Predictive Health Monitoring Systems for Electric Vehicle Powertrains Using Edge AI and CAN Bus Data

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ABSTRACT

Electric vehicles (EVs) are becoming increasingly important in the shift toward sustainable mobility. While their adoption is accelerating, ensuring the health and reliability of EV powertrains remains a critical challenge. Failures in subsystems such as batteries, motors, and controllers may cause unexpected breakdowns, reduced efficiency, and safety issues. Predictive Health Monitoring (PHM) systems aim to prevent such failures by identifying anomalies before they escalate. Traditional PHM solutions often depend on cloud platforms, but these face drawbacks such as latency, high bandwidth requirements, and privacy risks. To address these challenges, edge-based PHM employs embedded devices to process Controller Area Network (CAN) bus data locally, enabling real-time diagnostics, enhanced privacy, and cost efficiency.

This paper presents a structured survey of PHM techniques for EV powertrains using Edge Artificial Intelligence (Edge AI) and CAN bus data. The contributions include: (i) classification of PHM approaches into model-based, data-driven, security- focused, and edge-deployed methods, (ii) comparative analysis of recent works, (iii) a summary table of surveyed papers, (iv) discussion of hardware implementations reported in literature, and (v) identification of future research directions.

Key Words - Electric Vehicles, Predictive Maintenance, Edge AI, CAN Bus, Vehicle Diagnostics, Anomaly Detection.

INTRODUCTION

The transportation sector is witnessing a global transition toward electric mobility. EVs are valued for their efficiency, reduced environmental impact, and compliance with stricter emission norms. At the heart of every EV lies the powertrain, consisting of batteries, motors, controllers, and power electronics. Maintaining the health of these systems is crucial for safety and performance.

Traditional diagnostic systems are reactive in nature, identifying issues only after they occur. Cloud-based predictive approaches improve fault anticipation but face challenges such as reliance on internet connectivity, increased latency, and data privacy concerns. Edge Artificial Intelligence (Edge AI) provides an alternative by processing vehicle data locally using embedded devices, enabling real-time fault detection while minimizing external dependencies.

This survey reviews recent advances in predictive health monitoring for EV powertrains using Edge AI and CAN bus data. The contributions of this paper are as follows:

1) A detailed classification of PHM research into four categories.

2) A comparative review of literature from 2020–2025.

3) Inclusion of hardware-oriented implementations from recent studies.

4) Identification of open challenges and research opportunities for the future.

BACKGROUND

A. Controller Area Network (CAN Bus)

The CAN bus is a standard in-vehicle communication protocol that enables data exchange between electronic control units (ECUs), battery management systems, motor controllers, and sensors. It serves as the primary data source for PHM, offering real-time information on voltage, current, temperature, and system faults.

B. Edge Artificial Intelligence (Edge AI)

Edge AI refers to running machine learning models on embedded devices instead of cloud servers. This reduces latency, lowers dependence on internet connectivity, and safeguards privacy. Platforms such as Raspberry Pi and ESP32, when combined with optimized libraries like TensorFlow Lite, can perform anomaly detection on CAN data in real time, making them suitable for predictive monitoring applications.

LITERATURE SURVEY

I. Patil et al. (2025) introduced an AI-based predictive maintenance framework that combines Long Short-Term Memory (LSTM) networks with Federated Learning for secure fault detection in EVs [1]. While the approach enhances privacy and supports predictive modelling, it imposes significant computational requirements, limiting deployment on embedded devices.

II. In another study, Wang et al. (2025) utilized Support Vector Machines (SVM) and K-Means clustering on On-Board Diagnostics (OBD-II) data to monitor emissions and driving behaviour [2]. The method enables improved vehicle

diagnostics but requires standardized OBD-II datasets for consistent integration with CAN bus analytics.

III. Ahmed and Patel (2025) explored the use of Quantum Artificial Intelligence in combination with Federated Learning for EV fault diagnosis [3]. Their method achieved high accuracy in detecting system faults; however, it depends on experimental quantum hardware, which is not yet widely available for practical deployment.

IV. Roy et al. (2025) proposed a privacy-preserving predictive maintenance system using Homomorphic Encryption integrated with Edge AI [4]. This technique ensures secure CAN diagnostics by safeguarding sensitive data, but the computational overhead places a heavy load on edge devices.

