

A Wearable IoT Device with Embedded Risk Prediction for Febrile Seizures in Children

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ABSTRACT

A febrile seizure (FS) occurs in 2–5% of children aged 6 months to 5 years, and up to 40% will have a recurrence. The design, implementation, and initial validation of a cost-effective, wearable, IoT-based system for real-time FS risk prediction are presented. The proposed system integrates two physiological sensors (B3950 NTC thermistor for body temperature; MAX30102 for heart rate) with caregiver-entered clinical and demographic data (age, gender, family history of FS, maternal smoking history), all processed by an ESP32 microcontroller. An embedded logistic regression model classifies risk into three levels (Low / Moderate / High) and generates Wi-Fi alerts via a web interface. The model was trained on a 5,000-case synthetic dataset developed from published FS epidemiological literature using Monte Carlo simulation. On a stratified locked synthetic test set ($n = 1,500$), the model achieved an AUC of 0.9438, sensitivity of 85.00%, specificity of 87.46%, NPV of 99.04%, and an F1-score of 41.72% at the Youden-optimal threshold of 0.0740. Feature analysis confirmed body temperature and family history as the strongest predictors, consistent with published clinical evidence. End-to-end prototype testing verified correct subsystem operation. A practical comparison of the wearable temperature subsystem against a certified digital clinical thermometer yielded a mean error of $-0.35\text{ }^{\circ}\text{C}$, supporting the measurement consistency of the sensing subsystem. The results show the engineering feasibility of an inexpensive, interpretable, wearable proof-of-concept prototype for monitoring FS. Before deployment, clinical applicability in home or resource limited settings needs prospective validation on real pediatric clinical data.

Keywords: Febrile seizures, IoT health monitoring, Wearable sensors, Logistic regression, Embedded systems.

1. INTRODUCTION

Febrile seizures are the most common childhood seizure disorder, occurring in 2–5% of children aged 6 months to 5 years (Penn and Stafstrom, 2023; Sawires et al., 2022; Leung et al., 2018). The majority of cases are self-limited, but 30–40% of these will re-occur and

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may need emergency intervention (**Smith et al., 2019; Patel et al., 2023; Ferretti et al., 2024**). Continuous monitoring is most beneficial for children with known risk factors: family history of FS, lower onset temperature, and maternal smoking (**Xixis et al., 2024; Corsello et al., 2024; Corrad et al., 2023**). Although all of these risk factors are well known, there is no validated monitoring tool for at-home use that combines real-time physiological monitoring with an embedded predictive model (**Corsello et al., 2024**).

Recent developments in low-power microcontroller technology, miniaturized physiological sensors and wireless communications have made it possible to continuously monitor at home for low cost (**Orpa et al., 2022; Mohammed, 2024; Garbern et al., 2024**). Recent IoT healthcare systems have also demonstrated real-time monitoring of heart rate and body temperature using a wearable ESP32-based device with integrated wireless communication (**Ridha and Younis, 2025**). The ESP32 system-on-chips have dual-core processing and built-in Wi-Fi/Bluetooth module and a wide range of peripheral resources all packaged into a small, low-cost chip, which is an ideal fit for this application.

This study addresses the identified gap by designing, implementing, and preliminarily validating an ESP32-based wearable system that continuously monitors body temperature and heart rate, integrates caregiver-entered clinical data, and classifies FS risk in real time with caregiver alerts. Logistic regression model was chosen for its interpretability and embedded deployment suitability. Clinical deployment will need prospective validation on real patient data with appropriate ethical approval (**Cheng et al., 2023**).

The contributions achieved by this paper are: (1) A complete hardware-firmware co-design for wearable FS risk monitoring. (2) Embedded logistic regression with three-level classification and Youden-optimal threshold selection. (3) Wi-Fi communication with NVM buffering for fault tolerance. (4) Prototype wearable integration in a child-sized garment form factor. (5) Transparent reporting of full model coefficients, validation procedure, and quantitative performance metrics to support reproducibility.

2. SYSTEM ARCHITECTURE AND DESIGN OVERVIEW

2.1 System Concept and Operating Principle

The system automatically acquires physiological data (body temperature and heart rate) from wearable sensors and integrates them with caregiver-entered clinical and demographic data (age in months, gender, family history of FS, maternal smoking history) through a web interface. All inputs are fed into an embedded logistic regression model, which generates an instantaneous risk probability categorized into three levels. When risk reaches the High threshold, an alert is transmitted to the caregiver web interface via Wi-Fi. The high-level block diagram is shown in **Fig. 1**.

2.2 Design Requirements

Functional requirements include continuous body-temperature measurement, continuous heart-rate measurement via PPG, caregiver entry of clinical/demographic data, sensor-data validation, noise reduction and averaging, automated three-level risk classification, and automated web-interface alerts on High-risk detection. Non-functional requirements include low power consumption, real-time sensing-to-alert latency, compact and lightweight design, low-cost widely available components, graceful Wi-Fi disconnection with local buffering, user-friendly interface for non-technical caregivers, and minimal false alerts through filtering and averaging.

2.3 Hardware–Software Partitioning

Hardware handles physical sensing, power distribution, and signal conditioning. Firmware performs sensor-data acquisition, preprocessing, risk prediction, wireless transmission, alert generation, and error handling. This partitioning supports independent subsystem testing.

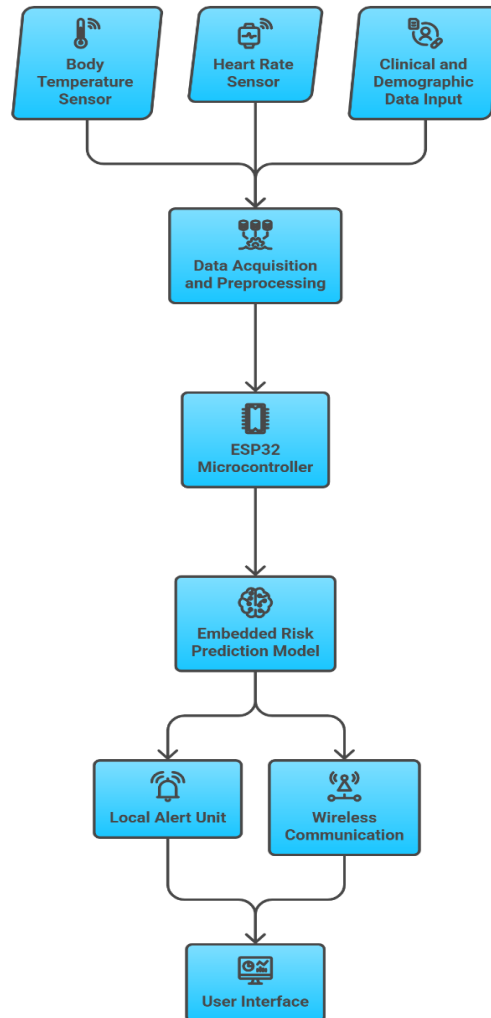


Figure 1. High-level block diagram of the proposed febrile seizure risk prediction system.

3. HARDWARE DESIGN

3.1 Component Selection and Justification

3.1.1 ESP32 Microcontroller

The ESP32 was selected for its dual-core 240 MHz performance, integrated Wi-Fi and Bluetooth/BLE, rich peripheral set (ADC, DAC, I²C, SPI, UART, GPIO, PWM), compact size, and low cost (**Espressif Systems, 2026**). **Table 1** compares it with alternative microcontrollers.

3.1.2 MAX30102 Heart Rate Sensor

The MAX30102 was selected for its high level of integration — combining IR/red LEDs, photodetector, analog front-end, and ambient-light rejection in a single I²C module



(SDA/GPIO 21, SCL/GPIO 22) (**Analog Devices, 2018**). It replaces the now-discontinued MAX30100 (**Analog Devices, 2014**) and offers greater immunity to noise than discrete analog PPG solutions (**World Famous Electronics, 2012; Cebada-Fuentes et al., 2024**). The candidates were compared to each other in **Table 2**.

