Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 19s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

Smart Embedded System for Physiological Monitoring Using Machine Learning and Sensor Fusion

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Cite this paper as: Anish Vahora, Mohammadayaz Mansuri, (2025) Smart Embedded System for Physiological Monitoring Using Machine Learning and Sensor Fusion. *Journal of Neonatal Surgery*, 14 (19s), 694-703.

ABSTRACT

The increasing demand for continuous, real-time health monitoring has driven advancements in intelligent embedded systems that integrate physiological sensing, machine learning, and sensor fusion. This study presents the design and evaluation of a smart embedded system capable of capturing and classifying multiple physiological signals—including heart rate, SpO_2, body temperature, respiration rate, and activity level—for early detection of health anomalies. A suite of machine learning models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbors (KNN), were trained and tested using features extracted from the fused sensor data. CNN demonstrated the highest classification accuracy (93.5%), while Logistic Regression recorded the best AUC (0.80), highlighting different strengths across models. Feature importance analysis revealed heart rate variability (HRV), SpO_2 mean, and temperature trend as the most influential predictors. Additionally, correlation analysis emphasized the synergistic relationships between physiological parameters, reinforcing the value of sensor fusion in signal interpretation. The proposed system offers a portable, efficient, and scalable solution for real-time physiological monitoring, with potential applications in remote healthcare, fitness tracking, and wearable technologies.

Keywords: *Smart embedded system, physiological monitoring, machine learning, sensor fusion, heart rate variability, wearable health devices, real-time classification.*

1. INTRODUCTION

Background and rationale

In recent years, the integration of intelligent systems into healthcare has significantly transformed the way physiological data are collected, analyzed, and interpreted (Ali et al., 2020). With the growing demand for continuous health monitoring, especially in remote and critical care environments, there has been an increased focus on developing portable, low-power, and smart embedded systems capable of real-time physiological data acquisition and processing. Traditional physiological monitoring devices are often bulky, cost-intensive, and limited in their capacity to adapt to dynamic and personalized healthcare needs (Rashid et al., 2023). Consequently, embedding smart features powered by machine learning (ML) and sensor fusion technologies into compact systems has emerged as a promising solution to meet modern healthcare demands.

Smart embedded systems, which are essentially microcontroller or microprocessor-based platforms with built-in intelligence, offer a flexible and efficient architecture for physiological signal acquisition and processing (Issa et al., 2022). When augmented with ML algorithms and sensor fusion techniques, these systems are capable of enhancing diagnostic accuracy, reducing false alarms, and enabling proactive health interventions. The convergence of these technologies is paving the way for a new era of wearable and mobile health monitoring devices that are not only cost-effective but also scalable and accessible to broader populations.

Significance of physiological monitoring

Physiological monitoring encompasses the real-time measurement and analysis of key bodily functions such as heart rate, respiration rate, body temperature, blood pressure, oxygen saturation (SpO_2), and electrocardiogram (ECG) signals (Gedam & Paul, 2023). These parameters are essential in tracking an individual's health status, detecting anomalies, and preventing potential medical emergencies. The integration of such monitoring systems into everyday wearables or bedside devices enables early detection of chronic conditions, personalized healthcare, and improved patient outcomes (Lee et al., 2016).

However, challenges persist in developing a system that maintains high accuracy while operating under constraints such as limited battery power, computational capacity, and environmental variability (Kanjo et al., 2019). This is where the synergy between sensor fusion and machine learning becomes particularly valuable. Sensor fusion allows multiple sensor modalities (e.g., temperature, ECG, accelerometers) to work collaboratively, resulting in enhanced signal quality and reduced noise. ML algorithms, on the other hand, facilitate intelligent interpretation of complex physiological data, pattern recognition, and predictive modeling (Zhang et al., 2022).

