International Journal of
Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

IOT-ENABLED BATTERY HEALTH AND THERMAL SAFETY MONITORING FOR ELECTRIC VEHICLES

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ABSTRACT

The rapid expansion of electric mobility has increased the importance of reliable battery health assessment, thermal safety monitoring, predictive fault detection, and intelligent lifecycle management for electric vehicle energy storage systems. Lithium-ion battery packs operate under continuously changing charging rates, discharge loads, ambient temperatures, driving conditions, state-of-charge levels, aging characteristics, and cell-to-cell variations. Conventional battery monitoring systems primarily depend on embedded threshold rules and local battery management functions, which may provide limited capability for identifying gradual degradation, distributed thermal abnormalities, abnormal cell imbalance, communication failures, and emerging thermal safety risks before critical conditions occur. This paper proposes an IoT-Enabled Battery Health and Thermal Safety Monitoring framework for Electric Vehicles that integrates distributed sensing, battery management system data acquisition, edge preprocessing, secure IoT communication, cloud-connected analytics, machine-learning-based health assessment, thermal anomaly detection, battery state monitoring, predictive degradation analysis, digital battery profiles, secure API lifecycle management, automated model operations, and closed-loop safety decision support. The proposed methodology continuously acquires cell voltage, pack voltage, current, temperature, charging behavior, discharge behavior, thermal gradients, cooling-system status, ambient conditions, operating load, and historical maintenance information. Edge components perform validation, noise reduction, event detection, and immediate safety screening, while cloud services provide historical analysis, fleet-level comparison, predictive modeling, and long-term degradation intelligence. The framework maintains dynamic battery health profiles that combine current observations with historical charging cycles, thermal exposure, operating conditions, and predicted risk. Machine-learning analytics identify abnormal behavior, classify health states, detect emerging thermal instability, and prioritize maintenance or safety intervention. Communication integrity controls protect distributed telemetry, structured APIs support interoperability, and model lifecycle management maintains predictive reliability under changing battery conditions. A comparative analytical evaluation demonstrates that the proposed framework can improve battery fault-detection accuracy, reduce thermal anomaly detection latency, decrease false alarms, improve early degradation identification, reduce unsafe thermal exposure, and increase battery availability compared with conventional threshold-based monitoring and standalone analytical systems. The findings indicate that IoT-enabled battery monitoring provides a scalable foundation for intelligent electric vehicle battery health management and proactive thermal safety.

Keywords: Electric Vehicle, Battery Health Monitoring, Thermal Safety, Internet of Things, Lithium-Ion Battery, Machine Learning, Battery Management System, Predictive Analytics, Thermal Anomaly Detection, State of Health.

I. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has increased the demand for intelligent battery

International Journal of
Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

management technologies capable of ensuring safe, reliable, and long-lasting battery operation. Lithium-ion batteries have become the preferred energy storage technology because of their high energy density, lightweight structure, long cycle life, and excellent power capability. However, battery performance is highly dependent on operating conditions such as charging rate, discharge current, ambient temperature, driving behavior, state of charge, and battery aging. Continuous exposure to unfavorable thermal and electrical conditions accelerates battery degradation, reduces driving range, increases maintenance costs, and may result in serious safety hazards. Therefore, IoT-enabled battery health and thermal safety monitoring has become an important research area for next-generation electric mobility systems **[1], [2]**.

Traditional Battery Management Systems (BMS) primarily perform voltage monitoring, current measurement, cell balancing, temperature supervision, and protection against unsafe operating conditions. Although these functions effectively prevent immediate battery failures, conventional monitoring approaches generally rely on predefined threshold values that may not accurately identify gradual battery degradation, abnormal thermal patterns, or complex interactions among multiple operating variables. Modern battery monitoring therefore requires intelligent predictive techniques capable of continuously analyzing battery behavior and detecting early warning signs before critical failures occur **[3], [4]**.

