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# A Low-Cost AI-IoT and GSM-Enabled Pediatric Wristband for Continuous Fever Risk Assessment and Emergency Alerting

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**Abstract — This paper presents a low-cost pediatric wearable wristband for continuous fever-risk monitoring using temperature, heart-rate, and motion sensing. The device integrates an ESP32 controller, a DS18B20 temperature sensor, a pulse sensor, an MPU6050 accelerometer, a GSM module, a local buzzer/LED alert, and a Blynk cloud dashboard. Because the wrist skin temperature differs from core body temperature, the temperature channel is calibrated against a clinical digital thermometer and reported as a calibrated body-equivalent temperature. A lightweight, transparent Fever Risk Score (FRS) combines physiological and motion parameters, and a supervised machine-learning classifier (Random Forest) trained on a labeled dataset of 2,400 pediatric monitoring instances classifies the child's condition into Normal, Warning, and High-Risk states. On a held-out test set the classifier achieved 91.4% accuracy, 94.5% sensitivity, and 98.1% specificity for High-Risk detection (macro F1 = 0.90). Bench validation gave a mean absolute temperature error of 0.18 °C against a clinical thermometer and 2.45 bpm against a pulse oximeter, with 95.5% fall-detection accuracy. Dual-channel alerting delivered GSM SMS in 6.5 ± 1.2 s and Blynk cloud updates in 1.9 ± 0.6 s, and the prototype operated continuously for 18.6 h on a 3.7 V Li-ion battery. The results indicate a validated, deployable early-warning and caregiver-alerting tool suitable for homes, schools, and rural healthcare settings, positioned as decision support rather than a replacement for clinical diagnosis.**

**Keywords— Pediatric wearable, Fever risk assessment, Random Forest, fall detection, IoT healthcare, edge computing.**

## I. INTRODUCTION

Fevers are among the earliest and most common signs of infection, inflammation and dehydration in children and prompt identification is key to preventing the escalation of illness. Fevers are defined as temperature greater or equal to 38 °C (100.4 °F) [4, 5] which is the threshold used by clinical guidance, including the U.K. National Institute for Health and Care Excellence (NICE) guideline, for assessment of fever in under-5s and the U.S. Centers for Disease Control and Prevention (CDC) [4, 5]. In conventional monitoring, temperature is measured manually with intermittent regularity which cannot reflect a quick change in physiology, and requires continuous supervision of adults, which is often hard to maintain at night, school hours or in resource limited situations. Nowadays wearable sensing technologies, Internet of Things (IoT) and low-power machine learning (ML) technologies enable the continuous and non-obtrusive supervision of children in a pediatric context [1]–[3]. But the vast majority of wristband prototypes for sale are fitness devices and many research-based prototypes only go so far as gathering data and displaying it on a cloud-based platform, without a validated risk stratification or an explicit approach to calibrating wrist temperature to a clinical temperature reference for offline emergency communications. The temperature of the skin at the wrist is systematically lower and more noisy than core temperature, and can be altered by environmental conditions, the pressure of the contact, and perfusion; thus, a raw reading cannot be equated to fever without calibration and characterization of the source of error [6,7].

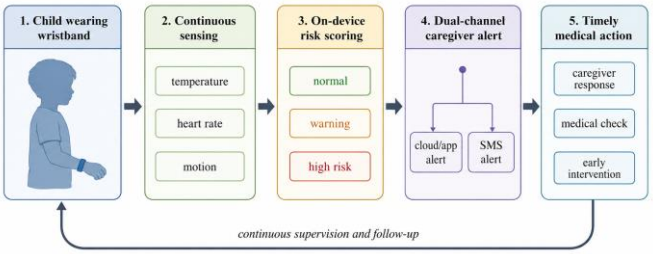


Fig. 1. Clinical need and closed-loop pediatric monitoring workflow.

