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# Design of Thermal Runaway Early Warning and Safety Management System for Polymer Lithium-ion Batteries in Wearable Pet Devices

**Haipeng Lin**[1]

[1] Shenzhen Jingteng Technology Co., Ltd., Shenzhen 518000, China
Correspondence: Haipeng Lin, Shenzhen Jingteng Technology Co., Ltd., Shenzhen 518000, China.

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**Abstract**

For smart pet collars and health monitors equipped with thin polymer lithium batteries, bending, extrusion and wide temperature swings easily trigger latent thermal runaway, while traditional BMS only supports basic overcharge/over-discharge protection without early detection and graded intervention. This paper analyzes electro-mechanical-environment coupled thermal runaway mechanisms, builds multi-source time-series datasets, and proposes a physics-driven lightweight embedded warning model. A complete perception-edge computing graded safety hardware-software system is developed and validated by finite element simulation, calorimetry and prototype tests. The model reaches 96.4% accuracy for early thermal runaway, issuing alarms 128–176 s earlier than single temperature threshold schemes. The overall system power consumption is only 8.7 mW, enabling staged current limiting and power cut-off to curb thermal runaway evolution. This research provides theoretical and engineering support for battery safety design of pet wearable electronics.

**Keywords:** wearable pet devices, polymer lithium-ion batteries, thermal runaway, multi-field coupling, lightweight early warning, edge computing

## 1. Introduction

### 1.1 Research Background

Smart pet wearables widely adopt 0.8–2.0 mm thin flexible lithium batteries. Long-term skin fitting, repeated mechanical deformation and −10 ℃~50 ℃ humid outdoor environments accelerate diaphragm degradation and internal micro-shorts (Goswami B R, Abdisobbouhi Y, Du H, et al., 2024), which gradually induce thermal runaway, causing device burnout or pet scalds. Commercial products merely rely on single-point temperature and overcurrent protection. Internal hotspots appear long before surface temperature rises, leaving insufficient response time when hazards erupt, which creates obvious safety defects and necessitates targeted research.

### 1.2 Research Status & Bottlenecks

1) Mechanism: Most thermal runaway studies target large rigid power batteries. Few investigations cover thin cells under cyclic bending; deformation-induced micro-shorts, the primary hazard trigger for pet devices, lack clear evolutionary rules.
2) Warning algorithms: Three mainstream

methods all have drawbacks: physical models demand massive computing resources; fixed thresholds suffer high false alarm rates; deep learning models carry excessive parameters unsuitable for miniature low-power chips. No multi-factor lightweight schemes exist for millimeter-thin batteries.

3) Safety management systems: Conventional wearable BMS lacks tiered early-warning loops, and bulky heat dissipation structures cannot fit compact collars.

Three core bottlenecks remain: ambiguous multi-field coupled failure laws, weak identification of subtle early faults, and safety hardware mismatched with miniature device constraints.

### *1.3 Research Contents & Three Core Innovations*

This paper conducts coupled mechanism analysis, simulation modeling, dataset construction, lightweight model development, integrated safety system design and multi-condition verification.

1) Theoretical innovation: Reveal progressive thermal runaway paths under bending-extrusion and wide-temperature aging, and distinguish failure characteristics of deformation-induced micro-shorts and normal overcharge.

2) Algorithmic innovation: Build a physics-constrained lightweight time-series model integrating temperature, internal resistance, stress and environmental data to capture incipient faults on low-power embedded hardware.

3) Engineering innovation: Develop miniaturized low-power sensing-edge control hardware, formulate four-level closed-loop risk intervention strategies, and complete physical prototype verification.

## 2. Analysis of Multi-Field Coupling Thermal Runaway Mechanism and Risk Characteristics of Polymer Lithium Batteries in Pet Wearable Devices

### *2.1 Research Object and Quantification of Typical Working Conditions*

This paper selects flexible polymer lithium-ion cells commonly used in pet wearable devices, with a rated voltage of 3.7 V, capacity of 450 mAh and thickness of 1.2 mm, and a minimum allowable bending radius of 15 mm. Basic cell parameters are shown in Table 1.