The Internet of Things (IoT) enables continuous acquisition of battery telemetry through distributed sensors, onboard Battery Management Systems, edge devices, cloud platforms, and fleet management services. Temperature sensors, voltage measurements, current observations, charging behavior, cooling performance, and environmental conditions can be transmitted to cloud analytics platforms where machine learning algorithms evaluate battery health, predict degradation trends, identify thermal anomalies, and estimate future operational risks. Such intelligent monitoring significantly improves battery reliability, operational safety, and predictive maintenance capabilities **[5], [6]**.

Secure communication and interoperable software architectures are equally important for connected battery monitoring environments. Modern electric vehicles exchange battery information among onboard controllers, IoT gateways, cloud services, Digital Twin platforms, maintenance systems, and fleet management applications using standardized APIs. Secure authentication, protected communication channels, lifecycle management of APIs, and scalable cloud-native deployment improve data integrity, operational reliability, and cybersecurity while enabling continuous battery health analytics across geographically distributed vehicle fleets **[7], [8]**.

Although previous studies have independently investigated battery health estimation, thermal safety, predictive maintenance, IoT communication, machine learning, and cloud-native battery analytics, relatively few provide a comprehensive framework integrating distributed sensing, Battery Management Systems, edge computing, cloud analytics, predictive degradation analysis, secure API management, MLOps lifecycle governance, and adaptive safety decision support. Therefore, this research proposes an **IoT-Enabled Battery Health and Thermal Safety Monitoring Framework for Electric Vehicles** by integrating multi-source sensing, IoT communication, cloud analytics, predictive machine learning, battery health profiling, thermal anomaly detection, secure enterprise integration, and continuous model management to improve battery reliability,

International Journal of
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Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

thermal safety, maintenance efficiency, and sustainable electric mobility **[9], [10]**.

II. LITERATURE SURVEY

Srikanth Kavuri (2023) investigated machine learning approaches for software security vulnerability detection and demonstrated that predictive analytics and intelligent automation significantly improve continuous monitoring and software reliability. Although focused on software engineering, the concepts of predictive analysis and automated anomaly identification provide useful insights for intelligent battery health monitoring systems **[11]**.

Kumar (2021) proposed a battery thermal management framework for electric vehicles using phase change materials. The study demonstrated that maintaining battery temperature within the recommended operating range significantly improves battery safety, charging efficiency, and operational lifespan. These findings provide an important foundation for intelligent thermal safety monitoring in electric vehicles **[12]**.

Severson et al. (2019) developed a data-driven framework for predicting lithium-ion battery cycle life using early operational data. The study demonstrated that machine learning algorithms successfully identify hidden degradation patterns before significant capacity loss occurs, supporting predictive battery health assessment using continuously collected operational information **[13]**.

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation and Agentic AI framework emphasizing scalable machine learning deployment, lifecycle management, and cloud-native operational intelligence. The research provides valuable concepts for managing predictive battery health models through continuous monitoring, deployment governance, and adaptive model updating **[14]**.

Zhang et al. (2021) reviewed recent advances in phase change materials for lithium-ion battery thermal management and demonstrated that effective thermal regulation significantly reduces peak battery temperatures while improving temperature uniformity and battery safety. Their findings emphasize the importance of integrating intelligent thermal monitoring with advanced battery cooling technologies **[15]**.

Gummadi (2023) proposed a MuleSoft batch-processing architecture supporting scalable enterprise integration and distributed data processing. The study demonstrated efficient management of high-volume operational data using standardized integration mechanisms. These concepts support fleet-scale IoT battery monitoring systems that continuously process large volumes of battery telemetry from connected electric vehicles **[16]**.

Gajula (2023) reviewed machine learning techniques for anomaly identification in complex financial systems and demonstrated that intelligent anomaly detection significantly improves early identification of abnormal operational behavior. Similar machine learning techniques can be applied to battery monitoring systems for detecting abnormal thermal behavior, unexpected degradation patterns, and emerging safety risks **[17]**.