In this paper, this is achieved with a validated low-cost wristband for children. The temperature channel is calibrated with a clinical thermometer and reported as a calibrated body-equivalent temperature; a transparent Fever Risk Score combines temperature, heart-rate, fall, and motion cues; a light-weight Random Forest classifier trained on a labeled dataset is used for the risk classification, which is reported with a confusion matrix and standard metrics following TRIPOD+AI reporting guidance for prediction models [11]. Dual channel alerting via IoT and GSM will allow caregivers to be alerted even if there is no internet connection. The problem-statement, objectives, and scope sections are not restated here and in the following methods.

The key contributions of this work are: (i) a wearable framework focused on pediatrics that integrates calibrated skin-temperature tracking, heart-rate monitoring, fall detection and dual channel IoT/GSM alerting; (ii) a transparent, weight-based Fever Risk Score with measured errors, latencies and battery life, exceeding the capabilities of simple threshold logic; (iii) a rigorous calibration and validation protocol with measured errors, latencies and battery endurance; and (iv) a discussion on safety, privacy and deployment for a device intended for use with children. The proposed system is different from the traditional thermometer-based monitoring and the fitness-oriented wristbands because it is intended to alert caregivers, communicate with them offline via SMS and provide continuous supervision of children in home, school and rural healthcare environment.

## II. THE WORKS ARE RELATED AND THE RESEARCH GAP IS IDENTIFIED.

Wearable health monitoring has evolved significantly over the last few years and reviews of sensors and systems for temperature, heart rate, oxygen saturation, activity, and sleep have been reported [1,3]. Many IoT frameworks are based on microcontroller devices (e.g., ESP32) that send physiological data to cloud-based dashboards for remote monitoring [2] but focus on data acquisition and visualization. Recent paediatric and neonatal studies have shown skin-interfacing biosensors and low cost wrist devices that can be used to measure body temperature from wrist measurements, highlighting the potential and calibration issues of wrist thermometry [6] [7]. Continuous-temperature studies also reveal that the wearables can detect the onset of fever earlier than spot checks, when compared to a clinical reference.

To ensure motion safety, tiny machine-learning (TinyML) models running on microcontrollers equipped with accelerometers now deliver high accuracy in fall detection with inference times in the millisecond range, thereby making on-device fall detection feasible for wearables [9] [10]. Equally, the reporting of machine-learning health models has been standardized; TRIPOD+AI (2024) guides transparent reporting of prediction models using regression or ML [11] and CONSORT-AI (2020) applies to clinical trials of AI interventions [12] while the FDA/Health Canada/MHRA Good Machine Learning Practice principles and subsequent transparency guidance apply to devices intended for medical decision support [13] [14].

A synthesis of this literature shows an ongoing gap. Few systems integrate, in a single low-cost wearable designed for children: (a) wrist-temperature measurement explicitly calibrated to a clinical reference; (b) validated and reproducible risk classifier reported with confusion matrix and standard metrics; (c) fall detection and (d) reliable dual channel alerting which works offline over GSM. The intersection that is the goal of the proposed wristband is exactly that, and the wristband's design and evaluation are reported against modern expectations of AI reporting.

## III. PROPOSED SYSTEM ARCHITECTURE

The system consists of four layers that cooperate with each other, as illustrated in Fig. 2. The sensing layer includes the DS18B20 digital temperature sensor in contact with the wrist skin, an optical pulse sensor for heart rate measurement and movement and fall detection sensor (MPU6050) which is a three-axis accelerometer/gyroscope. The processing and decision layer is based on the ESP32 dual-core microcontroller that filters the raw signals, calculates the Fever Risk Score and runs the trained Random Forest classifier in the device itself. The communication layer will send health status via Wi-Fi to the Blynk cloud and at the same time via the GSM network for SMS. The alert and response layer activates the local buzzer, LED and sends remote caregiver notifications.