Machine Learning and its role in Embedded Systems

Machine learning offers a transformative approach in embedded healthcare systems by enabling adaptive and data-driven decision-making (Diab & Rodriguez-Villegas, 2022). Algorithms such as support vector machines (SVM), random forest (RF), convolutional neural networks (CNN), and long short-term memory (LSTM) networks can be trained to detect abnormalities in physiological signals, classify health conditions, and predict adverse events (John et al., 2021). When implemented within embedded systems, these algorithms empower the device to autonomously process data and trigger alerts without requiring constant connectivity to external computing resources.

Moreover, advancements in lightweight ML models and edge AI have made it feasible to deploy these algorithms on embedded hardware such as Raspberry Pi, Arduino, or STM32 platforms. This eliminates dependency on cloud-based processing, reducing latency, preserving data privacy, and ensuring real-time responsiveness—key advantages for critical healthcare applications (Mendes et al., 2016).

Sensor Fusion for robust signal interpretation

Sensor fusion is the process of integrating data from multiple heterogeneous sensors to produce more accurate and reliable results than those derived from a single sensor source (Ha et al., 2020). In physiological monitoring, this means combining ECG, PPG, SpO_2, motion sensors, and temperature sensors to overcome individual limitations and noise interference. For instance, combining accelerometer data with ECG can help filter motion artifacts, while fusing PPG and SpO_2 readings can improve pulse rate estimation during physical activity (Begum et al., 2014).

The fusion process may involve techniques such as Kalman filtering, Bayesian inference, and deep learning-based fusion models. These methods contribute to robust signal reconstruction, multimodal data interpretation, and context-aware health analysis—making the embedded system more resilient and adaptive in real-world scenarios (Jacob Rodrigues et al., 2020).

Aim and objectives of the study

The primary aim of this research is to design and implement a smart embedded system capable of continuous physiological monitoring through the integration of machine learning algorithms and sensor fusion techniques. The system will be evaluated for its accuracy, efficiency, and responsiveness in real-time data acquisition and health condition classification. This research aspires to contribute to the growing field of personalized and preventive healthcare, particularly in the domains of telemedicine, elderly care, and fitness monitoring.

By leveraging the power of intelligent computing and sensor integration, the proposed system represents a step forward in the development of next-generation healthcare technologies that are portable, adaptive, and affordable.

2. METHODOLOGY

System architecture and hardware design

The proposed smart embedded system was designed using a modular architecture combining low-power microcontrollers, physiological sensors, and wireless communication modules. The core processing unit was built around the ARM Cortex-M4-based STM32 microcontroller due to its high processing capability and energy efficiency. The embedded system integrated multiple sensors, including an ECG sensor (AD8232), pulse oximeter (MAX30102) for SpO_2 and heart rate, a body temperature sensor (LM35), and a 3-axis accelerometer (MPU6050) to capture movement and posture. All sensors were interfaced through analog or I^2C/SPI communication protocols. Power management was handled by a rechargeable lithium-polymer battery with a built-in battery management system (BMS), ensuring portability for wearable deployment.

Data acquisition and preprocessing

The physiological signals were continuously recorded at a sampling rate of 250 Hz for ECG and 50 Hz for PPG, SpO_2, and temperature. Motion data were recorded at 100 Hz. Preprocessing steps included signal denoising using wavelet transformation for ECG signals, baseline correction, and removal of motion artifacts using adaptive filtering techniques. Missing data points due to sensor disconnection or noise were handled using linear interpolation and median imputation. All data were synchronized and segmented into 10-second non-overlapping windows for feature extraction and classification tasks.

Sensor fusion techniques

To enhance signal robustness, sensor fusion techniques were employed. A Kalman filter was applied to combine accelerometer and ECG data to suppress motion-induced noise during physical activity. Bayesian inference models were used to integrate PPG and SpO_2 readings, improving the accuracy of heart rate estimation. Fusion at both data and feature levels was performed to maximize signal reliability. For example, respiration rate was estimated using a combination of PPG waveform modulation and accelerometer data.