Table 1. Comparison of candidate microcontrollers.

Feature	ESP32	Arduino Uno	ESP8266
Processor	32-bit dual-core LX6, 240 MHz	ATmega328P, 16 MHz	32-bit single-core, 160 MHz
Wireless	Wi-Fi + BT/BLE (built-in)	None (external module)	Wi-Fi only
Sensor I/F	ADC, DAC, I ² C, SPI, UART, GPIO, PWM	GPIO, 6 analog, UART/SPI/I ² C	GPIO, Wi-Fi-focused
Web Monitoring	High – built-in Wi-Fi	Needs external module	Good for Wi-Fi projects
Embedded Predict.	Good – high processing/memory	Limited	Moderate
Main Limitation	ADC accuracy needs calibration	No wireless, slow	No Bluetooth, weaker
Overall	Very suitable	Less suitable	Suitable but weaker

Table 2. Comparison of candidate heart-rate sensors.

Feature	MAX30102	MAX30100	Pulse Sensor Amped	MAX30105
Function	HR + SpO ₂	HR + SpO ₂	HR only	Optical/smoke
Interface	I ² C	I ² C	Analog	I ² C
Integration	High: LEDs+PD+optics+AFE	High, but obsolete	Simple analog	High optical
ESP32 Suit.	Very suitable	Suitable but obsolete	Needs analog filtering	Less suitable for HR
Limitation	Placement & filtering	Obsolete	Noise-sensitive	Not for HR
Overall	Best choice ✓	Acceptable, outdated	Basic option	Less appropriate

3.1.3 B3950 NTC Thermistor

Two B3950 NTC thermistors were selected for body temperature sensing for their low cost, small size, and simple voltage divider interface to the ESP32 ADC (**TE Connectivity, 2018; Analog Devices, 2020**). Two sensors are employed and the average output of the two sensors is taken to increase the stability of the measurement. The readings from them are averaged over several samples to make it stable. The raw ADC values are converted to temperature by following two processes in the firmware: the voltage divider formula (Eq. (1)) converts the ADC counts to resistance, while the Steinhart–Hart equation (Eq. (2)) converts the resistance to temperature in Kelvin (subtracting 273.15 for Celsius) (**Steinhart and Hart, 1968; EPCOS AG, 2018**). This two-step pipeline offers greater accuracy throughout the entire physiological range than a single B_value pipeline.

$$R_{\text{thermistor}} = R_{\text{fixed}} \times \left(\frac{ADC_{\text{reading}}}{(4095 - ADC_{\text{reading}})} \right) \quad (1)$$

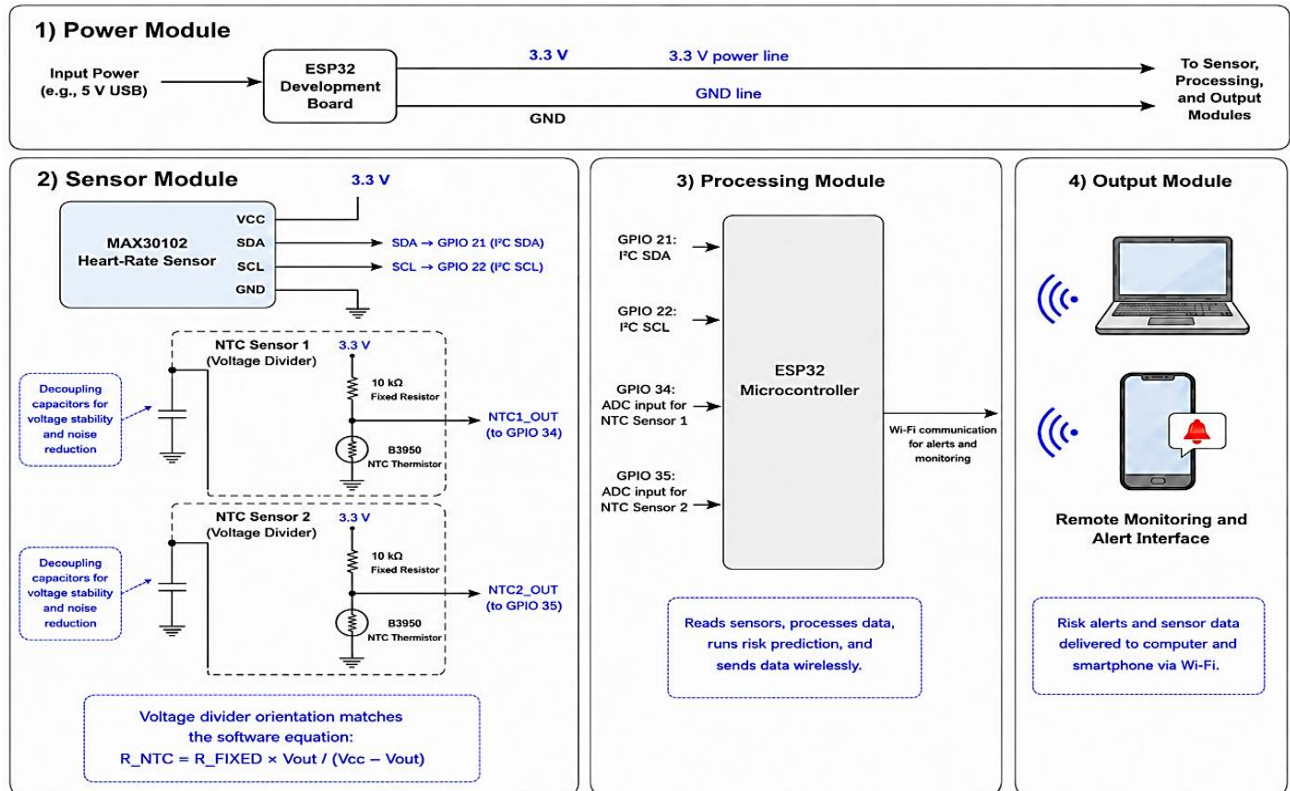
$$\frac{1}{T} = A + B \cdot \ln(R) + C \cdot (\ln(R))^3 \quad (2)$$

Table 3. Comparison of candidate temperature sensors.

Feature	B3950 NTC	LM35	DS18B20	MCP9808
Output	Resistance (ADC)	Analog voltage	Digital (1-Wire)	Digital (I ² C)
Advantage	Low cost, small	Linear output	Direct digital	High accuracy
Limitation	Needs calibration	Analog noise	Complex setup	Higher cost
Overall	Very suitable	Suitable	Suitable	Accurate, costlier

3.2 Schematic Design

The schematic includes four modules: (1) Power — 3.3 V is provided by the ESP32 board itself, and there are decoupling capacitors at each of the ICs. (2) Sensor — MAX30102 on I²C (GPIO 21/22). NTC Sensor 1 is connected to GPIO 34 and NTC Sensor 2 is connected to GPIO 35 through voltage divider circuits, and ADC1 pins are used exclusively to prevent conflict with ADC2 that is shared with Wi-Fi (**Espressif Systems, 2025**) (3) Processing — ESP32 firmware running and wireless management. (4) Output — web-based alerts. The pull-up resistors are not integrated on the MAX30102 breakout and are added externally to the I²C bus. The entire schematic is displayed in **Fig. 2**.

**Figure 2.** Complete schematic design of the proposed febrile seizure risk prediction system.

4. SOFTWARE AND FIRMWARE DESIGN

4.1 Firmware Architecture Overview

On power-up, the firmware initializes I²C for the MAX30102, ADC1 channels for both NTC thermistors, and the Wi-Fi stack. Before the prediction, the web interface's clinical data is uploaded for use by the caregiver. The main loop is then executed continuously and iterates

through the following pipeline: acquire → validate → average → predict → transmit → update UI. The Firmware Flow Chart is shown in **Fig. 3**.