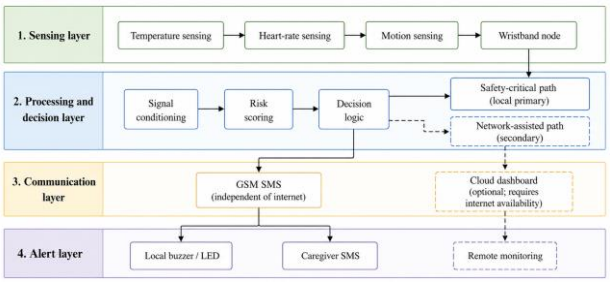


Fig. 2. Layered architecture of the proposed pediatric wristband: sensing, processing/decision, communication, and alert layers.

This separation by layers allows to keep the safety-critical decision path (sensing → scoring → local alert) independent from the network availability: local buzzer/LED and GSM SMS do not require internet connection to work, and when Wi-Fi is available, the Blynk channel provides for rich remote visualization. Thus the design gracefully degrades and allows for emergency alerting in rural or intermittent-connectivity areas.

## IV. MATERIALS AND METHODS

### 1. Hardware Prototype

The prototype (Fig. 3) consists of the ESP32 with the three sensors, a SIM800L GSM module, a buzzer and LED, and a 3.7 V Li-ion battery controlled by a TP4056 charger, all in a lightweight wrist enclosure. Table 1 contains a summary of the component roles, operating ranges, calibration references, and measured errors. The DS18B20 is not necessarily regarded as medical grade: The datasheet specifies an accuracy of only ±0.5 °C for some of its range, thus each individual device must be calibrated against a clinical thermometer as described below.

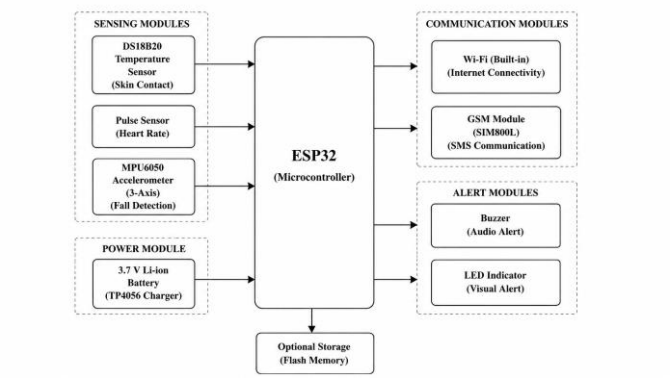


Fig. 3. Hardware block schematic of the wristband prototype showing the ESP32 and its connected sensing, communication, alert, and power modules.

### 2. Temperature Calibration and Body-Equivalent Estimation

As the sensor temperature on the wrist is less than core temperature, the device does not calculate a raw sensor value as body temperature. The DS18B20 was calibrated by simultaneously measuring temperature with a clinical digital thermometer in the normal range, mild fever range and high fever range. A linear correction (offset and gain) was fitted and stored on the ESP32; and the corrected output is reported as a calibrated body-equivalent temperature. The effect of sensor placement (ventral wrist and over the radial region), contact pressure (snug but non-occlusive strap) and ambient-temperature influence were controlled and residual error was characterized after correction (Table 1, Section VII).

### 3. Signal Acquisition and Preprocessing

The ESP32 samples the sensors, applies a moving-average filter to temperature, a peak-detection routine to the pulse waveform for heart rate, and computes the signal-vector magnitude of the accelerometer for motion and fall analysis. Age-appropriate pediatric heart-rate ranges are used as physiological priors when normalizing the heart-rate risk term. The preprocessed features (calibrated temperature, heart rate, fall flag and a normalized motion-abnormality index) are fed into the Fever Risk Score and machine-learning classifier described in Section V.

