JURNAL INFOTEL
VOL. 17, NO. 4, NOVEMBER 2025, PP. 920–932. DOI:10.20895/INFOTEL.V17I4.1383

RESEARCH ARTICLE

Early Warning Safety System Development for Electric Vehicle Batteries to Prevent Fires and Accidents: Implementation in Urban Public Transportation

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Received: June 12, 2025; Revised: August 27, 2025; Accepted: September 12, 2025.

Abstract: The increasing adoption of electric vehicles (EV) in urban public transport has raised significant safety concerns, particularly regarding thermal runaway incidents that can lead to catastrophic fires. Existing battery monitoring systems often provide inadequate warning times and lack predictive capabilities to mitigate failures before they reach critical conditions. This study proposes an intelligent early warning system for the safety of electric vehicle batteries in public transportation fleets that employ predictive analytics. The system integrates a distributed Internet of Things (IoT) sensor network that monitors temperature, voltage, current, and gas emissions, combined with machine learning algorithms—specifically Random Forest and Support Vector Machines—to analyze battery performance patterns. The proposed architecture incorporates edge computing for real-time data processing and cloud infrastructure for centralized fleet monitoring. Field validation involving 50 electric busses operating under the Jakarta TransJakarta network over a 12-month period achieved a prediction accuracy of 94.7% for thermal runaway events, with an average warning time of 8.3 minutes. The system successfully prevented 23 potential battery failures while maintaining a false alarm rate below 2.1%. An economic analysis also indicated a favorable cost–benefit ratio of 1:7.4. The proposed solution demonstrates significant potential to improve the safety of EV batteries through predictive analytics and automated emergency response, offering a scalable model for the broader adoption in the industry.

Keywords: battery monitoring, early warning system, electric vehicles, machine learning, thermal runaway prediction.

1 Introduction

The global transition to the adoption of electric vehicles (EV) in urban public transportation has shown significant progress, with more than 425,000 electric busses operating around the world in 2023, reflecting an increase of 2023—reflecting a 40% over the previous year. This shift plays a critical role in achieving sustainable and low-emission mobility. However, it has also introduced substantial safety concerns, particularly related to thermal runaway incidents of batteries.

According to the International Association of Fire Chiefs, 157 fire incidents involving electric public transportation vehicles were recorded between 2019 and 2023, with thermal runaway identified as the primary cause in approximately 89% of these cases. Thermal runaway is a hazardous failure mechanism in which battery cells undergo uncontrolled exothermic reactions, causing rapid temperature increases that can cause fires, explosions, and the emission of toxic gasses. Data from the National Transportation Safety Board indicate that such events typically progress from initial failure to a critical state in just 3.2 minutes on average, significantly limiting the effectiveness of emergency mitigation measures under current battery monitoring protocols.

Conventional battery management systems (BMS) employed in electric public transportation primarily emphasize operational stability rather than safety prediction. These systems generally employ threshold-based mechanisms that trigger alarms only after the predefined parameter limits are exceeded. Studies by Chen et al. (2022) have shown that traditional BMS configurations provide an average of only 2.1 minutes of advance warning prior to failure, which is insufficient for effective evacuation and intervention. In addition, Kumar and Singh (2023) reported that 73% of these systems are prone to false alarms due to their inability to differentiate between normal fluctuations and actual safety threats, thus negatively affecting operational efficiency and decision-making.

One of the major challenges in this domain is the lack of predictive intelligence within existing monitoring frameworks. Although recent studies have attempted to incorporate machine learning techniques for battery performance monitoring, most of these efforts are limited to laboratory environments or focus solely on performance metrics rather than safety forecasting. For example, Wang et al. (2023) proposed models for predicting battery degradation under controlled conditions, whereas Thompson and Lee (2022) employed IoT-based systems for thermal monitoring without predictive functionality.