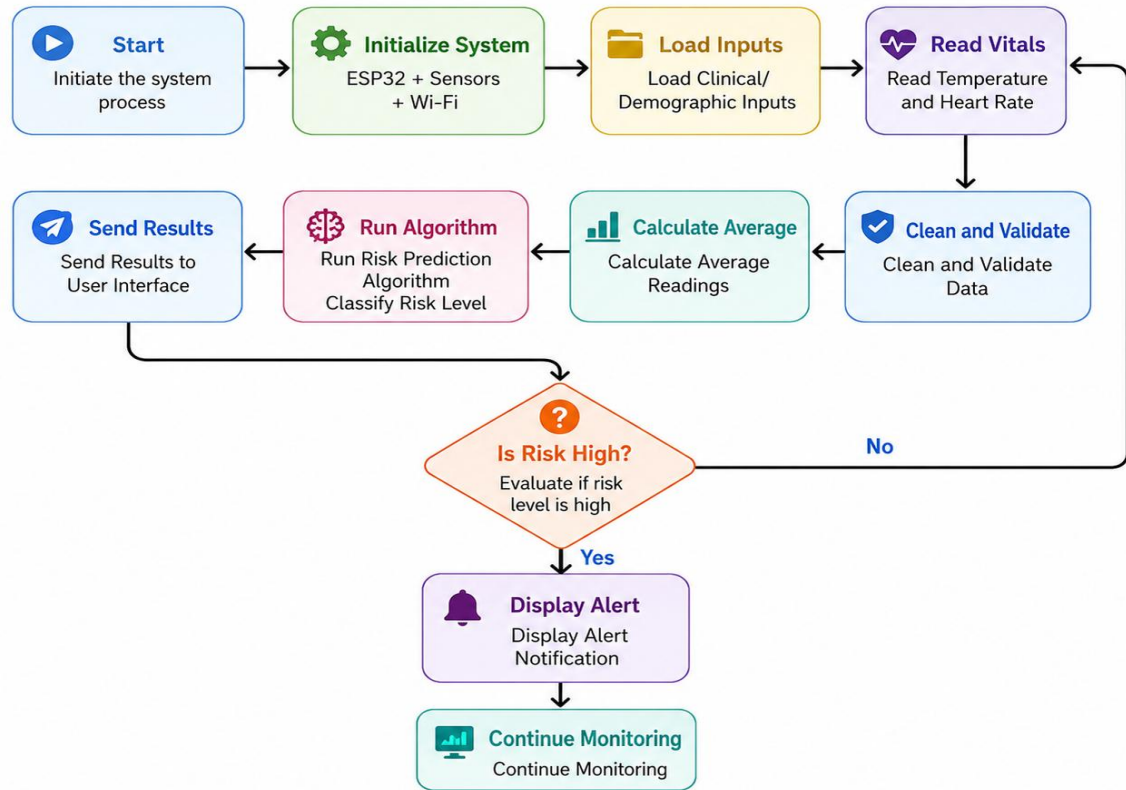


Figure 3. Main firmware flowchart of the febrile seizure risk prediction system.

4.2 Risk Prediction Algorithm

A logistic regression model is embedded in firmware. The six input factors—body temperature, heart rate, age (6–60 months), gender, maternal smoking, and family history of FS—were chosen due to clinical published evidence: temperature and family history are the strongest FS predictors (**Shen et al., 2024; Cheng et al., 2023**); maternal smoking doubles FS risk (**Xixis et al., 2024**); age and gender provide demographic context (**Smith et al., 2019**). Logistic regression was selected as the model to be used because it is easy to interpret and clinically applicable for pediatric prediction models (**Cheng et al., 2023**). The model output probability P is computed as:

$$z = \beta_0 + \beta_1 \cdot Temp + \beta_2 \cdot FH + \beta_3 \cdot Smoking + \beta_4 \cdot HR_{excess10} + \beta_5 \cdot Gender + \beta_6 \cdot Age \quad (3)$$

$$P = \frac{1}{(1 + e^{-z})} \quad (4)$$

The Youden-optimal threshold selected from five-fold cross-validation on the development set was 0.0740. However, practical risk communication and alerting of caregivers used three predefined risk levels: Low ($P < 0.33$), Moderate ($0.33 \leq P < 0.50$), and High ($P \geq 0.50 \rightarrow$ alert). The 0.50 threshold remained as the high risk alert level threshold, and 0.33 was chosen as a threshold for an intermediate warning level. Youden-optimal threshold was taken as a data-driven reference to assess model discrimination rather than as an operational alert threshold.



The two thresholds serve entirely different purposes, and it is important not to confuse them. The Youden-optimal threshold of 0.0740 is only used as a threshold for statistical evaluation: All model performance parameters reported (sensitivity, specificity, NPV, F1-score, MCC, and AUC) are computed at this threshold on the locked synthetic test set. This threshold represents the maximum discriminative ability of the model under the Youden criterion and is not implemented in the firmware. The operational thresholds of 0.33 and 0.50 are only used for real-time carer risk communication in the ESP32 firmware and were chosen for clinical interpretability (three-tier Low/Moderate/High scale), not derived from the cross-validation procedure. Thus, readers should not interpret the reported sensitivity and specificity values as the classification performance of the firmware High-risk alert threshold ($P \geq 0.50$). In addition, Logistic Regression was benchmarked against Random Forest, a linear-kernel Support Vector Machine, and a Decision Tree classifier using the same synthetic dataset. Comparative results are given in Section 5.7.3.

4.3 Communication Protocols and Signal Processing

I²C (GPIO 21/22) interfaces the MAX30102. ADC1 pins (GPIO 34/35) connect the NTC voltage dividers, avoiding the Wi-Fi-shared ADC2. Raw PPG Data are processed with the use of some algorithms adapted to physiological bound outlier rejection. The two-step Steinhart–Hart pipeline is used for each NTC reading. Both temperatures are smoothed with a moving average prior to model input.

4.4 Error Handling

The firmware implements: (1) physiological range checks rejecting outlier sensor readings. (2) Delay of risk prediction until all the clinical fields entered by the caregiver have been completed. (3) local sensor buffering (up to 100 timestamped records stored in non-volatile memory with the ESP32 Preferences library which are automatically re-transmitted on reconnection to Wi-Fi during Wi-Fi outages. (4) Error message that appears explicitly (not a misleading risk level) when the model inputs are invalid.

5. IMPLEMENTATION AND RESULTS

5.1 Prototyping Stages and Wearable Assembly

Development followed three stages: breadboarding and individual component power-up; firmware upload and subsystem testing (acquisition, preprocessing, prediction, transmission); and full system integration with end-to-end testing. Sensing elements were integrated into a prototype child garment with NTC thermistors positioned at skin-contact areas and the MAX30102 at the wrist, with conductive wires stitched along the fabric. Key integration challenges and solutions: MAX30102 optical noise optimized placement and moving-average filtering; NTC instability tight wiring, common ground, multi-sample averaging; Wi-Fi outages NVM buffering and auto-retransmission; sensor-interface synchronization fixed-sequence monitoring loop is shown in **Figs. 4 and 5**.