V. Zhang et al. (2024) conducted a survey of anomaly detection methods in in-vehicle networks, focusing on deep learning techniques and CAN bus analysis [5]. While their review provides a strong foundation for machine learning-based diagnostics, it lacks real- world validation.

VI. Lee et al. (2024) investigated battery health prediction using Deep Belief Networks (DBN) and Recurrent Neural Networks (RNN) [6]. Their model achieved accurate State of Health (SoH) estimation but remains unsuitable for resource-constrained edge devices, highlighting the need for lightweight alternatives.

VII. Singh et al. (2024) adopted Reinforcement Learning to optimize energy management in hybrid vehicles [7]. Although the approach is not explicitly health-focused, it shows potential for enhancing motor control fault tolerance.

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VIII. Fernandez et al. (2024) presented a digital twin framework to simulate EV powertrain operations and evaluate faults virtually [8]. The framework enables safe prototyping and model validation but requires a complex and resource-intensive setup.

IX. Gupta and Sharma (2023) employed statistical models and machine learning techniques to estimate the Remaining Useful Life (RUL) of automotive components [9]. While their models align with industry standards, they face challenges in real-time applications.

X. Hossain et al. (2023) applied Convolutional Neural Networks (CNN), SVM, and time-series analysis for lifecycle-based predictive maintenance in industrial equipment [10]. Although not EV-specific, the approach demonstrates transferable concepts applicable to EV systems.

XI. Kumar and Singh (2023) reviewed cybersecurity measures for electric vehicles, focusing on CAN bus security protocols and Intrusion Detection Systems (IDS) [11]. While their study strengthens the understanding of EV cybersecurity, it does not address diagnostic capabilities directly

XII. Zhang et al. (2023) provided a broad review of AI integration in EV technologies [12]. Their work highlights the role of AI in EV development but lacks depth in machine learning applications for predictive monitoring.

XIII. Das et al. (2023) applied DBN and LSTM models for accurate RUL estimation of EV batteries [13]. Although effective, the implementation faces limitations due to edge device constraints.

XIV. Wiki Contributors (2023) proposed a conceptual framework for integrated vehicle health management [14]. The framework outlines a system-wide monitoring structure but does not include practical hardware considerations.

XV. Another contribution by Wiki Contributors (2023) outlined strategies for Intelligent Maintenance Systems (IMS) [15]. While useful for designing high- level predictive systems, the study is not AI-specific.

XVI. Further, Wiki Contributors (2023) discussed Industrial Internet of Things (IIoT) architectures for predictive maintenance [16]. Though not designed specifically for EVs, these architectures can facilitate sensor integration in vehicular networks.

XVII. Zhao et al. (2020) described an edge AI framework for vehicular applications [17]. Their work demonstrates scalable deployment of AI at the edge, though it is not directly tailored to EVs.

XVIII. Mishra and Rao (2020) explored distributed vehicular computing through fog and AI technologies [18]. Their approach supports distributed EV monitoring but suffers from scalability challenges.

XIX. Chen et al. (2020) analyzed vulnerabilities in CAN bus systems and proposed IDS-based countermeasures [19]. While the study is vital for vehicle security, it does not integrate predictive maintenance aspects.

XX. Finally, Yadav et al. (2020) investigated machine learning-based IDS techniques for real-time fault detection in CAN networks [20]. Although effective in detecting attacks, the work does not directly address health diagnostics.

Summary:

The existing studies on **Predictive Health Monitoring (PHM)** in Electric Vehicles (EVs) demonstrate the use of a variety of modern techniques designed to enhance vehicle reliability, safety, and performance. Researchers have implemented multiple approaches such as **deep learning**, **anomaly detection**, **reinforcement learning**, and **digital twin systems** to improve fault prediction and maintenance efficiency.

Deep learning-based models process large amounts of vehicle data—particularly CAN bus signals—to

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estimate parameters like the **State of Health (SoH)** or **Remaining Useful Life (RUL)** of critical components including batteries, motors, and inverters. These models can automatically detect patterns in data and offer accurate health predictions under varying driving conditions.

Anomaly detection methods are applied to identify abnormal behaviours or irregular sensor readings in real-time. Early identification of such deviations enables preventive maintenance, reduces breakdown risks, and ensures vehicle safety.

Reinforcement learning allows systems to continuously learn from operational feedback and make data-driven decisions to improve energy efficiency, fault recovery, and system stability. This adaptive nature helps maintain optimal performance over time.