**Table 1.** Basic Parameters of Miniature Flexible Polymer Lithium-ion Cells

| Parameter | Value |
|---|---|
| Rated voltage | 3.7 V |
| Charging cut-off voltage | 4.2 V |
| Discharging cut-off voltage | 3.0 V |
| Nominal capacity | 450 mAh |
| Cell thickness | 1.2 mm |
| Operating current range | 0–150 mA |
| Recommended bending radius | ≥15 mm |

**Typical working condition quantification**:

1) Mechanical loads: Bending frequency 0–12 times/min, local extrusion stress 0–0.32 MPa, random vibration acceleration 0–2.8 g.

2) Environmental conditions: Ambient temperature −10 °C to 50 °C, relative humidity 25%–85% RH, equivalent heat transfer coefficient of sealed shell heat dissipation 3.2–6.5 $W \cdot m^{-2} \cdot K^{-1}$.

3) Electrical working conditions: Intermittent charge-discharge with an average discharge rate of 0.12 C, floating charge standby accounting for over 70% of total operation time.

### *2.2 Heat Generation Mechanism of Multi-Field Coupling Thermal Runaway*

1) Electrochemical intrinsic heat generation model: The total heat generation rate of the cell consists of polarization heat, reaction heat and side reaction heat, as shown in Formula (1): $Q_{total}=Q_{polar}+Q_{react}+Q_{side}$

variable definition: $Q_{total}$ = total heat generation rate (W); $Q_{polar}$ = polarization heat generation; $Q_{react}$ = reversible heat of electrochemical reactions; $Q_{side}$ = abnormal side reaction heat from SEI decomposition, electrolyte decomposition, negative electrode side reactions, etc. Under normal cycling conditions, the value of $Q_{side}$ remains small; when internal micro-short circuits emerge, side reaction heat rises exponentially and becomes the primary heat source of thermal runaway.

2) Mechanical-thermal coupling triggering mechanism: Repeated bending and

extrusion caused by pet movement lead to internal pole piece dislocation and local plastic deformation of the cell diaphragm, forming micro-pores on the diaphragm and hidden internal micro-short circuits. The contact area of micro-short circuit regions is small, which cannot immediately trigger high-current external short circuits, yet continuous accumulation of local Joule heat forms internal hot spots. Rising temperatures of hot spots further accelerate diaphragm aging and SEI film cracking, forming a positive feedback cycle of "mechanical damage – micro-short circuit – local heat accumulation – material degradation – aggravated short circuit". Such thermal runaway evolves progressively, and the rise of cell surface temperature lags behind internal hot spots, serving as the dominant safety risk source under pet wearable scenarios.

3) Environment-electrothermal coupling evolution law: High ambient temperatures accelerate SEI film decomposition rates and elevate side reaction rates; lithium precipitation occurs at negative electrodes during low-temperature charging, and lithium dendrites pierce the diaphragm to increase micro-short circuit risks; tiny gaps in the shell admit water under high humidity, causing corrosion of cell interfaces and increased leakage current. The sealed wearable shell delivers limited heat dissipation capacity, further amplifying temperature rise effects induced by abnormal heat generation.

4) Thermal runaway stage division & precursor extraction: The entire thermal runaway process of cells under pet wearable working conditions is divided into four stages, with typical observable characteristics of each stage listed in Table 2.

**Table 2.** Thermal Runaway Evolution Stages and Observable Precursors under Multi-field Coupling

| **Stage** | **State Description** | **Key Observable Signals** |
|---|---|---|
| Stage I: Safe steady state | Intact cell with no obvious damage | Stable internal resistance, minor temperature fluctuations, no abnormal temperature rise rate |
| Stage II: Early abnormal budding | Slight diaphragm micro-damage and faint micro-short circuits with no obvious external signs | Slight rise in internal resistance, increased local temperature difference, accumulated continuous stress, surface temperature rise rate <0.15 °C/min |
| Stage III: Thermal runaway development | Aggravated side reactions and expanding hot spots | Voltage fluctuations, significantly elevated internal resistance, temperature rise rate 0.15–1.0 °C/min |
| Stage IV: Thermal runaway eruption | Diaphragm melting, violent side reactions, gas generation and ignition | Sharp voltage drop, temperature rise rate >1 °C/min, cell bulging and gas emission |

Stage II is the golden window for early warning. At this stage, external voltage and overall temperature change faintly, which cannot be identified by traditional single-point temperature protection, requiring joint judgment of multi-source signals including internal resistance, temperature difference and stress.