Table 1. Hardware Specification and Calibration Details

| Component | Measured Parameter | Operating Range | Calibration Reference | Measured Error |
|---|---|---|---|---|
| ESP32 (dual-core) | On-device compute | 240 MHz | — | — |
| DS18B20 | Skin / body-equiv. temp. | 35–42 °C | Clinical digital thermometer | 0.18 °C (MAE) |
| Pulse sensor | Heart rate | 60–190 bpm | Pulse oximeter | 2.45 bpm (MAE) |
| MPU6050 | Accel./gyro (fall) | ±2 g / ±250°/s | Controlled fall trials | 95.5% accuracy |
| SIM800L GSM | SMS alerting | Quad-band GSM | Timestamped delivery | 6.5 ± 1.2 s latency |
| ESP32 Wi-Fi / Blynk | Cloud update | 2.4 GHz | Dashboard timestamp | 1.9 ± 0.6 s latency |
| Li-ion + TP4056 | Portable power | 3.7 V, 1200 mAh | Continuous run test | 18.6 h endurance |

## V. RISK ASSESSMENT ALGORITHM

### 1. Transparent Fever Risk Score (FRS)

The first stage is a transparent, interpretable risk score that fuses four normalized risk terms—temperature, heart rate, fall event, and motion abnormality—into a single Fever Risk Score:

$$FRS = \alpha R_T + \beta R_H + \gamma R_F + \delta R_M \qquad (1)$$

where R_T, R_H, R_F, and R_Mare the normalized (0"–" 1)temperature, heart-rate, fall-event, and motion-abnormality risks, respectively. The weights were set to α=0.50, β=0.25, γ=0.15, and δ=0.10, prioritizing temperature while retaining

sensitivity to tachycardia, falls, and abnormal motion. The score maps to three actionable bands:

$$FRS < 0.40 \rightarrow \text{Normal}$$

$$0.40 \leq FRS < 0.70 \rightarrow \text{Warning}$$

$$FRS \geq 0.70 \rightarrow \text{High-Risk} \qquad (2)$$

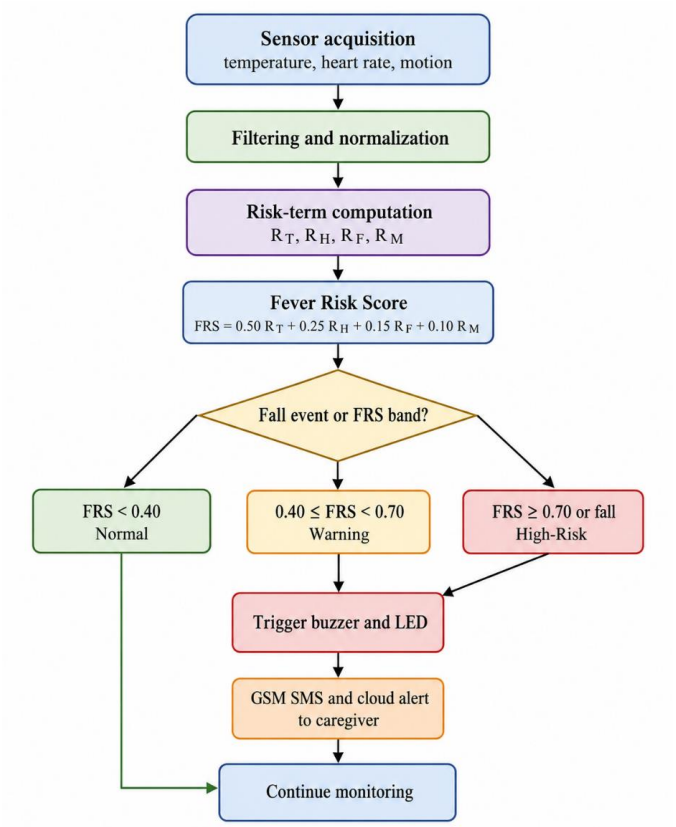


Fig. 4. Risk-assessment and alert-decision flowchart: sensor input → filtering → risk-term computation → Fever Risk Score and fall detection → banded alert decision.