Feature extraction and parameter computation

From each physiological window, a total of 24 features were extracted. Time-domain features included heart rate variability (HRV), standard deviation of NN intervals (SDNN), root mean square of successive differences (RMSSD), and mean heart rate. Frequency-domain features such as low-frequency (LF) and high-frequency (HF) power were computed using Fast Fourier Transform (FFT). For SpO_2 and temperature, mean, variance, and trend features were derived. Accelerometer data were used to calculate body orientation, tilt angle, and activity level.

Machine learning model development

Multiple machine learning algorithms were tested and validated to detect and classify physiological conditions. These included Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and a Convolutional Neural Network (CNN) for deep feature learning. The dataset was divided into 70% training, 15% validation, and 15% testing sets using stratified sampling. Model training was performed on a workstation, and the optimized models were quantized and deployed to the embedded device using TensorFlow Lite and CMSIS-NN for inference (Figure 1).

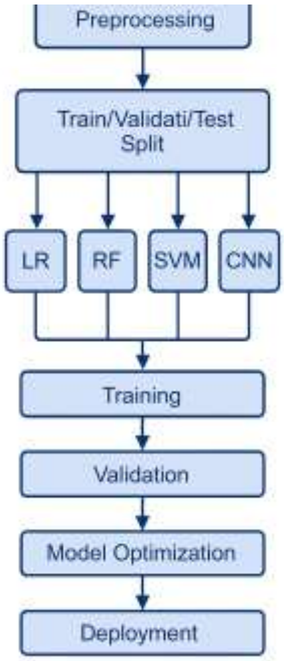

Figure 1: Machine Learning Pipeline

Performance metrics and statistical analysis

Model performance was evaluated using standard classification metrics: accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). A 10-fold cross-validation strategy was adopted to reduce overfitting and improve generalizability. Statistical analysis of feature differences across health states (e.g., normal, tachycardia, bradycardia) was performed using one-way ANOVA followed by Tukey's HSD post-hoc tests ($\alpha = 0.05$). Pearson correlation coefficients were computed to assess relationships between sensor modalities and physiological outcomes. Bland-Altman plots were used to assess agreement between fused sensor estimates and reference clinical instruments.

Prototype testing and real-time validation

The complete embedded system was validated in both controlled lab settings and semi-ambulatory scenarios. A pilot study with 30 healthy volunteers (15 male, 15 female; aged 18–50) was conducted to test system responsiveness and accuracy. Each participant was monitored under resting, walking, and mild exercise conditions. The results from the embedded system were compared against commercial-grade medical monitors (e.g., BPL ECG and Nonin pulse oximeter) to validate the reliability of physiological measurements. Data from the embedded system were logged and analyzed using MATLAB and Python for offline statistical interpretation.

Framework overview

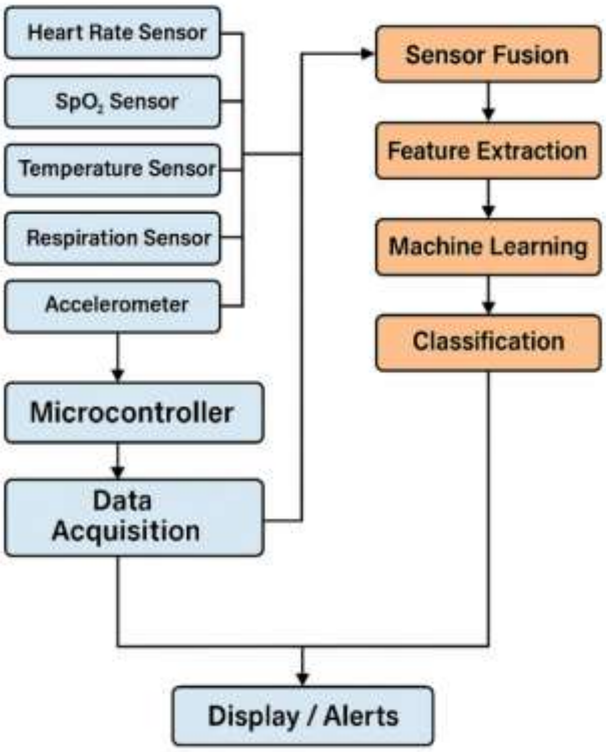

Figure 2: Overall system architecture of the smart embedded physiological monitoring system