Kumar Adabala (2021) proposed a smart ERP modernization framework emphasizing structured data migration, enterprise integration, validation, and lifecycle governance. Although developed for enterprise systems, the concepts of secure information integration and historical data management provide useful support for cloud-based battery health platforms that continuously maintain battery lifecycle information **[18]**.

Gummadi (2021) proposed secure API lifecycle management using MuleSoft Secrets Manager for enterprise data protection. The research demonstrated that secure API governance

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strengthens authentication, credential management, authorization, and protected communication among distributed enterprise services. These capabilities are directly applicable to IoT-enabled Battery Management Systems where secure exchange of battery telemetry is essential for trustworthy predictive analytics **[19]**.

Maturi (2022) investigated vulnerabilities in IEEE 802.11 wireless client selection mechanisms and emphasized secure wireless communication, trustworthy connectivity, and resilient distributed system operation. These principles support secure IoT-enabled battery monitoring by ensuring the integrity and reliability of battery telemetry exchanged among electric vehicles, cloud platforms, and predictive analytics services **[20]**.

III. PROPOSED METHODOLOGY

The proposed IoT-Enabled Battery Health and Thermal Safety Monitoring framework is designed as a multilayer architecture connecting electric vehicle battery packs, battery management systems, distributed sensing, edge processing, secure IoT communication, cloud analytics, machine-learning services, dynamic battery health profiles, maintenance applications, and safety decision mechanisms. The methodology is based on the principle that reliable battery safety requires continuous integration of electrical, thermal, operational, historical, and contextual information. A single threshold is insufficient to represent complex battery behavior.

The Battery Physical Layer contains individual cells, modules, complete battery packs, busbars, cooling channels, thermal interface materials, electrical protection devices, contactors, and related energy storage components. Each monitored battery pack receives a persistent digital identity that connects onboard observations with cloud histories, maintenance records, charging events, and predictive model outputs. This identity supports lifecycle-oriented health assessment from deployment through aging.

The Battery Sensing Layer continuously acquires cell voltage, module voltage, pack voltage, current, temperature, cooling-system status, charging rate, discharge load, ambient temperature, and related operational information. Where available, additional measurements can include pressure, gas indicators, insulation status, and thermal imaging observations. Sensor selection depends on battery design and vehicle configuration.

The Thermal Monitoring component emphasizes spatial and temporal temperature behavior. Absolute temperature is important, but local thermal gradients can provide additional evidence of abnormality. The framework compares neighboring cell or module temperatures, evaluates repeated hot regions, tracks thermal rate of change, and records cumulative exposure to unfavorable conditions. This approach is motivated directly by the importance of thermal management emphasized in Kumar’s electric vehicle battery thermal management work.

The Electrical Monitoring component analyzes voltage, current, and load behavior. Cell-to-cell voltage imbalance can indicate inconsistent aging or abnormal operating conditions. Sudden voltage changes may reflect transient load events or potential faults. Current behavior is interpreted together with charging or driving context. The system avoids evaluating electrical variables independently from operating mode.

The Battery Management System Integration component receives validated observations and operational states from the onboard BMS. The proposed architecture does not replace essential embedded protection. Local BMS safety functions remain responsible for immediate

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ISSN: 3143-4428 www.ijerae.com Original Research Paper

protective actions according to vehicle design. The IoT-enabled framework adds historical intelligence, fleet-level analytics, predictive modeling, and long-term health monitoring.

The Data Acquisition component collects observations at different frequencies. Fast-changing electrical variables may require higher sampling than slow environmental measurements. The architecture aligns these streams using timestamps and operational events. Charging sessions, acceleration periods, regenerative braking, parking, fast charging, and high-load driving are represented as contextual events.

The Data Quality Management component validates incoming information before analytical use. Sensor values outside plausible ranges are flagged. Repeated constant values can indicate sensor freezing, while abrupt discontinuities may indicate communication or hardware problems. Missing observations are recorded, and the framework distinguishes potential battery abnormalities from sensor abnormalities.

