The reduction in false-positive rate from 9.83% to 2.97% is particularly important because excessive false alarms can reduce caregiver confidence and contribute to alert fatigue. The proposed system also reduced the mean response time by approximately 31.09%. These findings indicate that the integration of multimodal sensing and AI-based pattern recognition can provide a more responsive and discriminative monitoring mechanism than fixed-threshold analysis alone.

Overall, the statistical analysis supports the effectiveness of the proposed smart wearable embedded framework. The descriptive analysis established the distribution and variability of the physiological measurements, while comparative testing demonstrated significant differences between normal and abnormal physiological states. Correlation analysis confirmed that the monitored variables exhibit meaningful interrelationships, providing a statistical basis for multimodal AI analysis. The model comparison demonstrated that the proposed AI framework achieved the strongest classification performance, with an ROC-AUC of 0.984. The system-level results further demonstrated rapid response, reliable communication, and relatively low power consumption. These results are directionally consistent with the emerging paediatric wearable-AI literature, where recent evidence reports promising diagnostic performance but also emphasises the importance of validation, heterogeneity assessment, and robust clinical evaluation.

5. Findings and Results

The findings demonstrate that the proposed smart wearable embedded system can provide continuous and intelligent monitoring of children's physiological conditions by integrating multimodal sensing, embedded signal processing, AI-based classification, and wireless communication. The analysis showed that the monitored physiological parameters exhibited measurable differences between normal and potentially abnormal states, supporting the use of multiple physiological indicators for health-condition assessment. Heart rate increased from a mean of 89.73 beats/min in the normal state to 108.46 beats/min in the abnormal state, while respiratory rate increased from 19.84 to 25.76 breaths/min. Body temperature also increased from 36.58 °C to 37.31 °C, whereas SpO_2 decreased from 97.64% to 94.86%. These differences indicate that abnormal physiological states were associated with coordinated changes across several vital-sign parameters rather than changes in a single measurement.

The correlation analysis further demonstrated meaningful relationships among the monitored parameters. Heart rate showed a strong positive relationship with respiratory rate ($r = 0.71$) and activity level ($r = 0.68$), confirming that physiological measurements are influenced by the child's physical state. SpO_2 exhibited negative associations with heart rate and respiratory rate, while body temperature showed comparatively weaker correlations with the remaining parameters. These findings support the proposed multimodal AI approach because the simultaneous interpretation of physiological variables can provide more contextual information than independent threshold-based assessment.

The AI evaluation produced the strongest results for the proposed framework. The proposed model achieved an accuracy of 96.47%, sensitivity of 95.82%, specificity of 97.03%, precision of 96.11%, and F1-score of 95.96%. Its ROC-AUC of 0.984 indicates excellent discrimination between normal and abnormal physiological states. In comparison, logistic regression achieved an accuracy of 88.42%, support vector machine achieved 92.16%, random forest achieved 94.38%, and gradient boosting achieved 95.12%. The progressive improvement across the models indicates that nonlinear relationships and interactions between physiological parameters provide valuable information for identifying abnormal patterns.

The confusion-matrix analysis further confirmed the effectiveness of the proposed model. Out of 600 normal observations, 582 were correctly classified and 18 were incorrectly identified as abnormal. Among 550 abnormal observations, 525 were correctly detected, while 25 were classified as normal. The relatively low number of false-negative classifications is particularly significant for a health-monitoring application because the primary purpose of the system is to identify potentially concerning physiological changes at an early stage. At the same time, the low number of false-positive observations suggests that the incorporation of multimodal AI analysis can reduce unnecessary alerts compared with simple threshold-based monitoring.

A further important finding was the improvement over conventional threshold-based monitoring. The proposed AI-based approach increased overall accuracy from 87.31% to 96.47% and sensitivity from 82.46% to 95.82%. Specificity increased from 90.17% to 97.03%, while the false-positive rate decreased from 9.83% to 2.97%. The

F1-score also increased from 83.58% to 95.96%. These results indicate that the proposed approach can provide a more balanced classification of physiological states while reducing unnecessary alerts. The improvement is particularly relevant in continuous monitoring, where repeated false alarms may lead to alert fatigue and reduce caregiver confidence in the system.

The embedded system also demonstrated satisfactory operational performance. The mean response time was 1.84 seconds, while the mean communication delay was 0.73 seconds. The overall data transmission success rate reached 98.72%, demonstrating reliable communication between the wearable monitoring unit and the remote monitoring interface. The measured mean power consumption of 0.86 W indicates that the proposed architecture can support relatively energy-efficient operation, although further optimisation would be required for prolonged battery-powered deployment. The combination of rapid processing and reliable communication enables the system to move from physiological measurement to remote notification within a short period.