*2.3 Finite Element Simulation Modeling of Multi-field Coupling*

- **Modeling settings**: Establish an electrochemical-temperature-stress multi-physics coupling simulation model geometrically built at a 1:1 scale for 1.2 mm thick flexible cells. Cyclic bending loads are applied to mechanical boundaries; the electrochemical module couples the intrinsic battery heat generation equation; the heat transfer module considers sealed heat dissipation boundaries of wearable shells.

- **Simulation objectives**: Solve the internal temperature field and stress field distribution of cells under different bending stress conditions, and obtain the evolution process of internal hot spots. Simulation results show that when local extrusion stress exceeds 0.27 MPa and the equivalent plastic strain of local diaphragms surpasses 0.08, millimeter-level local hot spots begin to form inside cells, with hot spot temperatures 12–21 °C higher than cell surface temperatures. This intuitively explains the physical phenomenon that "internal hot spots appear prior to surface temperature rise". Datasets output from simulations compensate for the shortcomings of scarce and high-cost real thermal runaway test samples, providing partial sample support for subsequent training of early warning models.

## 3. Construction of Lightweight Intelligent Thermal Runaway Early Warning Model Based on Multi-sensor Fusion

### *3.1 Design Constraint Indicators of Early Warning Model*

For embedded hardware of pet wearable devices, the model must balance identification accuracy and embedded computing power constraints, with key indicators shown in Table 3.

**Table 3.** Design Indicators of Early Warning Model

| **Indicator** | **Target Value** |
|---|---|
| Identification accuracy for Stage II thermal runaway | ≥95% |
| Single sample inference time | < 12 ms |
| Model parameter quantity | < 12 k |
| Power consumption of single-cycle inference | < 2.2 mW |
| False alarm rate | ≤3.0% |

### *3.2 Feature Set Construction and Data Preprocessing*

#### 3.2.1 Multi-dimensional Input Feature Set

Abandoning the traditional single temperature threshold scheme, a five-category time-series feature set is constructed:

- Electrical features: Terminal voltage $U_t$, charge-discharge current $I_t$, AC internal resistance $R_{ac}$, voltage fluctuation rate $\Delta U/\Delta t$.
- Temperature features: Multi-point cell surface temperatures $T_1, T_2, T_3$, maximum temperature difference $\Delta T_{max}$, temperature rise rate $dT/dt$.
- Mechanical features: Real-time extrusion stress $\sigma$, bending cycle count.
- Environmental features: Ambient temperature $T_{amb}$, ambient relative humidity RH.
- Aging features: Cycle count, capacity attenuation coefficient.

#### 3.2.2 Data Collection and Preprocessing

A working condition simulation test platform is built to conduct cyclic bending, high-low temperature cycling, accelerated aging and micro-short circuit induction tests on cells, collecting a total of 42,600 groups of time-series samples including 3,820 groups of abnormal samples (Shi H, Xu Y, Geng J, et al., 2026). Raw data contains noise and asynchronous timing issues, processed sequentially via outlier elimination, sliding window filtering, multi-sensor time alignment and min-max normalization. The Pearson correlation coefficient is adopted for feature screening to eliminate redundant features with a correlation coefficient lower than 0.3, finally retaining 11-dimensional core input features to reduce model input dimensions. The calculation formula of the Pearson correlation coefficient is shown in Formula (2):

$$r_{xy}=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}}$$

### *3.3 Architecture of Lightweight Time-Series Early Warning Model Integrated with Physical Information*

#### 3.3.1 Overall Model Architecture

1) The model adopts a hybrid architecture of "physical prior constraint + lightweight time-series network". Battery thermal

dynamics equations are embedded into the loss function as physical constraint terms to restrict model outputs to comply with battery heat generation physical laws, reducing the risk of generalization failure of pure data-driven models outside working conditions.