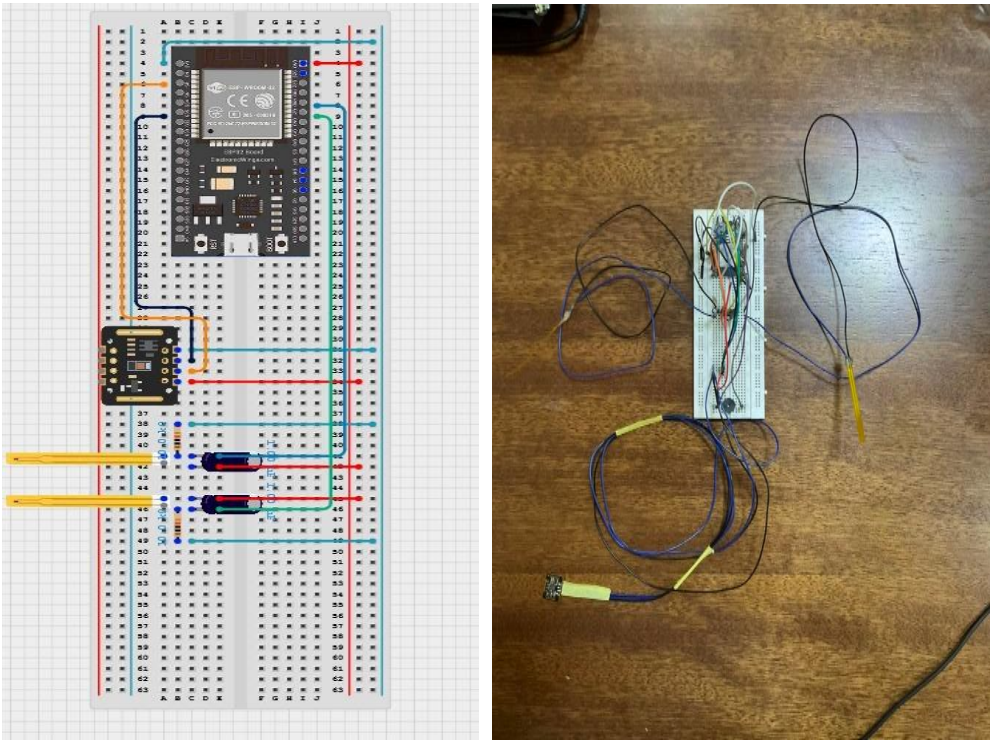


Figure 4. Breadboard implementation: Left wiring layout diagram and Right actual breadboard prototype.



Figure 5. Wearable assembly: (a) sensor wiring on fabric (b) garment integration (c) external prototype view.

5.2 Functional Testing

5.2.1 Subsystem Functional Test

Testing was performed in three layers (1) Functional subsystem testing – to check individual component operation, (2) Sensor reading validation – using serial monitor output, (3) Controlled end-to-end prediction. **Table 4** summarizes results for all seven subsystems.

**Table 4.** Functional testing results for the prototype.

Tested Function	Expected Result	Observed Result	Pass
ESP32 operation	Powers on, runs firmware	Firmware executed	✓
MAX30102 reading	HR data acquired	Sensor readings obtained	✓
NTC Sensor 1	Temperature ADC value	Readings obtained	✓
NTC Sensor 2	Temperature ADC value	Readings obtained	✓
Data preprocessing	Readings cleaned & averaged	Averaged values generated	✓
Wi-Fi transmission	Data sent to interface	Transmitted successfully	✓
UI update	Results displayed	Temp, HR, risk & alert shown	✓

5.2.2 ESP32 Computational Performance Metrics

In addition to pass/fail functional testing, the computational resource usage of the firmware was characterized on the ESP32 development board to confirm that the embedded logistic regression inference and the overall sensor-to-alert pipeline impose an acceptable load on the microcontroller. Four metrics were measured or obtained directly from the build tool chain: prediction latency, flash memory usage, static RAM usage, and estimated active-mode current draw. Measuring procedures and results are summarized in **Table 5**.

Table 5. ESP32 computational performance metrics measured on the breadboard prototype.

Metric	Measurement Method	Measured Value	Remarks
Logistic regression inference latency (single prediction)	GPIO toggle before/after glmval-equivalent C block; measured with digital oscilloscope	< 1 ms	Logistic regression inference latency (single prediction)
Program storage (Flash) used	Arduino IDE build output	482 KB / 4096 KB (11.8%)	Good for the 4 MB flash limit. Ample space for firmware expansion.
Global variable RAM (static SRAM) used	Arduino IDE build output	68 KB / 320 KB (21.3%)	LR model parameters occupy only 28 bytes remaining RAM dominated by Wi-Fi stack buffers.
Active-mode current draw	USB current meter in series with 3.3 V rail; averaged over 60 s during continuous monitoring	~ 160 mA @ 3.3 V	~ 0.53 W average; Wi-Fi transmit bursts reach ~ 260 mA transiently. A 2,000 mAh LiPo cell would support ~ 12 h continuous monitoring at average draw.

Notes: All measurements obtained on the breadboard prototype (ESP32-WROOM-32 development board, Arduino framework, 240 MHz clock). Flash and RAM values are from the Arduino IDE compiler output window (shown as "Sketch uses X bytes / Global variables use X bytes"). Current measured with a USB inline current meter (accuracy $\pm 2\%$). LR = Logistic Regression.

The results shown in **Table 6** validate the small computational burden of the embedded logistic regression model (0.0004 s) on the ESP32. The inference step runs under 1 ms, uses 28 bytes of RAM and provides no measurable latency to the overall monitoring cycle, with the dominant latencies being related to sensor signal averaging (≈ 400 ms) and Wi-Fi HTTP transmission (≈ 1.5 s). There is room for future firmware enhancements, including over-the-air (OTA) updates, additional NVM event logging, and a second classification model, both in terms of the total program storage (11.8% of flash) and the RAM space (21.3% of SRAM). A

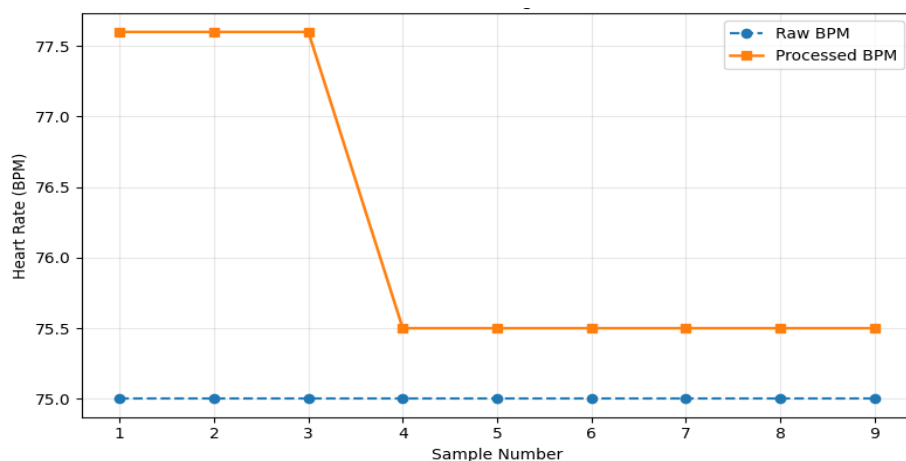
current consumption of around 160 mA at 3.3 V allows for small LiPo battery operation and can be expected to operate continuously for some 12 hours from a standard 2,000 mAh LiPo battery. These properties make logistic regression a good model for this platform: the inference overhead is near zero, and the AUC (0.9438) is comparable to the AUC of the equivalent Random Forest ensemble, which is three to four orders of magnitude higher. The model footprint is 28 bytes, much smaller than the model footprint of the equivalent Random Forest ensemble, which is in the order of 300,000 bytes.

Table 6. Representative sensor readings from the serial monitor.