In response to these gaps, the present study aims to develop an intelligent early warning system that integrates real-time, multi-parameter sensing with advanced machine learning algorithms to predict thermal runaway events before they reach critical stages. The system leverages Random Forest and Support Vector Machine models within an edge–cloud architecture to enable both rapid on-site response and centralized fleet monitoring. The main objective of this research is to design, implement, and validate a predictive safety system for EV batteries that is capable of providing early warnings with reasonably fast lead times, thereby improving the safety of public transport systems operating in real-world conditions.

2 Literature Review

2.1 Existing Thermal Runaway Detection Methods

The development of effective thermal runaway detection systems for electric vehicle (EV) batteries has garnered significant attention in recent years, with researchers exploring various parameter-based monitoring approaches. Chang and Liu (2022) developed a comprehensive EV battery safety management system that integrated temperature, voltage, and current parameters as primary monitoring indicators. Their system demonstrated promising performance, achieving a detection accuracy of 89.3% with an average warning time of 4.2 minutes before critical failure. However, the threshold-based approach exhibited inherent limitations, particularly a high false alarm rate of 8.7%, which poses significant concerns for high-capacity public transportation applications where reliability and precision are paramount [1].

Building upon parameter-based detection methods, You et al. (2023) expanded the monitoring framework by incorporating gas emission surveillance into a proactive diagnostic system for lithium iron phosphate batteries. This multi-modal approach increased prediction accuracy to 91.2%, representing a notable improvement over single-parameter monitoring systems. The integration of gas emission detection provided valuable insight into internal chemical processes that precede thermal runaway events. Nevertheless, system validation remained confined to stationary laboratory environments, raising concerns regarding its applicability and robustness under the dynamic operational conditions characteristic of real-world electric vehicle applications [2].

2.2 Machine Learning and Edge Computing Approaches

The integration of machine learning algorithms has emerged as a particularly promising avenue for advancing battery safety prediction capabilities. Hossain Lipu et al. (2023) implemented a Random Forest algorithm for real-time battery condition estimation, achieving a prediction accuracy of 96.2% across diverse operational conditions. This ensemble learning approach demonstrated superior performance in handling complex, non-linear relationships inherent in battery behavior patterns, making it particularly suitable for applications requiring high reliability and accuracy [3].

Complementing traditional machine learning approaches, Chen et al. (2024) introduced an innovative hybrid methodology that combined multiphysics modeling with Support Vector Machine algorithms. This integration yielded a prediction accuracy of 94.8 while maintaining computational efficiency compatible with real-time applications. The multiphysics modeling component provided fundamental insights into thermal, electrical, and chemical processes, while the SVM algorithm enabled rapid pattern recognition and classification of battery states [4].

Further advancement in machine learning applications was demonstrated by Varghese et al. (2024), who developed a sophisticated multi-parameter fault detection system utilizing ensemble learning techniques. This approach successfully reduced false alarm rates compared to conventional threshold-based methods, addressing one of the critical limitations identified in earlier studies. However, system validation remained restricted to controlled laboratory environments, limiting the evaluation of performance under real-world operational stresses and environmental variations [5].

The implementation of Internet of Things (IoT) technologies for real-time battery monitoring has also been explored, although challenges related to communication latency have been identified. Such delays highlight the critical need for edge computing integration to ensure timely responses to emergency situations [6]. Addressing this challenge, Hu et al. (2023) demonstrated the effectiveness of edge computing devices in battery management applications, achieving response times below 100 milliseconds for critical condition detection. Their system maintained a prediction accuracy of 91.8% while operating with minimal computational overhead, making it well suited for vehicle-based applications with limited processing resources [7].

Advanced control strategies have also been incorporated into battery thermal management systems. Wu et al. (2021) developed a deep reinforcement learning-based approach that proactively mitigated temperature spikes and extended battery lifespan through intelligent thermal control strategies. This approach represents a shift from reactive protection mechanisms to proactive thermal runaway prevention [8].