2) The main network adopts a lightweight time-series attention mechanism, assigning higher attention weights to time-series fragments with faint early abnormalities and strengthening extraction capacity of budding-stage features.

3) A risk judgment module is connected after the network to output a risk probability value ranging from 0 to 1, mapped to four risk levels.

Loss function definition, as shown in Formula (3): $L_{total}=L_{cls}+\lambda L_{phy}$ parameter explanation: $L_{cls}$ = classification cross-entropy loss; $L_{phy}$ = physical constraint loss; $\lambda$ = weight coefficient of physical constraint, set as $\lambda=0.25$ in this paper.

3.3.2 Graded Early Warning Judgment Logic

Risk grading standard: Four risk states are divided according to the model output risk probability $P_r$:

1) Safe (Green): $P_r<0.30$, normal cell status.
2) Level-I Early Warning (Yellow): $0.30\le P_r<0.55$, entering the early abnormal budding stage.
3) Level-II Alarm (Orange): $0.55\le P_r<0.80$, continuous deterioration of thermal abnormalities.
4) Level-III Emergency Alarm (Red): $P_r\ge 0.80$, imminent thermal runaway.

System linkage rule: Different risk levels directly correspond to differentiated intervention strategies of the back-end safety management system, realizing linkage between "early warning and control".

*3.4 Model Training and Comparative Evaluation*

To fully verify the comprehensive performance, generalization ability and engineering adaptability of the proposed lightweight early warning model, iterative training and hyperparameter optimization are carried out based on the preprocessed multi-source time-series dataset. Multiple groups of mainstream classic early warning algorithms are set as control groups for horizontal comparative tests, with quantitative evaluation conducted from multi-dimensions including identification accuracy, inference efficiency and early warning timeliness.

- Dataset partition: The dataset is divided into training set, verification set and test set at a ratio of 7:2:1. After hyperparameter tuning, the final model parameter quantity reaches 8.4 k, satisfying embedded deployment constraints.
- Control group setup: To highlight the superiority of the proposed model in early thermal runaway early warning scenarios, the industrially adopted fixed temperature threshold early warning algorithm and traditional standard LSTM time-series prediction model are selected as control groups for horizontal comparison tests under identical test datasets and hardware environments. A comparison of core performance indicators of each model is shown in Table 4.

**Table 4.** Performance Comparison of Different Early Warning Schemes

| **Model Scheme** | **Accuracy /%** | **Recall Rate /%** | **False Alarm Rate /%** | **Inference Time /ms** | **Advanced Warning Duration /s** |
|---|---|---|---|---|---|
| Fixed temperature threshold | 74.2 | 61.3 | 11.7 | <1 | 42 |
| Standard LSTM network | 94.7 | 92.1 | 3.8 | 47 | 113 |
| Proposed physical information lightweight model | 96.4 | 94.6 | 2.7 | 8.6 | 151 |

The traditional temperature threshold scheme delivers short advanced warning duration and low accuracy; the standard LSTM achieves favorable identification effects yet suffers long inference time, making it unsuitable for miniature wearable devices. The proposed model balances identification accuracy and inference speed, with significantly longer advanced warning duration than control schemes, capable of identifying faint abnormalities in the budding stage of thermal runaway.

## 4. Overall Hardware & Software Design of Battery Thermal Safety System for Pet Wearables

This chapter designs an integrated battery safety system targeting thin lithium batteries' risks (bending, wide temperature aging, hidden micro-shorts). It builds a full "sensing-inference-decision-protection-alarm" workflow for early battery fault detection and tiered protection, optimized for tiny, low-power wearable hardware.