Digital twin technology involves building a virtual model of vehicle components that mirrors real-time operations. This virtual replica supports continuous tracking, simulation, and prediction of component wear and degradation, leading to better diagnostic and maintenance planning.

However, despite these technological advancements, several **limitations** still remain. One major issue is the **lack of standardized and open-access datasets**, which restricts fair comparison and validation of different PHM techniques. Additionally, most existing systems are designed for **cloud platforms** rather than **edge computing**, which limits their ability to operate directly on low-power embedded devices inside the vehicle.

Another key challenge is the **insufficient real-world testing** of proposed methods. Many models are validated only in controlled or simulated environments, which may not fully capture the complexities of real driving conditions.

In conclusion, although notable progress has been made in predictive health monitoring for electric vehicles, the next step is to develop scalable, reliable, and secure PHM frameworks that are practical for deployment in real-world automotive systems.

Author(s), Year	**Method / Technique**	**Key Contribution**	**Limitation / Future Scope**
I. Patil et al., 2025	LSTM, Federated Learning	Secure EV fault prediction	High computational demand; needs optimization
II. Wang et al., 2025	SVM, K-Means	OBD-II based emission & behaviour diagnostics	Requires standardized OBD- II data
III. Ahmed & Patel, 2025	Quantum AI + Federated Learning	High accuracy in EV fault detection	Relies on experimental quantum hardware
IV. Roy et al., 2025	Homomorphic Encryption + Edge AI	Privacy-preserving CAN diagnostics	High processing load on devices
V. Zhang et al., 2024	Deep Learning + CAN Bus	Survey on anomaly detection	Lacks real-world testing
VI. Lee et al., 2024	DBN, RNN	Accurate battery State of Health (SoH) prediction	Not optimized for embedded devices
VII. Singh et al., 2024	Reinforcement Learning	Hybrid vehicle energy optimization	Not directly health-focused
VIII. Fernandez et al., 2024	Digital Twin Framework	Virtual testing of EV powertrains	Complex to implement

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IX. Gupta & Sharma, 2023	Statistical + ML Models	RUL estimation from sensor data	Limited real-time applicability
X. Hossain et al., 2023	CNN, SVM, Time Series	Industrial predictive maintenance methods	Not specific to EV systems
XI. Kumar & Singh, 2023	Security Protocols, IDS	Review of CAN bus cybersecurity	Does not address health monitoring
XII. Zhang et al., 2023	AI Technology Review	Overview of AI in EVs	Lacks ML-specific detail
XIII. Das et al., 2023	DBN + LSTM	Accurate EV battery RUL prediction	Limited by edge hardware constraints
XIV. Wiki Contributors, 2023	Conceptual Framework	Integrated vehicle health monitoring	No hardware implementation
XV. Wiki Contributors, 2023	Predictive Strategies	Intelligent maintenance system (IMS)	General strategies, not AI-specific
XVI. Wiki Contributors, 2023	IIoT Architecture	Predictive maintenance framework	Not EV-specific
XVII. Zhao et al., 2022	Edge AI Framework	Vehicular edge computing for AI	Not tailored to EVs
XVIII. Mishra & Rao, 2022	Distributed AI + Fog Computing	Distributed EV monitoring	Scalability challenges
XIX. Chen et al., 2022	IDS-based Security	Analysis of CAN vulnerabilities	No predictive health monitoring integration
XX. Yadav et al., 2022	ML-based IDS	Real-time CAN anomaly detection	Not combined with health diagnostics

TAXONOMY OF APPROACHES

From the surveyed literature, PHM approaches can be broadly classified into:

1. **Model-Based Approaches:** Simulation environments and digital twins for predicting potential failures.
2. **Data-Driven Approaches:** ML and DL techniques such as LSTM, CNN, and DBN applied to CAN bus data.
3. **Security-Focused Approaches:** IDS and encryption-based frameworks for secure data transfer.
4. **Edge-Based Implementations:** Deployment of lightweight ML models on embedded devices for real-time fault detection.

COMPARATIVE ANALYSIS

- Focus Areas: Battery health monitoring and anomaly detection dominate research efforts.
- Trends: Research peaked in 2023, with sustained developments in 2024 and 2025.
- Strengths: Accuracy improvements through ML/DL, reinforcement learning in hybrid systems, and integration of digital twins.