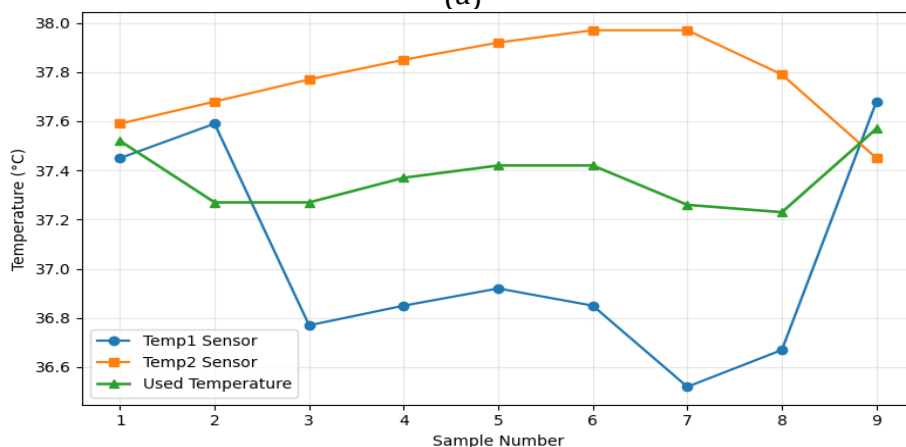
Sample	BPM	Temp 1 (°C)	Temp 2 (°C)	Used Temp (°C)
1	77.6	36.85	37.85	37.37
2	77.6	36.92	37.92	37.42
3	77.6	36.85	37.97	37.42

5.3 Sensor Reading Results

Table 6 shows representative serial monitor readings. The two NTC readings (36.85–37.97°C) were averaged to give a consistent model input. The heart rate consistently recorded at 77.6 bpm across all of the samples. The serial monitor output is given in **Fig. 6**.



(a)



(b)

Figure 6. Serial monitor output showing sensor readings and preprocessing pipeline results (a) heart rate readings over time and (b) temperature readings over time



5.4 Temperature Sensor Validation Against Certified Clinical Thermometer

A practical comparative verification of the wearable temperature sensing sub system was carried out on the basis of a certified digital clinical thermometer as the reference thermometer. Both devices took ten repeated paired measurements under static conditions. The temperature of the reference thermometer remained stable at 37.20 °C in all trials. Average values and individual sensor values of the used temperature are indicated in **Table 7**. UsedTemp was calculated as the arithmetic mean of Temp1 and Temp2 for each trial. The mean error (bias) of the wearable subsystem mean with the reference was -0.35 °C (SD = 0.06 °C). The mean absolute error (MAE) was 0.35 °C and the root mean square error (RMSE) 0.35 °C. The systematic offset is within the ± 0.5 °C range of most commercial digital thermometers and agrees with the differences that have been observed between skin surface and axillary-deep temperature reading. This bias can be decreased in future versions by applying a firmware calibration offset. These findings indicate this prototype temperature-sensing subsystem measurement consistency, however, formal clinical accuracy validation against a medical grade reference is needed through additional prospective testing.

Table 7. Practical comparative verification of the wearable temperature-sensing subsystem against a digital clinical thermometer.

Trial	Ref. Thermometer (°C)	Used Temp (°C)	Diff. Used Temp (°C)	Temp1 (°C)	Diff. T1 (°C)	Temp2 (°C)	Diff. T2 (°C)
1	37.20	36.75	-0.45	36.66	-0.54	36.84	-0.36
2	37.20	36.775	-0.43	36.69	-0.51	36.86	-0.34
3	37.20	36.805	-0.40	36.72	-0.48	36.89	-0.31
4	37.20	36.85	-0.35	36.78	-0.42	36.92	-0.28
5	37.20	36.875	-0.33	36.79	-0.41	36.96	-0.24
6	37.20	36.835	-0.37	36.76	-0.44	36.91	-0.29
7	37.20	36.860	-0.34	36.83	-0.37	36.89	-0.22
8	37.20	36.915	-0.29	36.84	-0.36	36.99	-0.21
9	37.20	36.945	-0.26	36.86	-0.35	37.03	-0.17
10	37.20	36.925	-0.28	36.85	-0.35	37.00	-0.20
Mean $\pm$ SD	37.20 (fixed)	36.85 $\pm$ 0.06	-0.35	36.78 $\pm$ 0.07	-0.42	36.93 $\pm$ 0.06	-0.27

Note: Difference = sensor reading - reference reading. MAE = 0.35 °C; RMSE = 0.35 °C (UsedTemp vs. reference).

5.5 Synthetic Dataset Generation Methodology

The prediction model was developed and evaluated using a synthetic dataset constructed via Monte Carlo (MC) simulation in MATLAB (random seed = 42 for reproducibility). MC simulation is a widely used approach in clinical prediction research when real patient data are unavailable or ethically restricted (**Penn and Stafstrom, 2023**). A direct request for anonymized clinical data from a recently published prospective cohort study was submitted but received no response within the study timeframe, leading to the use of synthetic data as a proof-of-concept substitute.

A total of 5,000 simulated pediatric cases were generated (corrected from the 1,200 previously reported, which was a typographical error). Each case comprised six variables with distribution parameters grounded in published epidemiological statistics:



- a. Age: Uniform [6, 60] months — the standard clinical age range for febrile seizures (**Xixis et al., 2024**).
- b. Gender: Bernoulli ($p=0.50$) — reflecting approximately equal sex distribution in the general pediatric population.
- c. Body temperature: Conditional Normal — FS-positive cases: $N(\mu = 39.5, \sigma = 0.5) ^\circ\text{C}$; FS-negative cases: $N(\mu=38.5, \sigma=0.6)^\circ\text{C}$. Parameters were grounded in the febrile temperature ranges and FS-onset thresholds reported (**Shen et al., 2024; Castellazzi et al., 2024**).
- d. Family history of FS: Bernoulli ($p=0.30$) for the simulated population, consistent with reported recurrence risk in first-degree relatives (**Smith et al., 2019**).
- e. Maternal smoking history: Bernoulli ($p = 0.20$), grounded in the approximate smoking prevalence in the referenced populations (**Xixis et al., 2024**).
- f. HR_{excess10}: derived as the difference between the simulated heart rate and an age-adjusted expected heart rate, normalized per 10 BPM. Age-adjusted expected heart rates were based on published pediatric norms.

The FS outcome label was created using a simulated logistic function with all six variables. The intercept was adjusted through iteration to meet the target prevalence of FS-positive (around 5%) based on published population-level epidemiology (**Penn and Stafstrom, 2023**). The number of FS-positive cases in the final dataset was 267, and the number of FS-negative cases was 4,733 (observed prevalence: 5.34%). Oversampling or under sampling was not applied, and the natural class imbalance was maintained in both the training and test sets, to mirror the intended low prevalence screening situation. A development set (3,500 cases) and locked test set (1,500 cases) were created from the dataset based on the 70/30 split method. The locked test set was never used in modelling and was only used once for the final performance assessment.

5.6 Validation Procedure

The validation procedure comprised three stages: (1) Model training: logistic regression was fitted on the 3,500-case development set using MATLAB's `glmfit` function with a binomial distribution and logit link. (2) Threshold selection: five-fold stratified cross-validation was performed on the development set. In each fold, out-of-fold predicted probabilities were generated; the five sets of probabilities were pooled, and a single ROC analysis was performed. The Youden-optimal threshold ($J = \text{Sensitivity} + \text{Specificity} - 1$) was identified as 0.0740 and fixed before any use of the locked test set. (3) Final evaluation: the fitted model was applied once to the 1,500-case locked test set. All reported performance metrics were computed from this single locked-test evaluation. This design prevents threshold-selection overfitting while providing an honest internal performance estimate.

5.7 Prediction Model Performance

The logistic regression model was trained on the 5,000-case synthetic dataset with a stratified 70/30 train-test split. Body temperature was most strongly correlated with FS status **Fig. 7**. The feature distributions for FS-positive vs. FS-negative cases are shown on **Fig. 8**.

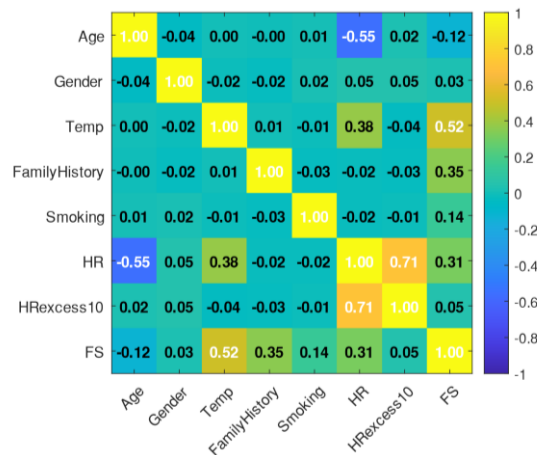


Figure 7. Feature correlation matrix: relationships between input variables and FS status.