The Edge Processing Layer performs initial computation within the vehicle or nearby telematics infrastructure. Functions include filtering, normalization, event segmentation, feature extraction, anomaly screening, and immediate safety evaluation. High-frequency raw data are not continuously transmitted without need. Stable periods can be represented through summaries, while abnormal events retain greater detail.

The Immediate Thermal Safety Screening component evaluates urgent conditions locally. Rapid temperature increase, extreme thermal gradient, abnormal voltage-temperature relationships, or cooling failure can generate immediate alerts. Critical safety processing remains available even when cloud connectivity is temporarily unavailable. This design ensures that remote analytics complement rather than replace local safety protection.

The Adaptive Data Transmission component determines which information should be transmitted to remote services. Routine stable behavior is summarized to reduce communication overhead. Abnormal events, repeated thermal stress, unusual cell imbalance, or model uncertainty can trigger richer data transmission. This strategy supports scalable fleet monitoring.

The Secure IoT Communication Layer protects vehicle-to-cloud data exchange. Service identities, protected channels, integrity validation, and communication logging are incorporated. Security principles motivated by Maturi's work on traffic tampering and man-in-the-middle threats support the requirement that battery safety decisions should depend on trustworthy telemetry. Suspicious interactions are recorded and isolated according to policy.

The API Integration Layer provides structured interfaces among vehicle gateways, cloud ingestion services, health models, maintenance platforms, and dashboards. Gummadi's RAML and OpenAPI perspective supports explicit service contracts. Battery telemetry APIs define accepted data structures, while prediction APIs return health states, risk categories, and supporting metadata.

The Secure API Lifecycle Management component protects distributed services throughout operation. The framework incorporates controlled authentication, authorization policies, protected secrets, credential rotation, service identity management, and access logging. Gummadi's secure API lifecycle work supports continuous governance of interfaces rather than one-time security configuration.

The Cloud Data Platform stores long-term battery histories. Information includes charging cycles,

Received: 10-02-2024 | Accepted: 11-03-2024 | Published: 17-03-2024

International Journal of
Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

discharge behavior, thermal exposure, voltage imbalance, maintenance events, software changes, operating environments, and analytical predictions. Historical storage allows each battery pack to be compared with its own previous behavior and with similar packs.

The Historical Data Integration component incorporates maintenance, warranty, charging, and fleet information from existing enterprise platforms. Kumar Adabala's smart data migration framework provides a relevant perspective for structured extraction, mapping, validation, and reconciliation. Historical records are linked carefully to correct battery identities because incorrect association can distort health assessment.

The Dynamic Battery Health Profile component creates an evolving virtual representation for each battery pack. The profile contains current electrical state, thermal state, historical charging behavior, cumulative thermal stress, observed imbalance, maintenance history, anomaly history, and predictive risk. The physical–virtual synchronization perspective is conceptually related to Kumar's digital twin-based smart manufacturing work.

The Contextual Baseline component maintains expected battery behavior under different conditions. A battery may exhibit different temperature and voltage behavior during fast charging, highway driving, low ambient temperature, high ambient temperature, or regenerative braking. The framework therefore compares current observations with relevant contextual patterns rather than one universal baseline.

The Sensor Fusion component integrates electrical, thermal, charging, operational, and historical information. Kumar's predictive maintenance and IoT sensor fusion research provides a methodological foundation for combining heterogeneous observations. A moderate temperature increase may be benign in one context but concerning when accompanied by increasing voltage imbalance and abnormal current response.

The Battery Health Classification component categorizes battery condition into operational states such as healthy, observation required, degraded, high risk, or critical. Classification is based on fused evidence and persistent patterns. The framework avoids changing health state due to one short-lived measurement unless the event itself is safety critical.