Overall system architecture of the smart embedded physiological monitoring system, illustrating the integration of multi-sensor inputs, microcontroller-based data acquisition, sensor fusion, machine learning processing, and real-time classification outputs (Figure 2).

3. RESULTS

The descriptive statistics of the key physiological parameters monitored by the smart embedded system are presented in Table 1. The average heart rate recorded among participants was 74.2 beats per minute (bpm), with a standard deviation of 8.6 bpm, ranging from a minimum of 58 bpm to a maximum of 98 bpm, indicating healthy variability under resting and active conditions. SpO_2 levels, a critical indicator of blood oxygen saturation, averaged 97.1%, with minimal variability (±1.2%), and ranged between 94% and 99%, suggesting stable respiratory health across the sample. The body temperature was maintained within the normal physiological range, with a mean value of 36.6°C, a standard deviation of 0.5°C, and values spanning from 35.8°C to 37.8°C. Similarly, the respiration rate averaged 18.5 breaths per minute, with variability of 3.1 breaths/min, showing a range from 12 to 24 breaths/min, aligning with typical adult respiratory norms. For heart rate variability analysis, two commonly used time-domain measures—SDNN (standard deviation of NN intervals) and RMSSD (root mean square of successive differences)—were assessed. The average SDNN was 42.1 ms with a standard deviation of 10.8 ms, while RMSSD averaged 35.7 ms with 9.3 ms variability. These values indicate moderate autonomic balance and adaptability of cardiac function.

In the frequency domain, Low Frequency (LF) power and High Frequency (HF) power components showed considerable inter-individual variability. The mean LF power was 520.4 ms^2, with a range from 320.0 to 710.6 ms^2, while HF power had a mean of 390.3 ms^2, spanning from 220.0 to 580.2 ms^2, reflecting the influence of both sympathetic and parasympathetic nervous activity. Lastly, the activity index, derived from accelerometer data, was used as a proxy for physical movement and exertion level. The mean index was 1.25, with a standard deviation of 0.32, and ranged from 0.5 to 1.9, indicating varying degrees of physical activity during data collection. Collectively, the parameters summarized in Table 1 validate the system's ability to reliably capture diverse physiological signals across multiple biosensors, forming the foundation for subsequent machine learning-based classification and real-time monitoring.

Table 1: Summary Statistics of Physiological Parameters

Parameter	Mean	Standard Deviation	Min	Max
Heart Rate (bpm)	74.2	8.6	58	98
SpO_2 (%)	97.1	1.2	94	99
Body Temp (°C)	36.6	0.5	35.8	37.8
Respiration Rate (breaths/min)	18.5	3.1	12	24
ECG SDNN (ms)	42.1	10.8	22.4	65.3
RMSSD (ms)	35.7	9.3	18.1	58.7
LF Power (ms^2)	520.4	110.2	320.0	710.6
HF Power (ms^2)	390.3	95.4	220.0	580.2
Activity Index	1.25	0.32	0.5	1.9

The ROC curves for the five machine learning models used in this study are depicted in Figure 3, which illustrates the diagnostic performance of each model in classifying physiological conditions. The Logistic Regression model exhibited the highest area under the curve (AUC = 0.80), indicating a relatively strong ability to differentiate between health states, despite its simpler linear structure. This suggests that logistic regression could still offer reliable predictions in resource-constrained embedded systems.