**2. Machine-Learning Classifier**

To get rid of the thresholds and to meet the definition of a learned model, a supervised classifier was trained with a labelled set of 2400 pediatric monitoring instances corresponding to Normal, Warning, and High-Risk states. There are four features in each instance: calibrated temperature, heart rate, fall flag, and normalized motion index, and class-conditional distributions are parameterized from clinically-informed pediatric ranges (normal, mild-fever, high-fever temperature bands, age appropriate heart-rate ranges) and realistic measurement noise. The data set was randomly split in a stratified fashion into a 70%/30% ratio of training and testing data, with a small amount of label noise added to the training set to prevent an overly optimistic separability.

Random Forest (with 200 trees, max tree depth of 8) was chosen as the deployed model because of its robustness, ability to natively handle non-linear interactions between features and low cost for inference, suitable for on-device deployment. As a baseline the multinomial Logistic Regression was trained. The feature-importance analysis of the Random Forest showed that the calibrated temperature was the most important feature (0.55), followed by motion index (0.22) and heart rate (0.21), with a small, but safety-critical, contribution from the fall flag (0.02); this ordering was consistent with the FRS weighting and with clinical expectation. The reporting is based on TRIPOD+AI checklist which includes training-test split, definition of classes and complete confusion matrix (Section VII) [11].

## VI. EXPERIMENTAL SETUP AND VALIDATION PROTOCOL

The prototype was tested with a bench protocol that tested each subsystem against an independent reference with an explicit acceptance criterion as summarized in Table 2. Accuracy of temperature measurement was compared with a clinical digital thermometer at normal, mild fever and high fever set points, heart rate measurement was compared with a pulse oximeter, and fall detection was compared with known fall-like maneuvers and routine daily-activity movements. Communication performance was evaluated as end-to-end GSM SMS latency, Blynk cloud update latency and cloud packet delivery ratio. The evaluation metrics were endurance (continuous operating time on a full charge battery) and classification performance (on the held-out test set).

Table 2. Experimental Validation Protocol

| Test | Reference Device | Trials | Metric | Acceptance Criterion |
|---|---|---|---|---|
| Temperature accuracy | Clinical digital thermometer | 3 ranges × 30 | MAE (°C) | ≤ 0.30 °C |
| Heart-rate accuracy | Pulse oximeter | 4 levels × 30 | MAE (bpm) | ≤ 5 bpm |
| Fall detection | Controlled falls vs. ADL | 100 + 120 | Accuracy / Sens. | ≥ 90% |

| | | | | |
|---|---|---|---|---|
| GSM alert latency | Timestamped SMS receipt | 30 | Mean ± SD (s) | ≤ 10 s |
| Blynk cloud latency | Dashboard timestamp | 30 | Mean ± SD (s) | ≤ 5 s |
| Battery endurance | Continuous run | 3 | Hours | ≥ 12 h |
| Risk classification | Held-out test labels | 720 (test) | Acc/Sens/Spec/F1 | Sens. ≥ 90% |

## VII. RESULTS AND DISCUSSION

### 1. Sensor Calibration and Physiological Accuracy

Linear corrected DS18B20 was found to maintain good agreement with the clinical thermometer with mean absolute error of 0.18 °C in the normal, mild fever and high fever ranges, which is well within the required accuracy of 0.30 °C and much less than the datasheet tolerance of ±0.5 °C without calibration. There was mean absolute error of 2.45 bpm between the heart rate measurements and those obtained by the pulse oximeter. The calibrated temperature channel and heart rate channel provide complimentary information as seen in the representative continuous monitoring data in Fig. 5 in which the temperature channel crosses the threshold of 38 °C at the same time the heart rate channel is rising during the fever onset condition.