### *4.1 System Framework & Design Rules*

Hierarchical Structure

- Sensing layer: Collect 6 signals (3-channel cell temperature, voltage/current, thin-film stress) as model inputs.
- Edge computing layer: Local low-power RISC-V MCU runs signal filtering, lightweight model inference and risk judgment; one inference cycle takes ~12 ms.
- Interaction layer: Onboard tri-color LEDs show real status; BLE pushes alerts to phones; cloud only stores 5-min interval logs without real-time calculation.

Core Design Constraints

Limited inner space (220 mm²) and standby current (142 μA) set five rules: miniaturized sensing PCB (210 mm²), ultra-low power with adjustable 1–10 s sampling, full local risk computation, four-tier closed-loop control, wide-temperature components (-10 ℃ ~ 50 ℃) supporting 6 bending cycles per minute.

### *4.2 Modular Hardware Design*

The hardware adopts split independent modules for compact layout and low power draw:

1) Multi-source sensing module: Three NTC temperature probes eliminate single-point measurement bias; thin-film stress sensor captures extrusion & bending deformation.
2) Edge MCU module: 32-bit low-power RISC-V chip with enough on-chip RAM to run the lightweight model without extra storage; handles sensor reading, data preprocessing and risk classification.
3) Dual electrical protection module: Software current limiting + independent hardware cut-off circuits. Hardware instantly disconnects charge/discharge loops at Level-III alarms to avoid software failure risks. Thermal buffer layers reduce impact and heat spread.
4) BLE human-machine module: Bluetooth syncs battery health and warnings to mobile APP; tri-color LEDs correspond to four risk levels for offline status viewing.

Power Test Results

The full prototype consumes 8.7 mW during operation and 142 μA in sleep mode; the safety system barely reduces device battery life.

### *4.3 Embedded Software & Tiered Protection Logic*

The embedded software on edge MCU handles data processing, fault prediction and dynamic protection, split into six decoupled sub-modules: bottom driver, data preprocessing, risk inference, tiered strategy scheduler, Bluetooth communication, battery health evaluation.

Operation Flow

Periodic multi-sensor data → filtering & normalization → local lightweight model outputs risk grade → system executes matched control, saves logs and sends mobile alerts when needed.

Four-Tier Closed-Loop Control

1) Safe (Normal): Standard charge-discharge management, continuous monitoring and real-time SOH update.
2) Yellow Level-I Warning (Minor anomaly): Lower charging current, disable idle peripherals, log data silently without mobile notifications.
3) Orange Level-II Alarm (Worsening fault): Disable fast charging, cap output power; push APP reminders for equipment inspection.
4) Red Level-III Emergency (Thermal runaway risk): Hardware cuts power entirely, device locks; APP sends high-risk alerts to stop usage immediately.

## 5. System Test Verification and Result Analysis

To verify the early warning capacity, protection functions and environmental adaptability of the battery thermal safety management system, a test platform is built, and control groups and experimental groups are set for multi-dimensional comparative testing. Verification is completed from three layers: model algorithm, whole machine reliability and physical prototype, followed by analysis of test results and existing deficiencies.

*5.1 Test Platform and Test Scheme*

The test platform mainly includes a high-low temperature environmental test chamber, dynamic bending-extrusion testing machine, accelerated rate calorimeter (ARC), multi-channel battery test system and power analyzer.

- Control group: Adopt original BMS of commercial pet wearable devices, only supporting single-point temperature monitoring and basic overcharge-overdischarge protection.
- Experimental group: Equipped with the complete early warning and safety management system designed in this paper.

*5.2 Special Verification of Early Warning Model*

Multiple groups of progressive micro-short-circuit thermal anomalies are induced under different ambient temperature, bending stress and cell aging conditions, and early-warning trigger moments are recorded. Test results indicate that for deformation-induced progressive thermal runaway, this system achieves an average early-warning lead time of 151 s, with a range of 128-176 s (Li H G, Zhou D, Zhang M H, et al., 2022); the single-point temperature protection of the control group mostly responds at the late stage of thermal runaway, with an average of merely 44 s. Under high-low temperature conditions of -5 ℃ and 45 ℃, the model recognition accuracy is higher than 93%, the false-alarm rate is controlled within 3.0%, and multi-source feature input can effectively reduce misjudgment caused by environmental disturbance.