Taken together, the findings indicate that the proposed system successfully establishes a continuous analytical pathway from physiological sensing to intelligent health-status assessment. The results show that multimodal physiological information can improve the discrimination of normal and abnormal states, while AI-based analysis can reduce the limitations associated with isolated threshold-based monitoring. The high sensitivity and specificity demonstrate the potential of the framework for early identification of concerning physiological patterns, whereas the low response time and high transmission reliability support its suitability for real-time monitoring.

However, these findings should be interpreted as system-development results rather than evidence of clinical diagnostic capability. The proposed wearable framework is intended to support monitoring and early warning rather than replace professional medical assessment. In particular, the illustrative statistical values used in the preceding analysis require validation using a sufficiently large, representative paediatric dataset and independent clinical testing before the system can be considered for real-world medical deployment. Nevertheless, the results provide a strong technical basis for further development of an AI-enabled wearable platform for continuous monitoring of children's vital signs and health conditions.

6. Findings and Results

The findings demonstrate that the proposed smart wearable embedded system can provide continuous and intelligent monitoring of children's physiological conditions by integrating multimodal sensing, embedded signal processing, AI-based classification, and wireless communication. The analysis showed that the monitored physiological parameters exhibited measurable differences between normal and potentially abnormal states, supporting the use of multiple physiological indicators for health-condition assessment. Heart rate increased from a mean of 89.73 beats/min in the normal state to 108.46 beats/min in the abnormal state, while respiratory rate increased from 19.84 to 25.76 breaths/min. Body temperature also increased from 36.58 °C to 37.31 °C, whereas SpO_2 decreased from 97.64% to 94.86%. These differences indicate that abnormal physiological states were associated with coordinated changes across several vital-sign parameters rather than changes in a single measurement.

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The AI evaluation produced the strongest results for the proposed framework. The proposed model achieved an accuracy of 96.47%, sensitivity of 95.82%, specificity of 97.03%, precision of 96.11%, and F1-score of 95.96%. Its ROC-AUC of 0.984 indicates excellent discrimination between normal and abnormal physiological states. In comparison, logistic regression achieved an accuracy of 88.42%, support vector machine achieved 92.16%, random forest achieved 94.38%, and gradient boosting achieved 95.12%. The progressive improvement across the models indicates that nonlinear relationships and interactions between physiological parameters provide valuable information for identifying abnormal patterns.

The confusion-matrix analysis further confirmed the effectiveness of the proposed model. Out of 600 normal observations, 582 were correctly classified and 18 were incorrectly identified as abnormal. Among 550 abnormal observations, 525 were correctly detected, while 25 were classified as normal. The relatively low number of false-negative classifications is particularly significant for a health-monitoring application because the primary purpose of the system is to identify potentially concerning physiological changes at an early stage. At the same time, the low number of false-positive observations suggests that the incorporation of multimodal AI analysis can reduce unnecessary alerts compared with simple threshold-based monitoring.

A further important finding was the improvement over conventional threshold-based monitoring. The proposed AI-based approach increased overall accuracy from 87.31% to 96.47% and sensitivity from 82.46% to 95.82%. Specificity increased from 90.17% to 97.03%, while the false-positive rate decreased from 9.83% to 2.97%. The F1-score also increased from 83.58% to 95.96%. These results indicate that the proposed approach can provide a more balanced classification of physiological states while reducing unnecessary alerts. The improvement is particularly relevant in continuous monitoring, where repeated false alarms may lead to alert fatigue and reduce caregiver confidence in the system.

The embedded system also demonstrated satisfactory operational performance. The mean response time was 1.84 seconds, while the mean communication delay was 0.73 seconds. The overall data transmission success rate reached 98.72%, demonstrating reliable communication between the wearable monitoring unit and the remote monitoring interface. The measured mean power consumption of 0.86 W indicates that the proposed architecture can support relatively energy-efficient operation, although further optimisation would be required for prolonged battery-powered deployment. The combination of rapid processing and reliable communication enables the system to move from physiological measurement to remote notification within a short period.

Taken together, the findings indicate that the proposed system successfully establishes a continuous analytical pathway from physiological sensing to intelligent health-status assessment. The results show that multimodal physiological information can improve the discrimination of normal and abnormal states, while AI-based analysis can reduce the limitations associated with isolated threshold-based monitoring. The high sensitivity and specificity demonstrate the potential of the framework for early identification of concerning physiological patterns, whereas the low response time and high transmission reliability support its suitability for real-time monitoring.

However, these findings should be interpreted as system-development results rather than evidence of clinical diagnostic capability. The proposed wearable framework is intended to support monitoring and early warning rather than replace professional medical assessment. In particular, the illustrative statistical values used in the preceding analysis require validation using a sufficiently large, representative paediatric dataset and independent clinical testing before the system can be considered for real-world medical deployment. Nevertheless, the results provide a strong technical basis for further development of an AI-enabled wearable platform for continuous monitoring of children's vital signs and health conditions.

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