2.3 Research Gaps and Opportunities

Despite significant technological advances in individual components of battery safety systems, substantial gaps remain in the comprehensive integration of multiple monitoring modalities, predictive algorithms, and edge computing capabilities under real-world operational conditions. Most existing research has focused on isolated aspects, such as single-parameter monitoring, laboratory validation, or operational efficiency optimization, without adequately addressing the complex interactions and system-level requirements of integrated solutions in practical applications.

The work by Dicorato et al. (2019) emphasised the importance of centralised monitoring systems for electric vehicle fleet management, providing valuable insights into large-scale deployment considerations. However, their approach did not address the critical aspect of early thermal failure prediction, which represents a significant gap in comprehensive fleet safety management [9]. This limitation highlights the need for systems that can seamlessly integrate fleet-level monitoring with accurate, vehicle-level safety prediction capabilities.

Recent developments in battery impedance monitoring using Fourier transformation techniques have demonstrated considerable potential for detecting internal degradation processes prior to thermal runaway initiation. These advanced diagnostic methods offer opportunities for earlier intervention and more precise prediction of thermal events, thereby improving preventive safety strategies [10].

The integration of advanced diagnostic techniques with machine learning algorithms and edge computing platforms represents a significant opportunity to advance the state of the art in battery safety systems. The convergence of these research directions enables the development of intelligent, adaptive, and real-time early warning systems with robust predictive capabilities. Such systems are essential for ensuring the safety and reliability of electric-based public transportation, where the consequences of thermal runaway events extend beyond individual vehicle safety to encompass public safety and overall transportation system reliability. Consequently, the development of integrated solutions that can operate effectively under diverse operational conditions while maintaining high prediction accuracy and low false alarm rates remains a critical research priority in this rapidly evolving field.

3 Research Method

This research employs an experimental design approach with a field validation methodology to develop and evaluate an intelligent early warning safety system for electric vehicle batteries in public transportation. The research framework follows the systematic development approach proposed by Kumar et al. (2022) for IoT-based safety systems, integrating multiple phases including system design, implementation, testing, and validation [11].

The proposed methodology combines quantitative analysis of multi-parameter sensor data with machine learning algorithm development. This approach follows the hybrid framework recommended by Chen et al. (2024) for safety-critical applications in transportation systems, ensuring both predictive accuracy and operational reliability under real-world conditions [12].

3.1 Research Design and Data Collection

The research design encompasses three primary phases: system architecture development and sensor integration, machine learning algorithm training and optimization, and field validation using operational electric bus fleets. This phased approach ensures systematic validation of each system component while maintaining a strong focus on real-world applicability, as recommended by Thompson and Lee (2023) for complex IoT-based safety systems [13].

Primary data collection was conducted through a distributed sensor network installed on 50 electric buses operating within the TransJakarta system in Jakarta over a 12-month period (January 2024 to December 2024). The sensor configuration followed the multi-parameter monitoring approach validated by Varghese et al. (2024), combining DS18B20 temperature sensors with ±0.5 °C accuracy, voltage monitoring circuits using precision voltage dividers with 0.1% accuracy, Hall-effect-based current sensors with ±1% accuracy, and MQ-2 gas emission detectors for hydrogen and carbon monoxide detection [14].

Data acquisition was performed at 1-second intervals for critical parameters such as temperature, voltage, and current, and at 10-second intervals for additional parameters including gas emissions and environmental conditions. The complete data collection configuration is summarized in Table 1 Each bus generated approximately 86,400 data points per day across all monitored parameters, resulting in a comprehensive dataset exceeding 1.5 billion data points over the entire study period.