*5.3 Whole Machine System Function and Reliability Test*

1) Power consumption & function test: Power analyzer measurement shows the whole machine operating power consumption is 8.7 mW, consistent with design indicators. Simulated four-level risk scenarios are repeated 50 times, with graded alarms, current limiting and power-off protection triggered normally without missed or false triggering.
2) Environmental reliability test: A total of 120 h temperature cycle impact tests from −10 °C to 50 °C are completed, alongside cyclic bending durability tests at 6 times per minute. No failure occurs in sensor collection, model inference and protection functions after testing, proving the system’s adaptability to complex pet wearable working conditions.

*5.4 Physical Loading Test*

The system is integrated into a pet smart collar prototype for a 30-day simulated wearing test reproducing pet movement and diurnal outdoor temperature variations, using a total of 8 prototypes (4 for the experimental group and 4 for the control group). Three Level-I early warnings emerge in the experimental group induced by slight internal resistance rise from accumulated battery stress. The system automatically limits charging current without safety accidents. Two local overheating phenomena occur in the control group, with protection activated only after a sharp temperature rise and lacking capacity for early intervention. Endurance tests show that equipment endurance declines by 6.2% after installation of the safety system, an acceptable margin. (Zhang J R & Xuan F Z, 2026)

*5.5 Discussion of Test Results*

Tests prove that relying solely on single temperature parameters fails to identify early internal micro-short circuits induced by deformation. The proposed system fuses multi-source features including internal resistance, stress and temperature difference, capturing faint abnormal cell characteristics via the lightweight model to realize early warning in the budding stage of thermal runaway. The system still has certain limitations: the fault evolution speed of instantaneous severe external short circuits leaves insufficient identification windows for algorithms, making system safety protection highly dependent on hardware backup protection. Individual cell differences under mass production working conditions cause baseline offset of monitoring features. Online self-calibration logic can be optimized in follow-up research to further improve model robustness.

## 6. Conclusions and Prospects

*6.1 Main Conclusions*

Repeated bending and extrusion under pet wearable scenarios cause diaphragm micro-damage inducing internal micro-short circuits, serving as the primary inducement of thermal runaway of miniature polymer lithium batteries with progressive evolution characteristics. Internal hot spots emerge earlier than cell surface temperature rise, leading to obvious hysteresis in traditional single-point temperature protection.

The lightweight time-series early warning model integrated with physical information constructed in this paper contains only 8.4 k parameters, achieving a test set identification accuracy of 96.4%. It significantly advances thermal runaway alarm time compared with traditional schemes and adapts to embedded low-computing-power hardware.

The designed integrated multi-source perception-edge control safety management system delivers an average hardware power consumption of 8.7 mW and establishes a four-level risk closed-loop graded intervention strategy (Mussa A S, Klett M & Lindbergh G, 2024), realizing complete protection covering early current limiting regulation to hardware power-off under high-risk states. Physical loading tests verify that the system can effectively identify and suppress thermal runaway risks with limited impact on endurance, suitable for pet wearable devices.

*6.2 Research Deficiencies*

Under extreme instantaneous short-circuit working conditions, fault signals leave limited identification windows for algorithms, and system safety protection relies heavily on hardware backup protection. Meanwhile, individual differences of cells from different batches induce baseline offset of monitoring features. In addition, after long-term aging cycles of batteries, the online self-calibration capacity of model parameters in the current framework remains to be further improved, increasing the difficulty of battery fault identification and risk early warning implementation for smart pet wearable devices.

*6.3 Future Prospects*

Follow-up research can be carried out in the following directions: adding online adaptive calibration algorithms for cells oriented to mass-produced products; introducing digital twin technology into full-life-cycle health management of miniature batteries; exploring integrated integration schemes of flexible sensors and cells; further compressing model scale to expand application to lower-power miniature wearable terminals.

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