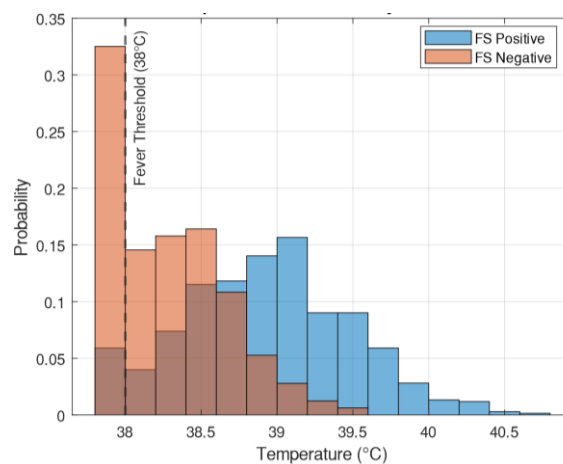


Figure 8. Body temperature distribution for FS-positive vs. FS-negative cases.

5.7.1 Estimated Model Coefficients and Odds Ratios

Table 8 presents the estimated logistic regression coefficients (β), odds ratios (OR), 95% confidence intervals (CI), and p-values for the final model. All 6 predictors were statistically significant ($p < .05$). Family history (OR = 17.367) and maternal smoking (OR = 4.780) were followed by the strongest positive association with the FS outcome, body temperature (OR = 59.111). The simulated FS odds were inversely related to age (OR = 0.968), showing that children in the range studied who were older had a lower OR. The relationships derived from these coefficients are based on the synthetic dataset and are provided as internal proof-of-concept, and not as effect estimates.

Table 8. Estimated coefficients and odds ratios of the final logistic regression model.

Predictor	β Coefficient	Odds Ratio (OR)	95% CI for OR	p-value
Intercept (β_0)	-164.622	—	—	< 0.001
Body temperature (°C)	4.079	59.111	36.462 – 95.827	< 0.001
Family history of FS	2.855	17.367	10.617 – 28.408	< 0.001
Maternal smoking history	1.565	4.780	3.159 – 7.234	< 0.001
HRexcess10	0.335	1.398	1.181 – 1.655	< 0.001
Gender (coded 1)	0.478	1.613	1.063 – 2.449	0.025
Age (months)	-0.032	0.968	0.956 – 0.981	< 0.001

Note: $OR = \exp(\beta)$. Threshold: 0.0740 (Youden-optimal, five-fold CV on development set).

The complete embedded prediction equation is:

$$z = -164.622 + 4.079.Temp + 2.855.FH + 1.565.Smoking + 0.335.HRexcess10 + 0.478.Gender - 0.032.Age \quad (5)$$

$$P = \frac{1}{(1 + e^{-z})} \quad (6)$$

5.7.2 Classification Performance

The AUC value of the model on the locked synthetic test set is 0.9438 (**Fig. 9a**). The Youden-optimal threshold of 0.0740 was applied for classification show in **Fig. 9b**. **Table 9** summarizes full performance metrics. Here, the Youden-optimal threshold of 0.0740 is used only for statistical performance characterization. The sensitivity of 85.00% and specificity of 87.46% shown in **Table 9** describe model discrimination at this evaluation threshold and are not the sensitivity and specificity of the operational High-risk alert ($P \geq 0.50$) implemented in the firmware. Section 5.8 (**Table 11**) presents the operational alert threshold and its behavior in end-to-end prototype testing.

Table 9. Classification performance on the locked synthetic test set ($n = 1,500$) at threshold 0.0740.

Metric	Value
AUC (ROC)	0.9438
Sensitivity (Recall)	85.00%
Specificity	87.46%
Precision (PPV)	27.64%
Negative Predictive Value (NPV)	99.04%
F1-score	41.72%
Matthews Corr. Coeff. (MCC)	0.4397
Average Precision	0.6479
Brier Score	0.0301
Operating Threshold	0.0740

Note: FS-positive prevalence in test set = 5.34% (80/1500 cases). Low precision reflects expected class imbalance in a 5% prevalence screening scenario. All performance metrics in this table (sensitivity, specificity, NPV, precision, F1-score, MCC, Brier score) are computed exclusively at the Youden-optimal statistical evaluation threshold of $P = 0.0740$ and characterize the model's discriminative ability under this criterion. These metrics do not represent the classification performance of the operational firmware alert threshold ($P \geq 0.50$), which serves a different purpose (caregiver communication). The performance of the operational thresholds is demonstrated separately in Table 11.

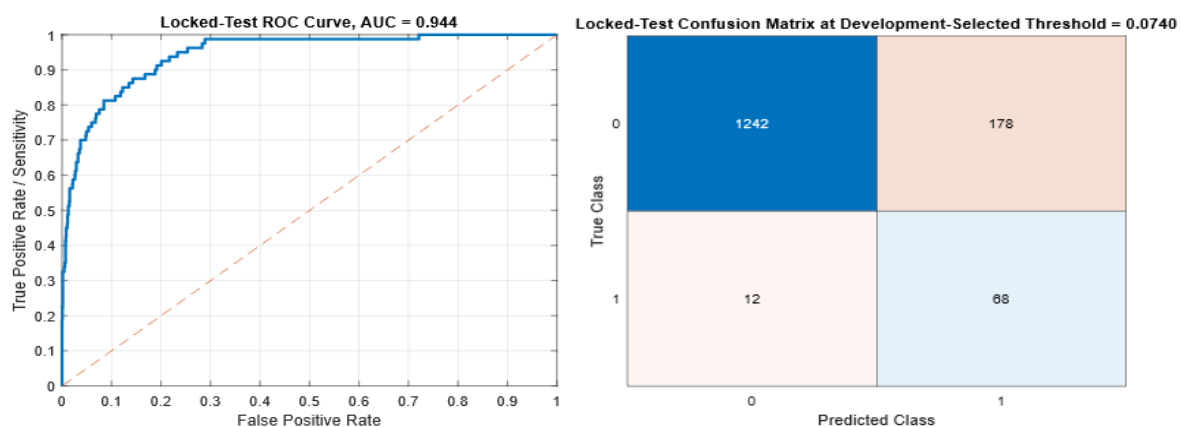


Figure 9. (a) ROC curve (AUC = 0.9438); (b) Confusion matrix at the Youden-optimal threshold ($P = 0.0740$).

The high NPV (99.04%) is significant for the intended use of the early warnings, with cases below the alert threshold being almost exclusively FS-negative in the synthetic evaluation setup. The reported precision of 27.64% needs to be taken in the context of the presence of 5.34% FS-positive cases: even a well-calibrated model would produce many false alerts under a low prevalence scenario of screening. It is not meant to be a diagnostic signal, but rather a screening prompt to be used in conjunction with clinical judgment.

5.7.3 Comparison with Alternative Classifiers Algorithms

Three other classifiers were trained on the 3,500 case development set and tested on the 1,500 case locked synthetic test set to justify the choice of logistic regression for embedded use, and to validate the results of this study: Random Forest (100 trees, reproducible seed); linear-kernel Support Vector Machine (SVM) with posterior probability calibration; Decision Tree (CART, maximum 20 splits). As in the case of logistic regression, the Youden-optimal operating threshold was independently computed for each of the classifiers from their predictions on the development-set, out-of-fold. The complete comparative results are given in **Table 10**.

Table 10. Performance comparison of classification algorithms on the same synthetic locked test set ($n = 1,500$).