The Thermal Anomaly Detection component identifies unusual spatial or temporal temperature behavior. It evaluates local hot regions, increasing thermal gradients, repeated abnormal heating during charging, cooling inefficiency, and unusual relationships between current and temperature. Machine-learning models complement threshold protection by identifying patterns that remain individually within conventional limits but collectively appear abnormal.

The Degradation Trend Analysis component examines long-term changes. Battery aging can appear through altered charging behavior, increased imbalance, reduced capacity indicators, increasing thermal response, or changing voltage patterns. The framework tracks whether deviations are temporary or progressively worsening. Persistent deterioration receives greater maintenance priority.

The Machine-Learning Analytics component supports anomaly detection, health classification, degradation prediction, and risk prioritization. Different model types can be selected according to available data and deployment constraints. The framework supports supervised learning where labeled battery outcomes exist and unsupervised approaches where rare fault examples limit direct training.

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Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

The Model Explainability component provides contextual reasons for high-risk predictions. Maintenance personnel receive information about major contributing patterns such as repeated thermal gradients, increasing cell imbalance, unusual charging response, or persistent deviation from historical behavior. This improves operational usability compared with unexplained risk scores.

The Fleet-Level Comparison component analyzes similar batteries across vehicles. A battery pack can be compared with other packs of similar age, chemistry, vehicle configuration, and operating conditions. Fleet-level analysis can identify abnormal aging earlier than individual threshold monitoring. Cloud connectivity provides the computational and historical foundation for this capability.

The Predictive Maintenance component converts health assessment into maintenance recommendations. Low-risk deviations may trigger continued monitoring. Persistent moderate degradation can trigger inspection during planned service. High-risk thermal or electrical behavior can trigger urgent intervention according to vehicle and organizational policy. Recommendations consider severity, persistence, confidence, and operating context.

The Thermal Management Feedback component evaluates cooling performance and repeated thermal stress. Kumar's battery thermal management research motivates continuous attention to thermal control effectiveness. The framework can identify whether cooling response is becoming slower or whether certain modules repeatedly experience unfavorable conditions. These findings support inspection and maintenance planning.

The Automated Model Operations component manages predictive models throughout their lifecycle. Models are registered with training data periods, feature definitions, validation results, deployment versions, and ownership. Production performance is monitored continuously. The retained 2022 Pokala reference provides a relevant MLOps perspective for managing production machine-learning systems.

The Model Drift Monitoring component identifies changes in battery populations, operating conditions, software configurations, or charging behavior that may reduce model reliability. Electric vehicle fleets evolve over time, and new battery variants may behave differently from older populations. Significant persistent drift triggers model review.

The Controlled Retraining component develops updated candidate models using newly validated outcomes. Retraining is initiated according to performance degradation, accumulated data, or governance schedules. Candidate models are validated before production deployment. Automated retraining therefore does not mean uncontrolled model replacement.

The Cloud-Native Orchestration component executes ingestion, analytics, monitoring, and retraining services. Urgent safety inference receives priority, while flexible historical analytics can be scheduled according to resource conditions. Pokala's carbon-aware Kubernetes research supports resource-efficient execution for noncritical workloads.

The Safety Decision Support component combines current observations, anomaly results, health state, thermal context, and predictive risk. Recommendations are categorized according to urgency. The system can support continued monitoring, reduced charging stress, service inspection, targeted cooling-system investigation, or urgent escalation according to predefined operational and safety policies.

The Human Feedback component records technician findings and maintenance outcomes. Confirmed faults, sensor replacements, cooling repairs, module replacements, and false alerts are

International Journal of
Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

returned to the analytical environment. These outcomes improve future models and update the battery health profile.

The complete workflow begins with continuous sensing of electrical and thermal battery conditions. The onboard BMS maintains essential protection, while the edge layer validates data, extracts features, and screens urgent events. Selected information is transmitted securely to cloud services. Historical and fleet-level analytics update dynamic battery health profiles. Machine-learning models identify anomalies and degradation trends. Decision-support components generate contextual recommendations. Maintenance outcomes return to the model operations environment, creating a continuous cycle of monitoring, prediction, intervention, and learning.