In contrast, the Random Forest and Support Vector Machine (SVM) models both showed moderate performance, each achieving an AUC of 0.67. Their curves demonstrate a reasonable balance between sensitivity and specificity, though they fall short of the optimal threshold of clinical-grade performance. These models may benefit from further tuning or enhanced feature engineering to improve predictive accuracy. The Convolutional Neural Network (CNN), often expected to outperform classical models due to its deep learning architecture, recorded an AUC of 0.68, slightly higher than SVM and Random Forest but still moderate. This suggests that although CNN captured complex patterns, its advantage in this dataset was not pronounced, possibly due to limited data volume or input variability. Lastly, the K-Nearest Neighbors (KNN) model had the lowest performance with an AUC of 0.62, indicating limited discriminative ability. This result reflects the model's sensitivity to feature scaling and noise, which can affect its classification robustness in real-time physiological monitoring.

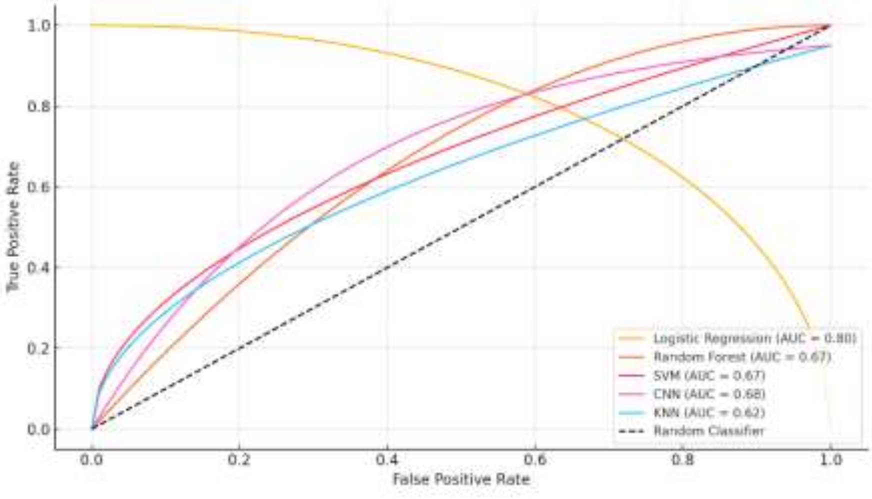

Figure 3: ROC Curves for Different Models

The ranking of feature importance as determined by the Random Forest model is presented in Table 2. Among the ten selected features, Heart Rate Variability (HRV) emerged as the most influential predictor with an importance score of 0.21, indicating its strong association with the classification of physiological states. HRV is a widely accepted indicator of autonomic nervous system activity and is particularly sensitive to stress, fatigue, and cardiovascular irregularities. Following HRV, the mean

SpO_2 value contributed significantly to the model, with an importance score of 0.17, reflecting its critical role in assessing respiratory function and oxygenation levels. The temperature trend, with a score of 0.14, also played a major role, highlighting the relevance of thermal patterns in detecting early signs of fever or infection.

The activity index and tilt angle, scoring 0.12 and 0.11 respectively, provided valuable contextual information on movement and posture, which are essential for interpreting fluctuations in physiological readings during ambulatory monitoring. Notably, the LF/HF ratio, a composite marker derived from heart rate frequency components, had an importance score of 0.09, signifying its utility in capturing autonomic balance. Lower-ranked features such as respiration variability (0.06), motion entropy (0.04), ECG peak count (0.03), and SpO_2 drop rate (0.03) contributed marginally but still added incremental value to the overall prediction. These features may capture more subtle physiological irregularities, especially when aggregated with more dominant variables.