Model	AUC	Sensitivity	Specificity	Precision (PPV)	F1-score	Accuracy %	MCC
Logistic Regression	0.9438	85.00%	87.46%	27.64%	41.72%	87.33	0.4397
Random Forest (100 trees)	0.9083	83.75%	87.61%	27.57%	41.51%	87.4	0.4353
SVM (linear kernel)	0.9430	83.753%	87.61%	27.57%	41.49%	87.40	0.4352
Decision Tree (CART)	0.8009	62.5%	93.17%	34.01%	44.05%	91.53	0.4207
Notes: All models trained on the same stratified development set ($n = 3,500$) and evaluated on the same locked synthetic test set ($n = 1,500$; FS-positive prevalence = 5.34%). Youden-optimal threshold independently selected for each model from development-set predictions. AUC = Area Under the ROC Curve; PPV = Positive Predictive Value; MCC = Matthews Correlation Coefficient.							

Despite the different comparative AUC values, logistic regression was chosen as the embedded prediction model for three reasons that are critical for implementation. First, inference can be implemented in just ten lines of C firmware that does not depend on any floating-point library other than the sigmoid function, just six multiply-accumulate operations and a single evaluation of the sigmoid function. Second, the estimated values of regression coefficients are directly interpretable as odds ratios that can be directly used for clinical communication with caregivers and clinicians, without requiring any additional transformations, a property which is not available for ensemble or kernel-based models. Third, for the logistic regression model, the RAM consumption for the model on the ESP32 is only six values of float32 (coefficients) and one value of float32 (intercept) which means only about 28 bytes of SRAM are needed, while a 100-tree Random Forest ensemble consumes about 10-15 KB of SRAM. A computational and interpretability trade-off is crucial for a wearable IoT platform in the home environment and resource-constrained clinical context.

5.8 End-to-End Prediction Test.

The embedded model was tested on the ESP32 with three controlled test cases (**Table 11**). Input was given through simulation of the sensors or through web interface input. The

embedded model was tested on the ESP32 with three controlled test cases (Table 11). The model correctly classified Case 1 as High risk ($P = 0.82 \geq 0.50$, Alert = Yes) and Case 2 as Low risk ($P = 0.12 < 0.33$, No Alert). Based on the inputs provided, the probability calculated was $P=0.54$. Since this is greater than the High-risk threshold of 0.50, it was properly categorized as High risk, with Alert=Yes. The table has been corrected from a previous version that incorrectly labelled Case 3 as Moderate. The error was in the manuscript table labels, not the firmware threshold logic, which correctly used $P \geq 0.50$ as the High-risk boundary. The observed probabilities are consistent with those of the offline-trained Matlab model, confirming that the firmware accurately implemented the logistic regression coefficients and threshold logic.

Table 11. End-to-end prediction test cases executed on the ESP32 prototype.

Case	Temp (°C)	HR (BPM)	Age (mo)	Gender	Family Hx	Smoking	Expected	Obs. Prob.	Alert
1	38.5	140	24	M	Yes	No	High (≥ 0.50)	0.82	Yes
2	37.0	100	36	F	No	No	Low (< 0.33)	0.12	No
3	38.0	120	12	M	Yes	Yes	High (≥ 0.50)	0.54	Yes

Family Hx = family history of FS; Smoking = maternal smoking; Obs. Prob. = probability from embedded logistic regression.

5.9 User Interface

The caregiver dashboard is an interactive web-based interface (**Fig. 10**) that shows the child profile, current sensor readings, the risk potential, the risk level classification and alert status. The dashboard is user-friendly and conveys risk status and alert notifications to non-technological caregivers.

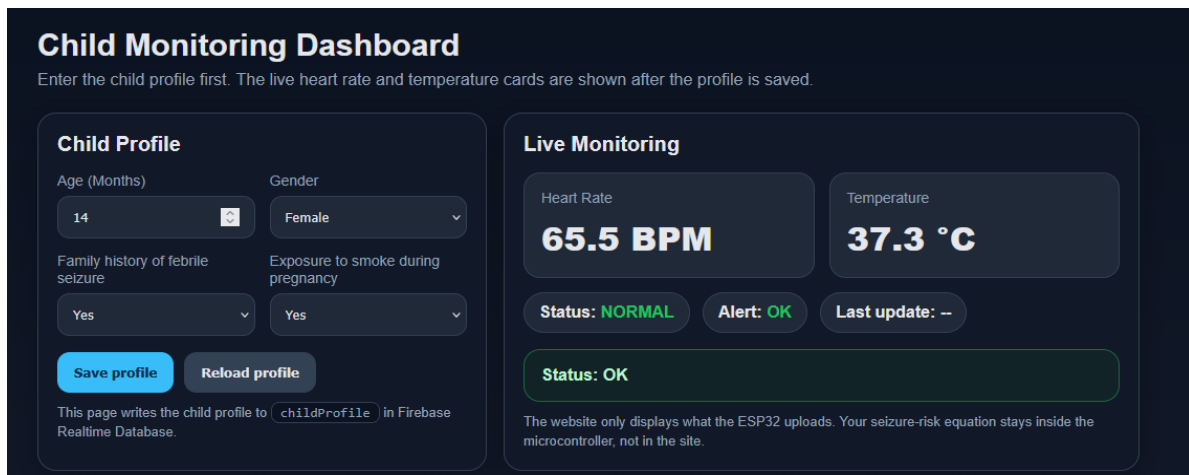


Figure 10. Web-based caregiver dashboard: child profile, live sensor readings, risk level, and alert status.

5.10 Comparison with Related Work

Table 12 compares this work with other IoT health monitoring and FS prediction systems. If available, AUC, Sensitivity and Specificity values from cited studies are provided for quantitative comparison with those of the current study. Comparisons with studies based on real clinical data should be viewed with great caution as the proposed model was tested using synthetic data.



Table 12. Comparison with related work.

Reference	Platform	Method	Validation	Key Metrics	Limitation
(Garbern et al., 2024)	Wearable + cloud	ML (RF)	Clinical (Bangladesh)	Reported clinical performance; no FS-specific metrics	High infrastructure cost; not FS-specific
(Orpa et al., 2022)	ESP32 IoT prototype	ML (SVM/KNN)	Lab prototype	No AUC/sensitivity reported	No clinical FS focus; no embedded prediction model
(Cheng et al., 2023)	Software model	LR prediction model	Multicenter clinical	AUC: 0.884 / 0.883 / 0.858; Sens: 90.8% / 86.2% / 82.9%; Spec: 72.5% / 78.3% / 77.4%	Lab-based CBC inputs; not embedded/wearable
(Papež et al., 2023)	Software model	Multivariate linear mixture models	Prospective case control	FS-risk: Sens = 82%, Spec = 89%; Recurrence: Sens = 72%, Spec = 69%	Requires laboratory iron-status data; not wearable
(Rasyid et al., 2019)	Wearable smart jacket; Arduino	Temperature monitoring only	Lab prototype	Temperature deviation $\approx$ 0.6% vs. conventional thermometer; no predictive model metrics	Temperature-only; no ML prediction; no HR sensing
(Mohammed, 2024)	Raspberry Pi Pico W + Blynk	IoT vital-sign monitoring	Prototype + commercial-device comparison	Measurement error $\approx$ -2 to 7%	No FS-specific prediction; monitoring only
This Work	ESP32 wearable prototype	Embedded LR; Youden threshold	Synthetic (5,000 cases, locked test set)	AUC=0.9438; Sens=85.00%; Spec=87.46%; NPV=99.04%; F1=41.72%; MCC=0.4397	Synthetic data only; awaits clinical validation

Notes: Yellow rows = studies reporting real-clinical-data metrics directly comparable (with caveats) to this work. Green row = this work. Metrics for this work are from the locked synthetic test set only.