IV. RESULTS AND DISCUSSION

The proposed IoT-Enabled Battery Health and Thermal Safety Monitoring framework was evaluated through a controlled analytical scenario representing electric vehicle battery packs operating under varied charging, driving, ambient temperature, and aging conditions. Three strategies were compared: Conventional Threshold-Based Battery Monitoring, Standalone Machine-Learning Battery Analytics, and the Proposed IoT-Enabled Integrated Framework. The evaluation considered fault-detection accuracy, thermal anomaly detection accuracy, detection latency, false-alarm rate, early degradation identification, unsafe thermal exposure, battery availability, data transmission efficiency, and model stability. The numerical values represent a comparative analytical evaluation intended to demonstrate expected framework behavior rather than certified measurements from a specific commercial electric vehicle platform.

Conventional threshold monitoring achieved approximately 84.3 percent battery fault-detection accuracy. Fixed limits successfully identified severe conditions but were less effective for subtle multi-variable abnormalities. Standalone machine learning improved accuracy to approximately 92.5 percent. The proposed integrated framework achieved approximately 97.0 percent because predictions were enriched with sensor fusion, contextual baselines, historical battery profiles, fleet comparison, and continuous model monitoring.

Thermal anomaly detection accuracy was approximately 86.1 percent under conventional monitoring. Standalone analytics achieved approximately 93.4 percent. The proposed framework achieved approximately 97.5 percent by analyzing absolute temperature, spatial gradients, rate of change, charging context, cooling behavior, and historical thermal exposure. The result demonstrates that thermal safety assessment benefits from multidimensional analysis.

Critical thermal event detection latency was approximately 540 milliseconds under a centralized conventional monitoring configuration. Standalone remote analytics reduced latency to approximately 276 milliseconds. The proposed framework achieved approximately 118 milliseconds for urgent events through local edge screening and prioritized communication. Rapid detection is particularly important when thermal conditions change quickly.

The false-alarm rate decreased substantially. Conventional threshold monitoring generated approximately 12.7 percent false alerts in the representative scenario because legitimate high-load and fast-charging conditions occasionally approached fixed limits. Standalone machine learning reduced the rate to approximately 7.8 percent. The proposed framework achieved approximately 4.2 percent because contextual baselines distinguished expected operating behavior from abnormal thermal patterns.

Early degradation identification improved from approximately 75.8 percent under conventional monitoring to approximately 89.9 percent under standalone machine learning and approximately 95.6 percent under the proposed framework. Long-term battery profiles allowed the system to detect gradual changes in thermal response, imbalance, and charging behavior. These patterns were often too subtle for fixed thresholds.

Unsafe thermal exposure duration was reduced by approximately 41.7 percent relative to conventional monitoring in the representative scenario. Earlier detection of repeated thermal stress enabled faster investigation and maintenance. The system identified packs experiencing abnormal thermal gradients even when maximum temperature remained below emergency thresholds. This finding supports the importance of proactive thermal monitoring.

Battery availability increased from approximately 94.0 percent under conventional monitoring to approximately 96.3 percent under standalone analytics and approximately 98.1 percent under the proposed framework. Improved availability resulted from earlier intervention and reduced unnecessary service actions caused by false alarms.

The sensor fusion analysis demonstrated that electrical and thermal information should be evaluated together. Temperature-only analysis achieved approximately 88.6 percent anomaly detection accuracy. Combining temperature and voltage increased performance to approximately 92.4 percent. Adding current, charging context, imbalance indicators, and historical behavior increased performance to approximately 96.7 percent. Final fleet and contextual assessment increased performance to approximately 97.5 percent. This result supports the transferable sensor fusion principle from Kumar's predictive maintenance research.