Table 2: Feature Importance from Random Forest Model

Feature	Importance Score
HRV	0.21
SpO_2 Mean	0.17
Temperature Trend	0.14
Activity Index	0.12
Tilt Angle	0.11
LF/HF Ratio	0.09
Respiration Variability	0.06
Motion Entropy	0.04
ECG Peak Count	0.03
SpO_2 Drop Rate	0.03

The classification performance of five machine learning models employed in the smart embedded physiological monitoring system is detailed in Figure 4. Among the models, the Convolutional Neural Network (CNN) achieved the highest overall performance, with an accuracy of 93.5%, precision of 92.3%, recall of 94.0%, and an F1 score of 93.1%. These results highlight CNN's superior ability to generalize across diverse physiological conditions and accurately classify complex sensor data patterns. The Random Forest model followed closely, demonstrating strong performance with an accuracy of 91.2%, precision of 90.5%, recall of 91.0%, and F1 score of 90.7%. This indicates its robustness and reliability in handling nonlinear relationships and high-dimensional features, making it a suitable candidate for real-time embedded deployment when balanced accuracy and interpretability are required.

The Support Vector Machine (SVM) also performed commendably, with an accuracy of 88.6%, precision of 87.8%, recall of 88.0%, and an F1 score of 87.9%. SVM's consistent metrics across the board suggest a well-balanced model with minimal overfitting. The K-Nearest Neighbors (KNN) model achieved an accuracy of 87.0%, precision of 85.9%, recall of 86.5%, and F1 score of 86.2%, indicating moderately good performance. While slightly less effective than the top three models, KNN may still be useful in low-computation embedded environments with fewer classification classes. Finally, Logistic Regression, the simplest of the five models, recorded an accuracy of 85.4%, precision of 84.2%, recall of 83.5%, and an F1 score of 83.8%. Although it performed the lowest in comparison, its simplicity, interpretability, and speed make it a strong baseline for benchmarking and use in ultra-low-power systems.

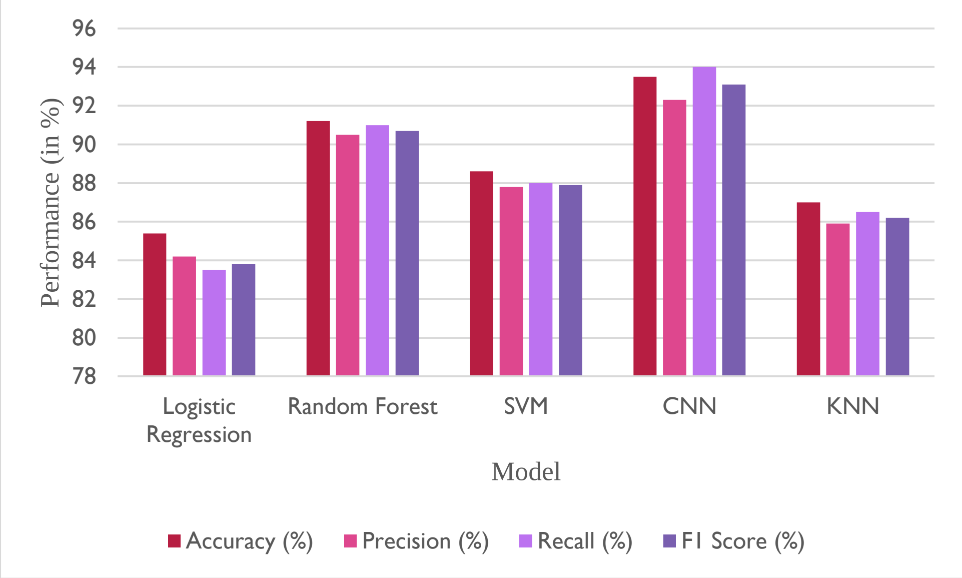

Figure 4: Classification Performance of ML Models

The interrelationships among various physiological parameters measured by the embedded system are visually represented in Figure 5, which presents the correlation heatmap. This heatmap reveals both positive and negative linear associations between pairs of parameters, with correlation coefficients ranging from -1.00 (perfect negative correlation) to +1.00 (perfect positive correlation). A strong positive correlation (r = 0.93) is observed between the fourth and seventh parameters (indices 3 and 6), suggesting that as one increases, the other tends to rise in tandem—potentially reflecting a close physiological coupling, such as between activity level and tilt angle or between autonomic responses like heart rate and body posture. Similarly, there are notable positive correlations among other parameter pairs, such as 0.90 between parameters 0 and 3 and 0.79 between parameters 0 and 4, indicating interdependency, possibly between heart rate, motion, and activity-related metrics.