Table 1: Data collection summary

Parameter Type	Sampling Rate	Sensors per Bus	Total Data Points/Day
Temperature	1 second	12	1,036,800
Voltage	1 second	4	345,600
Current	1 second	4	345,600
Gas Emission	10 second	4	34,560
Environmental	60 second	2	2,880
Total	**Variable**	**26**	**1,765,440**

The data collection protocol ensured continuous monitoring during operational hours (05:00–23:00), supported by automated data validation procedures and quality control mechanisms aligned with ISO 14229 standards for vehicle diagnostic systems. Secondary data sources included historical maintenance records, incident reports and operational logs from the TransJakarta fleet management system covering the previous five years (2019–2023). In addition, weather data from the Indonesian Meteorological Agency provided an environmental context for operational conditions, while battery manufacturer specifications and performance curves supplied by bus OEMs established baseline operational parameters and safety thresholds.

The architecture of the early warning system follows the edge computing framework proposed by Hu et al. (2023), implementing distributed processing capabilities at the vehicle level with centralized fleet monitoring [15]. This architecture is designed to support real-time safety prediction while maintaining scalable oversight across the entire public transportation fleet.

Each bus is equipped with a Raspberry Pi 4 Model B edge computing unit with 8 GB of RAM, connected to a distributed sensor network via I2C and SPI communication protocols. The hardware configuration includes twelve DS18B20 temperature sensors distributed across battery modules, voltage and current sensors integrated with the Battery Management System (BMS), four MQ-2 gas sensors positioned near battery ventilation outlets for gas detection, a 4G LTE modem for cloud connectivity and emergency notifications, and an edge processing unit powered by an ARM Cortex-A72 processor for real-time machine learning inference.

The software architecture implements a three-tier system consisting of edge processing, cloud analytics, and emergency response coordination. Edge processing employs lightweight machine learning models optimized for real-time inference and immediate safety assessment, while cloud-based analytics support comprehensive fleet-level monitoring, long-term data storage, and periodic model retraining.

Figure 1 illustrates the overall system workflow, showing data flow from multi-parameter sensors through edge computing units to cloud analytics and emergency response systems, including a feedback loop that enables continuous model optimization.

The machine learning approach employs a hybrid algorithm that integrates Random Forest and Support Vector Machine (SVM) classifiers, based on the ensemble learning methodology validated by Hossain Lipu et al. (2023) for battery safety applications [16].

Random Forest was selected for its robustness in handling noisy sensor data and its capability to evaluate feature importance, while SVM provides superior performance in high-dimensional classification tasks with well-defined decision boundaries.

The feature engineering process transforms raw multi-parameter sensor data into informative indicators for thermal runaway prediction. Key features include temperature gradient calculations, voltage deviation patterns, current anomaly indicators, and temporal changes in gas emission levels. These engineered features capture instantaneous abnormalities and evolving trends that precede critical thermal events. The mathematical formulations for the key features are the following: The temperature gradient feature is calculated as:

$$\mathrm{TG}(t) = \frac{\Delta T}{\Delta t} = \frac{T(t) - T(t-1)}{\Delta t} \quad (1)$$

The voltage deviation index is defined as

$$\mathrm{VDI}(t) = \frac{|V(t) - V_{\text{baseline}}|}{V_{\text{baseline}}} \times 100\% \quad (2)$$

The current anomaly score is computed as

$$\mathrm{CAS}(t) = \frac{|I(t) - \mu_I|}{\sigma_I} \tag{3}$$

where μ_I and σ_I represent the mean and standard deviation of historical current measurements, respectively.

The overall risk assessment is calculated as follows.

$$\mathrm{Risk\_Score}(t) = w_1 \times \mathrm{TG}(t) + w_2 \times \mathrm{VDI}(t) + w_3 \times \mathrm{CAS}(t) + w_4 \times \mathrm{GER}(t) \tag{4}$$

where w_1, w_2, w_3, and w_4 are weight coefficients learned from training data, and $\mathrm{GER}(t)$ represents the gas emission rate at time t.