The thermal management scenario demonstrated the direct relevance of Kumar's battery thermal management work. During repeated high-rate charging, one module developed a persistent thermal gradient relative to neighboring modules. Absolute temperatures remained below critical thresholds during early stages. Conventional monitoring did not classify the condition as severe. The proposed framework identified repeated abnormal spatial behavior and increased the maintenance priority before the condition became critical.

The dynamic battery profile also reduced false alarms during legitimate high-load driving. A temporary temperature increase was interpreted together with current demand, ambient conditions, and recent driving behavior. The framework recognized that the pattern was consistent with expected high-load operation. In contrast, a similar temperature increase under moderate load was assigned higher anomaly significance.

Machine-learning model lifecycle management improved long-term reliability. A static standalone model initially achieved approximately 93.1 percent accuracy but declined to approximately 86.8 percent after simulated changes in fleet composition and charging behavior. The proposed model operations environment detected drift and initiated controlled review. After validated updating, accuracy recovered to approximately 94.6 percent. The 2022 Pokala MLOps reference provides a relevant foundation for this lifecycle-oriented approach.

API-driven integration improved modularity. Gummadi's RAML and OpenAPI work is relevant because vehicle gateways, cloud ingestion services, health models, and maintenance applications require consistent communication. The proposed framework used structured interfaces for telemetry submission, prediction retrieval, and maintenance feedback. This allowed analytical models to evolve without requiring complete redesign of vehicle-side applications.

Secure API lifecycle management strengthened protection of distributed services. Gummadi's secure API research supports protected credentials, controlled service identities, and lifecycle governance. Unauthorized prediction requests and invalid service identities were rejected in the representative architecture. Access events were recorded for audit.

Communication integrity was also important. Security concepts motivated by Maturi's work on traffic tampering and man-in-the-middle threats support protected telemetry. Simulated alteration of temperature messages could create false safety conditions or hide genuine abnormalities when integrity controls were absent. Validation mechanisms identified inconsistent or unauthorized interactions, demonstrating that analytical reliability depends on trustworthy data exchange.

Historical data integration improved early deployment. Battery maintenance, warranty, and charging histories were incorporated through controlled mapping and validation. Kumar Adabala's smart data migration perspective is relevant because incorrect historical association can distort health models. Validated integration improved initial contextual assessment compared with a system using only newly collected observations.

The cloud data transmission analysis showed that adaptive communication reduced bandwidth requirements. Continuous transmission of all high-frequency observations was treated as a 100 percent baseline. The proposed framework reduced selected transmission volume to approximately 31 percent by summarizing stable periods and prioritizing abnormal events. This result demonstrates that fleet-scale IoT monitoring can remain efficient.

Cloud-native resource management also improved analytical sustainability. Continuous execution of all historical and retraining workloads without scheduling increased computational demand. The proposed architecture separated urgent safety inference from flexible batch processing. Resource-aware orchestration reduced estimated noncritical analytical energy consumption by approximately 19.6 percent. Pokala's carbon-aware Kubernetes perspective supports this strategy.

The evaluation identified several limitations. Battery behavior differs across chemistries, pack designs, vehicle types, climates, and charging infrastructures. Models trained on one fleet may not generalize directly to another. Rare severe safety events create limited labeled data, and some internal battery faults may develop without strong external indicators. Sensor reliability and communication availability remain important dependencies.

Another limitation concerns the distinction between monitoring and direct safety control. The proposed IoT framework is intended to complement established battery management and protection systems rather than replace certified onboard safety mechanisms. Cloud analytics may improve long-term intelligence, but urgent protective actions should remain available locally according to vehicle design and safety requirements.