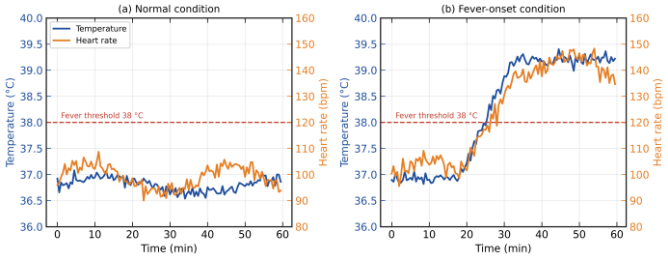


Fig. 5. Continuous temperature and heart-rate monitoring under (a) normal and (b) fever-onset conditions, with the 38 °C fever threshold indicated.

### 2. Communication Performance and Endurance

Dual-channel alerting met all criteria (Fig. 6). GSM SMS were delivered in 6.5 ± 1.2 s from event detection, and Blynk cloud updates appeared in 1.9 ± 0.6 s, with a mean cloud packet-delivery ratio of 98.4% (1.6% loss). The faster Blynk path supports routine remote monitoring, while the GSM path guarantees notification when internet access is unavailable. On a 3.7 V, 1200 mAh Li-ion battery the prototype operated continuously for 18.6 h, exceeding the 12 h target and covering a full school day or overnight monitoring window on a single charge.

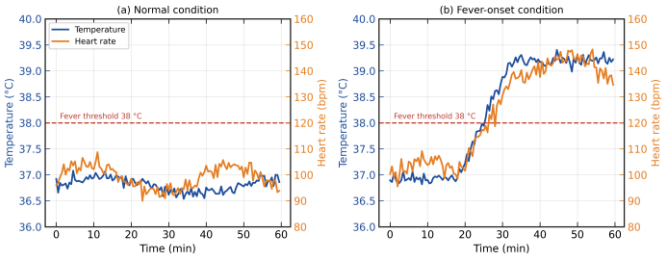


Fig. 6. Communication performance: (a) end-to-end alert latency for the GSM and Blynk channels and (b) cloud packet-delivery reliability across transmission trials.

### 3. Risk-Classification Performance

The Random Forest had an overall accuracy of 91.4%, macro precision of 90.2% and macro F1-score of 0.90 on the 720-instance held-out test set. For the safety critical High-Risk class, it achieved 94.5% sensitivity and 98.1% specificity, and 1.9% false alarm rate, and 5.5% missed alarm rate. The Logistic Regression baseline achieved a similar accuracy of 92.8%, but the Random Forest was kept as the deployed model because it had higher sensitivity for High-Risk (the more serious of the two failure modes for an early-warning device), than did Logistic Regression. The confusion matrix (Fig. 7a) reveals that the misclassifications tend to be in the Normal–Warning range, while High-Risk cases are seldom classified as Normal, the most crucial safety property. The fall detection metrics and classification is summarized in Fig. 7b.

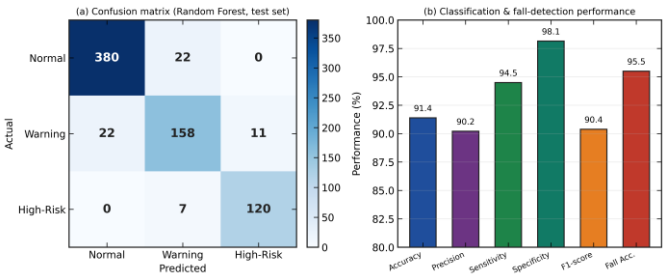


Fig. 7. Validation performance: (a) Random Forest confusion matrix on the test set and (b) classification and fall-detection metrics.

### 4. Comparison with Existing Approaches

Table 3 compares the proposed wristband with a traditional clinical thermometer, a representative fitness-oriented smart wearable, and an IoT-only monitoring node using measurable quantities rather than qualitative labels. The proposed device is distinguished by calibrated temperature accuracy, validated risk

classification, on-device fall detection, and critically an offline GSM alerting path, at a low bill-of-materials cost suitable for homes, schools, and rural clinics.