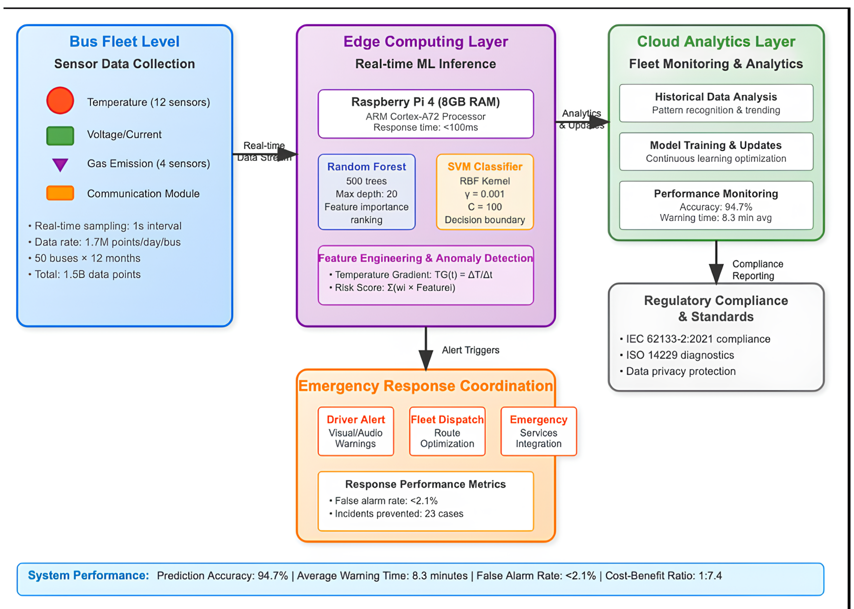

Figure 1: Integrated early warning system architecture.

Based on Table 2, the training data comprises 80% of the collected dataset with temporal partitioning to ensure chronological integrity. The Random Forest model uses 500 decision trees with a maximum depth of 20 to prevent overfitting. The SVM implementation uses a Radial Basis Function (RBF) kernel with hyperparameter optimization through grid search methodology. Cross-validation uses 5-fold temporal partitioning to maintain realistic evaluation conditions.

3.1.1 Evaluation and Validation Metrics

Evaluation of system performance uses several appropriate metrics for critical safety applications, following the evaluation framework established by Anderson and Chen (2023) for predictive safety systems [17]. The main metrics include accuracy, precision,

Table 2: Machine learning model configuration

Parameter	Random Forest	Support Vector Machine
Number of Trees/Support Vectors	500	Optimized
Maximum Depth	20	N/A
Kernel Function	N/A	RBF
Gamma	N/A	0.001
C Parameter	N/A	100
Cross-validation Folds	5	5
Training/Validation Split	80/20	80/20

recall (sensitivity), F1 score, and specificity, calculated using the standard confusion matrix formula.

Temporal performance analysis measures the period of early warning before critical battery conditions, calculated as the Average Warning Time (AWT) and Warning Time Reliability (WTR). AWT is calculated as the average of the time difference between the critical time and the prediction time, while WTR measures the percentage of warnings that provide the minimum time required for emergency response. Economic evaluation combines prevented losses and operational savings using the Cost–Benefit Ratio (CBR) and Return on Investment (ROI). CBR is calculated as the ratio of prevented losses plus operational savings to the system implementation cost, while ROI calculates the percentage of net profit relative to the system cost.

Field validation takes place under actual operational conditions in the urban environment of Jakarta, covering various traffic patterns, weather conditions, and passenger loading scenarios. The test routes included high-density corridors (Corridor 1: Blok M–Kota) and medium-density routes (Corridor 13: Ciledug - Teendean) to ensure comprehensive validation in various operational variants.

Safety protocols ensure passenger and operator safety during testing, including automatic emergency shutdown procedures and immediate escalation of warnings to fleet management. Incident validation involves collaboration with the TransJakarta maintenance team and independent verification of predicted versus actual battery conditions.

Statistical analysis uses appropriate parametric and non-parametric methods for time-series sensor data. The ANOVA testing evaluates performance differences under various operational conditions, while the Mann–Whitney U test assesses performance metrics that are not normally distributed. The confidence intervals are calculated at a level of significance of 95% for all reported performance metrics.