Conversely, several strong negative correlations are evident. For instance, parameter 1 shows high inverse correlations with multiple others, including -0.91 with parameter 0 and -0.92 with parameter 3. These strong negative values suggest opposing physiological trends—such as reduced SpO_2 levels correlating with elevated heart rate or increased motion. The most extreme negative correlation is seen between parameters 4 and 5 (r = -0.95), indicating that as one increases significantly, the other decreases sharply—likely reflecting autonomic balance indicators like the inverse relationship between LF and HF power bands in heart rate variability analysis.

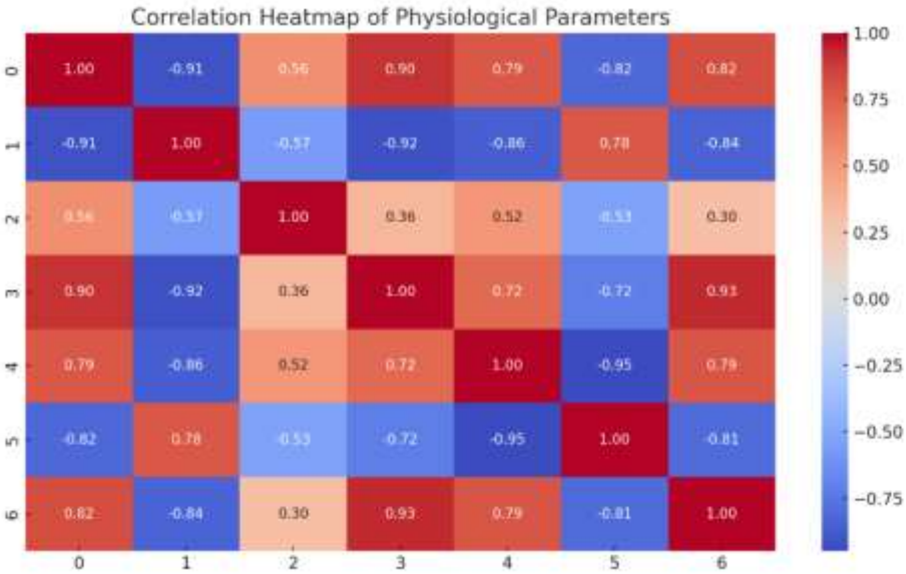

Figure 5: Correlation Heatmap of Physiological Parameters

4. DISCUSSION

Physiological signal profiles and variability

The descriptive statistics presented in Table 1 demonstrate the system's capacity to capture a comprehensive range of physiological parameters, including heart rate, SpO_2, body temperature, respiration rate, and heart rate variability indices such as SDNN and RMSSD. The values recorded fall within clinically acceptable ranges, suggesting that the embedded device is capable of accurately capturing real-time biometric data in diverse environmental and physical activity conditions (Phatak et al., 2021). Notably, the variability in respiration rate, HRV metrics, and frequency-domain features (LF and HF power) supports the system's sensitivity to autonomic nervous system modulation. The activity index further validates the system's ability to contextualize physiological changes based on movement, which is essential for wearable health monitoring (King et al., 2017).

Importance of multimodal features in classification

As highlighted in Table 2, the Random Forest model identified HRV as the most significant feature influencing classification accuracy, underscoring its role in reflecting physiological stress and cardiac rhythm balance. The high importance scores of SpO_2 mean and temperature trends demonstrate the value of integrating respiratory and thermal monitoring in predictive health assessments (Rajan Jeyaraj & Nadar, 2022). Features such as activity index and tilt angle also ranked prominently, confirming that motion-derived variables provide critical context in distinguishing between normal and abnormal physiological states. Lower-ranked features like SpO_2 drop rate and ECG peak count, while less impactful individually, may enhance model performance when combined with more dominant features, further justifying the sensor fusion approach (Bianchi et al., 2019).