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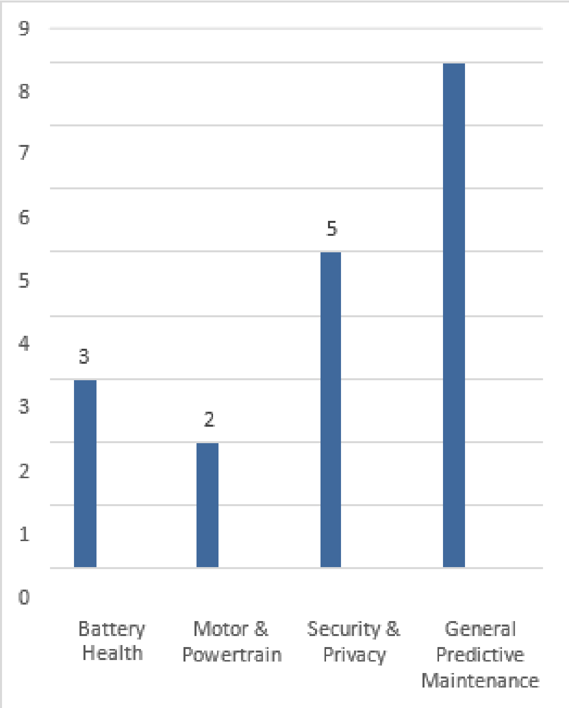
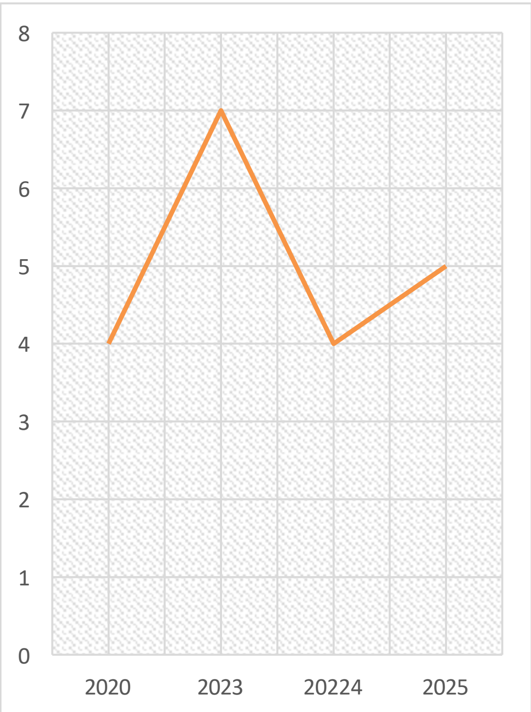
- Weaknesses: Limited real-world deployment, lack of standardized datasets, and resource constraints on edge hardware.

Distribution of Research Focus in PHM of EV Powertrains (2020-2025)



Research Trends in Predictive Health Monitoring of Powertrains (2020-2025)



HARDWARE IMPLEMENTATIONS

Several studies have demonstrated the feasibility of deploying PHM systems on embedded hardware:

- **Hardware Platforms:** Raspberry Pi (5), MCP2515 CAN interface modules.
- **Data Acquisition:** CAN signals accessed via the OBD-II port for real-time monitoring.

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- **Software Tools:** Python with TensorFlow Lite, Scikit-learn, and python-can.
- **Algorithms:** One-Class SVM, Isolation Forest, and lightweight LSTM variants.
- **Output Interfaces:** Dashboards, LEDs, or mobile apps for driver alerts.

FUTURE DIRECTIONS

1. **Standardized Datasets:** Development of open CAN bus datasets for benchmarking predictive models.
2. **Optimized Edge Models:** Model compression and pruning techniques for resource-constrained hardware.
3. **Digital Twins:** Virtual replicas for safe and accurate fault simulation.
4. **Explainable AI:** Enhancing interpretability and trust in fault predictions.
5. **Cybersecurity Integration:** Strengthening PHM systems against in-vehicle cyber threats.
6. **Hybrid Edge–Cloud Frameworks:** Combining edge responsiveness with cloud scalability.

CONCLUSION

This paper surveyed predictive health monitoring methods for EV powertrains using Edge AI and CAN bus data. The review highlighted progress in battery diagnostics, anomaly detection, security, and real-time implementations. Edge computing offers significant advantages over cloud-based systems, including reduced latency, privacy, and cost-effectiveness. However, gaps remain in dataset availability, scalability, and model optimization. Addressing these challenges will be critical to establishing PHM as a standard feature in future EV ecosystems.

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