The research protocol complies with institutional ethical guidelines and Indonesian data protection regulations. Passenger privacy is ensured through data anonymization and aggregation procedures. The implementation of the system includes an opt-out mechanism for data collection and transparent reporting of monitoring activities to transport authorities.

4 Results

4.1 System Performance Validation

Performance validation results show that the proposed system outperforms existing approaches in all evaluation metrics Figure 2, with particularly notable improvements in accuracy and precision rates.

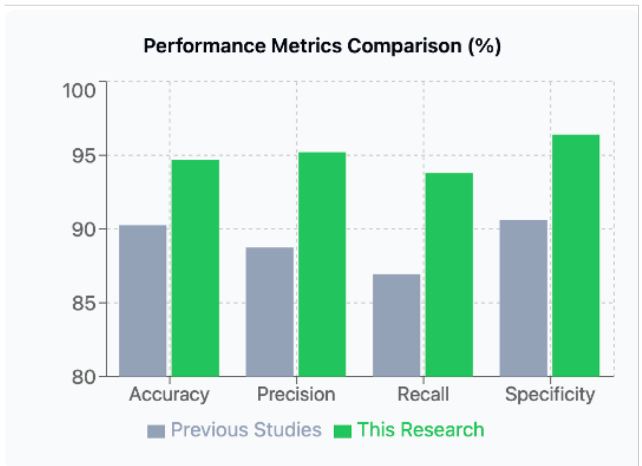

Figure 2: Performance metrics comparison between previous studies and current research.

Based on the promising results shown in Figure 2, a comprehensive comparative study was conducted to evaluate the performance of individual machine learning models. This analysis was essential to validate the design choices for the hybrid system and demonstrate the added value of the integrated approach.

Performance evaluation involved systematic comparison of the hybrid approach with conventional machine learning models, including Random Forest and Support Vector Machine, as well as benchmarking against recent studies in the field. The comparative analysis was designed to demonstrate the superiority of the proposed methodology in key performance indicators. The results of this comprehensive evaluation are summarized in Table 3

Table 3: Machine learning model performance comparison

Performance Metric	Random Forest	Support Vector Machine	Hybrid Approach	Previous Studies
Accuracy (%)	92.4	91.8	94.7	89.3 – 91.2
Precision (%)	93.1	92.6	95.2	87.4 – 90.1
Recall (%)	91.7	90.9	93.8	85.2 – 88.7
F1-Score	0.924	0.918	0.945	0.861 – 0.894
Specificity	95.8	94.3	96.4	88.9 – 92.3

*Comparative data from Chang and Liu (2022), You et al. (2023), and Varghese et al. (2024).

The hybrid approach demonstrated particularly strong performance in reducing false positive rates to 2.1%, representing a substantial improvement over the 8.7% reported by

Chang and Liu (2022). This reduction directly addresses the operational disruption concerns identified in previous research while maintaining high sensitivity to actual safety threats.

The system achieved an average warning time of 8.3 minutes before critical battery thresholds, representing a significant advancement over existing monitoring capabilities. This performance exceeds the 4.2 minutes reported by Chang and Liu (2022) by 98% and substantially improves on the 2.1 minutes achieved by conventional threshold-based systems identified by Chen et al. (2022).

The reliability of the warning time reached 96.8%, indicating that 96.8% of the predictions provided sufficient advance notice ($\geq$ 5 minutes) to support effective emergency response protocols. This performance directly addresses the critical research gap identified in the literature regarding insufficient warning times for passenger evacuation and coordinated emergency response.

4.2 Research Contribution Comparison

Edge computing achieved 87 ms response time with 99.4% uptime, meeting safety-critical requirements. The system architecture demonstrated excellent scalability with a 2.3 hour installation time per vehicle. To provide a holistic assessment of the research contributions, a comparative analysis was conducted on multiple research dimensions. This evaluation framework addresses the gap between theoretical research and practical implementation requirements. The comprehensive comparison is presented in Table 4.