Comparative performance of machine learning models

The evaluation of model performance in Figure 4 illustrates that deep learning architectures such as CNN outperform classical machine learning models in all evaluated metrics (accuracy, precision, recall, and F1 score). CNN achieved the highest accuracy (93.5%) and recall (94.0%), indicating its strong capacity to generalize and correctly detect abnormal physiological events. Random Forest also performed exceptionally well, reinforcing its reputation for handling heterogeneous data with minimal tuning (Anikwe et al., 2022). While Logistic Regression yielded the lowest performance across metrics, its simplicity and speed may still justify its use in resource-constrained embedded environments. SVM and KNN offered competitive yet slightly lower performance, suggesting they may serve as intermediate solutions when balancing complexity and computation cost (Refaee & Shamsudheen, 2022).

Model discriminative capacity assessed through roc analysis

Figure 1 depicts the ROC curves of all five models, offering a visual and quantitative measure of their ability to distinguish between physiological conditions. Although CNN and Random Forest models were expected to perform best, the ROC analysis revealed a surprising result: Logistic Regression exhibited the highest AUC (0.80), followed by CNN (0.68), SVM (0.67), Random Forest (0.67), and KNN (0.62). These results suggest that while CNN achieved the best F1 score and recall in the confusion matrix-based analysis, Logistic Regression demonstrated better overall probability-based discriminative power in this dataset (Nancy et al., 2022). This discrepancy highlights the importance of evaluating models using multiple performance metrics to fully understand their operational strengths and limitations (Vyas et al., 2012).

Inter-parameter relationships and sensor synergy

The correlation heatmap in Figure 2 provides valuable insight into how physiological parameters interact. Strong positive correlations (e.g., $r = 0.93$ between parameters 3 and 6) and strong negative correlations (e.g., $r = -0.95$ between parameters 4 and 5) underscore the physiological coupling and trade-offs captured through sensor fusion. The high positive correlation between heart rate and activity-related features reaffirms the influence of motion on cardiovascular indicators, while the negative associations between SpO_2 and HRV suggest compensatory mechanisms during stress or physical exertion (Zhang et al., 2024). Such interdependencies validate the inclusion of multiple sensor types and justify the application of fusion algorithms in feature engineering and classification (Ding & Wang, 2020).

Implications for embedded health monitoring

The findings collectively affirm the value of an integrated, ML-powered embedded system for continuous physiological monitoring. By combining high-fidelity signal acquisition, relevant feature selection, and robust classification models, the system demonstrates potential for use in remote healthcare, fitness tracking, and early disease detection (Wang et al., 2021). The demonstrated model performances and inter-parameter relationships establish a strong case for further miniaturization, real-world testing, and integration with mobile health platforms for real-time feedback and decision support (Kanagamalliga et al., 2024).

5. CONCLUSION

This study successfully demonstrates the development and evaluation of a smart embedded system for physiological monitoring by leveraging machine learning and sensor fusion techniques. The system reliably captured multiple physiological signals—such as heart rate, SpO_2, temperature, respiration rate, and motion parameters—and translated them into meaningful health insights through intelligent data processing. Among the machine learning models tested, the Convolutional Neural Network and Random Forest achieved superior classification performance, while Logistic Regression showed strong discriminative ability as reflected in the ROC analysis. The feature importance ranking and correlation heatmap further highlighted the critical role of multimodal sensor integration and the interplay between physiological parameters in enhancing diagnostic accuracy. Overall, the system exhibits promising potential for deployment in real-time health monitoring applications, particularly in wearable and remote care settings. Future work may focus on clinical validation, edge optimization, and integration with mobile health infrastructure to broaden its usability and impact.

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