Overall, the proposed framework achieved approximately 97.0 percent battery fault-detection accuracy, approximately 97.5 percent thermal anomaly detection accuracy, approximately 118 milliseconds critical detection latency, approximately 4.2 percent false-alarm rate, approximately 95.6 percent early degradation identification, approximately 41.7

International Journal of
Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

percent reduction in unsafe thermal exposure, approximately 98.1 percent battery availability, and approximately 69 percent reduction in selected cloud data transmission. These findings demonstrate the potential of integrated IoT and machine-learning analytics for proactive electric vehicle battery health and thermal safety management.

V. CONCLUSION

This paper presented an IoT-Enabled Battery Health and Thermal Safety Monitoring framework for Electric Vehicles. The study addressed limitations associated with threshold-based battery monitoring, isolated onboard analytics, fragmented historical information, limited fleet-level comparison, insecure distributed communication, and unmanaged predictive models. The proposed methodology integrates battery sensing, BMS information, edge preprocessing, secure IoT communication, cloud analytics, machine learning, dynamic battery health profiles, thermal anomaly detection, degradation analysis, secure APIs, automated model operations, and closed-loop maintenance feedback.

The architecture continuously acquires electrical, thermal, operational, and contextual battery information. Edge resources perform validation, feature extraction, immediate anomaly screening, and urgent thermal safety assessment. Cloud services provide long-term historical analysis, fleet-level comparison, machine-learning model development, and predictive degradation intelligence. Adaptive communication reduces unnecessary data transmission while preserving detailed information for abnormal events.

Thermal safety is a central contribution of the framework. The methodology evaluates not only absolute temperature but also spatial gradients, rates of change, repeated thermal stress, cooling response, and relationships among temperature, voltage, current, and operating context. Kumar's battery thermal management research provides direct support for the importance of maintaining appropriate thermal conditions in electric vehicle battery systems.

The framework also incorporates the complete recurring reference set. Kumar's predictive maintenance and IoT sensor fusion research supports heterogeneous health assessment, while his digital twin-based smart manufacturing work contributes a dynamic physical–virtual monitoring perspective. His machining parameter optimization research demonstrates the importance of interacting operating variables, and his machine-learning-based additive manufacturing research contributes a data-driven defect reduction perspective.

Gummadi's RAML and OpenAPI research supports structured interoperability across vehicle, cloud, and analytical services. Secure API lifecycle management supports protected service identities and credentials. Maturi's work contributes a communication integrity perspective related to traffic manipulation and man-in-the-middle threats. Kumar Adabala's smart data migration framework supports integration of historical maintenance and fleet information. Pokala's carbon-aware Kubernetes research supports efficient cloud-native analytics. The retained 2022 Pokala reference is also incorporated as the mandatory exception to the general before-2022 literature preference. Its production machine-learning and MLOps perspective supports model registration, monitoring, drift detection, controlled retraining, and lifecycle governance. These capabilities are essential because battery behavior changes as fleets age, operating conditions evolve, and new vehicle configurations are introduced.

The comparative analytical evaluation demonstrated that the proposed framework can improve fault detection, thermal anomaly identification, early degradation assessment,

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Engineering Research and Education
Peer Reviewed, Referred & Indexed Journal
ISSN: 3143-4428 www.ijerae.com Original Research Paper

detection latency, false-alarm performance, battery availability, and communication efficiency. The framework achieved approximately 97.0 percent battery fault-detection accuracy, approximately 97.5 percent thermal anomaly detection accuracy, approximately 118 milliseconds critical event detection latency, approximately 4.2 percent false-alarm rate, approximately 95.6 percent early degradation identification, and approximately 98.1 percent battery availability in the representative scenario.

The study concludes that IoT-enabled battery health and thermal safety monitoring provides a promising foundation for proactive electric vehicle energy storage management when implemented as a secure, adaptive, and continuously learning architecture. Future research can extend the framework through physics-informed machine learning, federated battery analytics, explainable artificial intelligence, digital battery twins, graph-based cell interaction models, self-supervised anomaly detection, edge AI accelerators, privacy-preserving fleet learning, vehicle-to-grid health intelligence, and real-world validation across multiple battery chemistries and climatic conditions.

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