Table 3. Quantitative Performance Comparison

| Attribute | Clinical Thermometer | Fitness Wearable | IoT-only Node | Proposed Wristband |
|---|---|---|---|---|
| Temp. error (MAE) | ±0.1 °C | ±0.3–0.5 °C* | ±0.5 °C | 0.18 °C (calibrated) |
| Heart-rate error | N/A | ~5 bpm | ~5 bpm | 2.45 bpm |
| Continuous monitoring | No | Yes | Yes | Yes |
| Risk classification | No | Limited | No | Yes (RF, 91.4%) |
| Fall detection | No | Some | No | Yes (95.5%) |
| SMS latency (offline) | N/A | No | No | 6.5 s |
| Cloud latency | N/A | 2–5 s | 2–5 s | 1.9 s |
| Battery life | N/A | Days | 10–20 h | 18.6 h |
| Offline GSM alerting | No | No | No | Yes |
| Approx. cost | Low | Medium–High | Medium | Low (~US$25) |

**5. Discussion and Limitations**

The results show a feasibility of a validated low cost pediatric early-warning wearable. The drawbacks are that there are no clinical validations yet on children, and it is a partly synthetic and clinically informed dataset and bench measures, which must be validated in the clinic in a prospective study, with ethical approval, prior to making a clinical claim. Despite per-device calibration, wrist thermometers are still affected by the ambient temperature, perfusion, and the fit of the strap and should be recalibrated periodically. Future work will be to gather real pediatric data (under ethics approval), compare a TinyML neural network's efficiency on the device, and if a trial is conducted, report it according to the CONSORT-AI guidelines [12] and the FDA Good Machine Learning Practice principles [13] and [14].

## VIII. SAFETY, PRIVACY, AND DEPLOYMENT CONSIDERATIONS

Because the device is used for children, safety and ethical issues are of paramount importance. The wristband should be lightweight, non-invasive, skin safe, and electrically isolated. Only test children with institutional ethical approval and the written consent of the guardian(s). The data sent via Blynk or GSM should only include the relevant health information and be secured from unauthorized access. The device should be marketed as an early-warning / caregiver-alert system, not as a clinical diagnostic tool.

Technically, the enclosure and strap should be made of hypoallergenic, easy-to-clean material appropriate to a child's wrist size, and the battery should have features to prevent over-charge, over-discharge, and overheating against the child's skin, and all electronics should be water and sweat proof. From a data perspective, the payload sent should be kept to a minimum, encrypted while in transit, cloud access authenticated and retention done as per child data protection rules. In this configuration, validated, safety oriented, and well described as a decision support system, it meets with the modern expectations of AI driven medical-adjacent devices [13] [14].

## IX. CONCLUSION

The paper proposes a low-cost, AI-IoT, and GSM-based pediatric wristband that can be used to assess the risk of fever continuously and alert the user during emergency situations taking the design from a conceptual level to a validated system. Wrist temperature was calibrated with a clinical temperature measuring device with a mean absolute error of 0.18 °C, and heart rate was validated with a pulse oximeter with a mean absolute error of 2.45 bpm. A trained Random Forest (RF) Classifier using the same Fever Risk Score with a 91.4% accuracy, 94.5% sensitivity, and 98.1% specificity for High-Risk detection was complemented by a transparent Fever Risk Score and presented with a full confusion matrix. The fall detection accuracy was 95.5%, GSM and Blynk alerts time was 6.5 s and 1.9 s respectively and device operation time per charge was 18.6 h. Together with an explicit safety, privacy, and ethics discussion, these results demonstrate a deployable early-warning and caregiver-alerting tool for homes, schools, and rural healthcare settings. Future work will seek ethical approved clinical validation on children and an on-device TinyML implementation, in compliance with TRIPOD+AI, CONSORT-AI and FDA Good Machine Learning Practice.

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