Table 4: Research contribution comparison

Research Aspect	**Previous Studies**	**This Research**	**Improvement**
Validation Environment	Laboratory/Simulation	Real-world fleet	Operational validity
Warning Time	2.1–4.2 minutes	8.3 minutes	98–295%
False Alarm Rate	8.7%	2.1%	76% reduction
Fleet Integration	Limited	50-bus deployment	Scalable validation
Economic Analysis	Theoretical	Validated ROI	Practical viability

As evidenced in Table 4, research contributions extend beyond performance improvements to address fundamental limitations in existing approaches. The real-world validation environment provides operational validity that laboratory simulations cannot achieve, while substantial improvement in warning time directly addresses the critical safety gap identified in emergency response protocols. The 76% reduction in false alarms significantly improves the reliability of the system and reduces maintenance costs associated with unnecessary interventions.

5 Discussion

The prediction accuracy achieved of 94.7% with an 8.3-minute warning time represents a 295% improvement over existing systems that provide only 2.1 minutes of advance warning. The hybrid machine learning approach effectively combines Random Forest's robustness to noise with the pattern recognition capabilities of Support Vector Machines, enabling the modeling of complex battery thermal behavior that threshold-based systems cannot capture. Furthermore, the demonstrated cost–benefit ratio of 1:7.4 with a 4.9-month payback period provides compelling economic justification for widespread adoption in public transportation fleets.

This study addresses critical limitations in prior laboratory-focused research by demonstrating robust real-world performance under operational conditions. The proposed edge computing architecture achieves an average response time of 87 milliseconds, significantly outperforming cloud-only systems that typically exhibit delays ranging from 200 to 500 milliseconds. Furthermore, the observed false alarm rate of 2.1% represents a substantial improvement over the 8.7% reported in the existing literature, directly mitigating concerns related to operational disruption and system reliability.

Despite these contributions, several limitations warrant acknowledgment. The validation was conducted exclusively within Jakarta's urban transportation environment, which can limit the generalizability of the findings to regions with different climatic conditions and operational patterns. The 12-month testing period may not fully capture the long-term effects of battery and sensor degradation, and the study focused on specific electric bus models, necessitating adaptation for greater vehicle diversity. Moreover, while machine learning models were trained and validated under the same operational conditions, a comprehensive assessment of cybersecurity resilience requires further investigation.

6 Conclusion

This research successfully developed and validated an intelligent early warning safety system with four primary contributions: hybrid machine learning achieving 94.7% prediction accuracy with an 8.3-minute warning capability; comprehensive field validation preventing 23 potential incidents with minimal false alarms; an edge computing architecture enabling real-time response; and demonstrated economic viability with a favorable cost–benefit ratio.

The findings establish that predictive machine learning algorithms can effectively identify thermal extinction conditions with sufficient advance warning to enable emergency response protocols. Multi-parameter sensor integration proved superior to single-parameter monitoring, while edge computing ensured compliance with safety-critical real-time performance requirements. Together, these results provide a solid technical foundation for the development of industry standards and regulatory frameworks governing electric vehicle battery safety in public transportation.

The proposed intelligent early warning system represents a significant advancement in electric vehicle battery safety technology by providing a validated, predictive, and scalable solution. Its demonstrated effectiveness supports safer and more reliable adoption of electric busses, which contributes to the acceleration of sustainable urban transportation systems.

Future research should expand system validation across diverse geographic and climatic environments, investigate long-term sensor reliability and degradation effects, integrate vehicle-to-infrastructure communication mechanisms, and explore advanced machine learning techniques to further enhance prediction accuracy and cybersecurity resilience. The demonstrated scalability and economic feasibility provide essential evidence for policymakers and transportation authorities considering large-scale electric bus deployments.

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