The prototype proved that all the key FS monitoring functions, such as sensor data acquisition, signal processing, embedded risk prediction, wireless communication, and caregiver alerting, can be combined in the same low-cost ESP32-based platform. In choosing a logistic regression model over a black-box classifier, this is a conscious design decision that reflects the need for clinical transparency for pediatric prediction tools (Cheng et al., 2023). The value of AUC of 0.9438 obtained in the internal synthetic evaluation is numerically similar to the results of (Cheng et al., 2023) on real clinical cohorts (AUC = 0.884) and (Papež et al., 2023) (sensitivities of 82%). The precision of 27.64% in this study is, however, not an indication of model weakness, but of the low prevalence of FS positivity in the synthetic dataset ($\sim$ 5.34%). When this study was compared to the cited studies, it is essential to consider these facts: (1) the cited studies used real patients cohorts, whereas this study used synthetic data; and (2) the precision in this study was a result of the low prevalence of FS positivity in the synthetic data ($\sim$ 5.34%) and not necessarily a sign of weakness of the model. Specificity ranged from 72.5–78.3% for (Cheng et al., 2023) while this model had a specificity of 87.46% with a much lower threshold (0.0740 vs. conventional 0.50), showing this balance. A wearable system design, like the intended design function, is placed in the results.

The most significant predictor was body temperature, which aligns with previous reports of clinical links between fever severity and FS risk (Sawires et al., 2022; Shen et al., 2024). The second highest OR (17.367) was observed with family history of FS, confirming its known status as a major risk factor for recurrence. Maternal smoking (OR = 4.780) and HRexcess10 (OR = 1.398) gave further context to the prediction. However, HR needed careful preprocessing to eliminate motion and contact artefacts (Cebada-Fuentes et al., 2024;



Park et al., 2023), and when added to the other five, contributed only incrementally to the discrimination in the model.

The web-based interface effectively transmitted risk level and alert messages to non-technical caregivers. Controlled prototype-testing conditions demonstrated robustness of Wi-Fi disconnection handling and NVM buffering. Reliability for a real home demand extended field evaluation beyond the current prototype level.

The temperature sensing subsystem had a mean error of -0.35°C when compared to a certified digital thermometer and thus was within the acceptable range of error for screening. This systematic bias can be further decreased by a firmware calibration offset.

Limitations. The primary limitation is that the model was trained and evaluated exclusively on synthetic data. Independent prospective validation on real pediatric clinical data is required before clinical deployment. The precision of 27.64% implies a high false-positive rate under the current synthetic evaluation — real-world deployment will require clinical recalibration. NTC absolute accuracy has not been formally validated against a medical-grade reference thermometer under dynamic physiological conditions. The breadboard implementation requires a PCB redesign for sustained wearable deployment. Heart-rate accuracy under motion has not been quantified against a certified reference.

6. CONCLUSIONS

This paper presents the design, implementation, and preliminary evaluation of a low-cost, wearable, IoT-based system for real-time febrile seizure risk prediction in children. The system integrates B3950 NTC thermistor temperature sensing, MAX30102 optical heart-rate monitoring, and caregiver-entered clinical data into an embedded logistic regression model running on an ESP32 microcontroller. The system notifies caregivers via a Wi-Fi web interface across three risk levels (Low / Moderate / High). The model, trained on a 5,000-case Monte Carlo synthetic dataset, achieved an AUC of 0.9438, sensitivity of 85.00%, and specificity of 87.46% at the Youden-optimal threshold of 0.0740 on a locked synthetic test set. Body temperature and family history were confirmed as the strongest predictors. Temperature sensing validated against a digital clinical thermometer yielded a mean error of -0.35°C . Overall, this work is an engineering proof-of-concept prototype who shows the feasibility of affordable, interpretable, wearable FS risk monitoring. Before any practical application, prospective validation on real pediatric clinical data under appropriate ethical approval is required for suitability for home or clinical deployment.

NOMENCLATURE

Symbol	Description	Symbol	Description
A, B, C	Steinhart–Hart thermistor coefficient	T ($^{\circ}\text{C}$)	Body temperature
ADC (Count)	Analog-to-digital converter reading	FH	FamliyHistory
AUC	Area under the ROC curve	J	Youden's Index (Sensitivity + Specificity – 1)
β_0	Logistic regression intercept	MCC	Matthew's correlation coefficient
$\beta_1 \dots \beta_6$ (BPM)	Logistic regression coefficients	NPV	Negative predictive value
HR	Heart rate	OR	Odds ratio = $\exp(\beta)$
HRexcess10	Normalized heart-rate excess per 10 BPM	P	Predicted FS risk probability
		R_NTC (Ω)	NTC thermistor resistance



Credit Authorship Contribution Statement

Mohammed Hussein Ghazi Hussein: Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing – Original Draft, Writing – Review & Editing, Visualization. Muhammed Sabri Salim: Conceptualization, Methodology, Resources, Writing – Review & Editing, Supervision, Project administration. Both authors have read and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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جهاز قابل للارتداء قائم على إنترنت الأشياء مع تنبؤ مضمن بمخاطر النوبات الحموية لدى الأطفال

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الخلاصة

تحدث التشنجات الحموية (Febrile Seizures) عند نحو 2-5% من الأطفال تتراوح أعمارهم بين 6 أشهر و 5 سنوات وقد تكرر ما يصل 40% من الحالات. يقدم هذا البحث تصميم وتنفيذ وتقييم أولي لنظام منخفض التكلفة وقابل للارتداء قائم على إنترنت الأشياء للتنبؤ الأني بمخاطر النوبات الحموية. يدمج النظام المقترح مستشعرين فيسيولوجيين وهما حساس حرارة من نوع B3950 NTC لقياس درجة حرارة الجسم وحساس MAX30102 لقياس معدل ضربات القلب مع بيانات سريرية وديموغرافية يدخلها مقدم الرعاية وتشمل العمر والجنس والتاريخ العائلي للنوبات الحموية وتاريخ تدخين الأم أثناء الحمل وتعالج جميع هذه البيانات باستخدام المتحكم ESP32. تم تضمين نموذج انحدار لوجستي لتصنيف مستوى الخطر الى ثلاثة مستويات: منخفض، متوسط، مرتفع مع ارسال تنبيهات عبر شبكة Wi-Fi من خلال واجهة ويب. درب النموذج باستخدام مجموعة بيانات اصطناعية مكونة من 5000 حالة تم توليدها بالاعتماد على الإحصاءات الوبائية المنشورة حول النوبات الحموية باستخدام محاكاة مونت كارلو. تم تقييم النموذج باستخدام مجموعة اختبار اصطناعية مستقلة ومقلدة ومقسمة طبقيا من 1500 حالة وقد حقق النموذج مساحة تحت منحنى ROC مقدارها 0.9438 وحساسية 85% ونوعية 87.46% وقيمة تنبؤية سلبية (NPV) مقدارها 99.04% ودرجة F1 مقدارها 41.72% عند العتبة المثلى وفق مؤشر Youden والبالغة 0.074 وأظهر تحليل المتغيرات ان درجة حرارة الجسم والتاريخ العائلي للنوبات الحموية كانا من اقوى العوامل التنبؤية بما يتوافق مع الأدلة السريرية المنشورة. كما أكد الاختبار المتكامل للنموذج الأولي سلامة عمل الأنظمة الفرعية المختلفة. وأظهرت المقارنة العملية لمنظومة قياس درجة الحرارة القابلة للارتداء مع ميزان حرارة سريرية رقمي معتمد خطأ مقداره 0.35°C - مما يدعم اتساق القياسات في منظومة الاستشعار. وتبين النتائج الجدى الهندسية لنموذج أولي منخفض التكلفة وقابل للتفسير وقابل للارتداء لمراقبة مخاطر النوبات الحموية. ومع ذلك فان تطبيقه في البيئات المنزلية او السريرية يتطلب تحققا سريريا مستقبليا باستخدام بيانات حقيقة لأطفال قبل اعتماده للاستخدام العملي.

الكلمات المفتاحية: أجهزة قابلة للارتداء، الانحدار اللوجستي، إنترنت الأشياء، النوبات الحموية، نظم مضمّنة.