A Survey on Battery Passport – A Digital Identity

Dr. Prashant Wakhare, Suyog Dhage, Harsh Gangurde, Aditi Janwade
Department of Artificial Intelligence and Data Science
AISSMS Institute of Information Technology, Pune, Maharashtra, 411001, India
Emails: prashant.wakhare@aissmsioit.org, suyogdhage@gamil.com, harshgangurde04@gmail.com, janwadeaditi@gmail.com

***Abstract*—The accurate estimation of Electric Vehicle (EV) battery State of Health (SOH) is a critical component for ensuring vehicle reliability, optimizing performance, and assessing residual value. However, real-world applications are often constrained by the limited availability of comprehensive operational data, as direct sensor feeds are typically inaccessible to end-users and thirdparty systems. This survey provides a comprehensive review and comparative analysis of machine learning (ML) methodologies designed to overcome this data-gap challenge. We investigate a spectrum of regression-based approaches, from traditional models like Linear Regression and Support Vector Regressors (SVR) to ensemble methods such as Random Forest and Gradient Boosting, and neural networks. A central focus of this review is the "multi-stage prediction pipeline," an architectural pattern designed to infer high-value SOH metrics from minimal, userprovided inputs. This pipeline operates in two distinct stages: (1) It first leverages easily obtainable data points, specifically Charging Duration, Total KM Traveled, and Battery Type, to model and predict a set of unobserved, intermediate operational parameters, including SOC , Battery Temp (°C), Ambient Temp (°C), and Charging Cycles. (2) These inferred features are then combined with the original user inputs to form a complete feature set, which is used to train a second set of models for predicting the final SOH indicators: Efficiency and Degradation Rate . By synthesizing the performance of various algorithms (evaluated using R^2 and MAE) within this two-stage framework, this paper identifies and validates this "feature-inference" architecture as a robust and practical solution. It effectively bridges the gap between data intensive laboratory models and the exigent demands of real-world battery diagnostics, paving the way for scalable and accessible SOH estimation tools. Index Terms Electric Vehicles, Battery State of Health (SOH), Machine Learning, SOH estimation, Degradation prediction, Battery diagnostics, Feature inference, Multi-stage prediction, Regression analysis, Ensemble methods, Random Forest, Gradient Boosting.**

I. Introduction

Electric vehicles represent a cornerstone of the sustainable energy transition. However, the performance and safety of EVs are deeply tied to battery management and traceability throughout the lifecycle from manufacturing to recycling. Traditional Battery Management Systems (BMS) often rely on static or model based estimations that fall short in dynamic real-world environments. Recent literature emphasizes two key domains of innovation: 1. AI-Driven Battery Health Prediction, employing LSTM, CNN, and ensemble learning for SoC, SoH, and RUL estimation. 2. Blockchain-Based Battery Passports, focusing on traceability, circular economy compliance, and digital certification. This survey aims to connect these two paradigms exploring how predictive intelligence can inform blockchain-based lifecycle management thereby supporting the development of a Battery Passport.

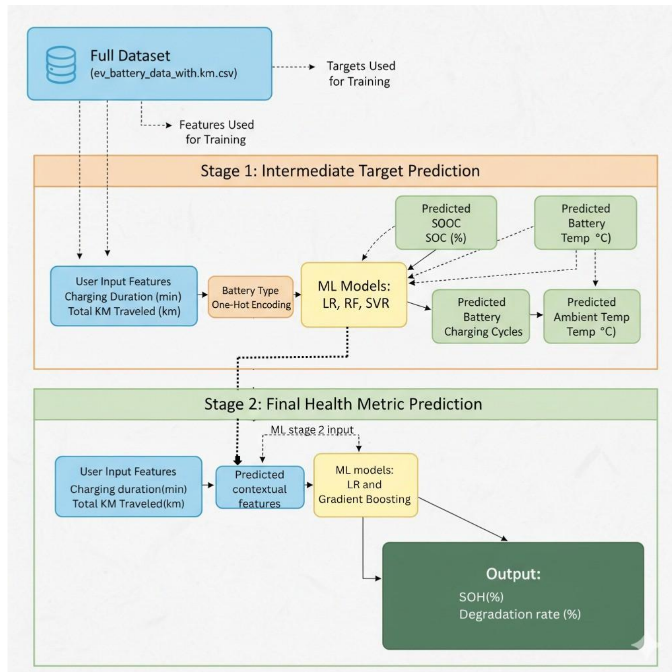

Fig. 1. Two-Stage Machine Learning Pipeline for Battery State Prediction and Final Health Metric Estimation.

In addition, the rapid adoption of EVs has increased the demand for transparent, reliable, and interoperable battery information. Manufacturers, regulators, and consumers now require standardized mechanisms to track battery usage, degradation, ownership, and environmental impact. Emerging global policies such as the EU Battery Passport mandate for 2026 further highlight the urgent need for digital ecosystems capable of securely storing and sharing battery lifecycle data. Moreover, advances in IoT enabled sensing, cloud analytics, and edge intelligence have enabled continuous monitoring of battery performance across different climatic, geographic, and operational conditions. These technologies not only enhance predictive maintenance but also support second life plan- ning, recycling optimization, and carbon footprint assessment. Together, these developments underscore the importance of integrating AI driven diagnostics with blockchain enabled traceability to enable a future ready Battery Passport system.

II. Literature Review

This section summarizes findings from fifteen recent research papers related to AI-based skin disease classification and diagnosis.

[1] WS. Pourbunthidkul.(2025) proposed a cascaded deep learning framework using LSTM networks for multi-cell voltage forecasting and SoC estimation in EV batteries. The model achieved high accuracy in predicting cell behavior under varying operational conditions, improving real-time health estimation for BMS applications.

[2] J. Gong.(2025) A systematic review of SoH prediction methods, comparing electrochemical, statistical, and deep learning-based models. The authors emphasized the importance of dataset diversity and feature interpretability in predictive battery health modeling.

[3] R. Mamidi. (2025) This study presented an AI-integrated BMS capable of simultaneous SoC, SoH, and fault diagnosis using machine learning models. The hybrid model achieved superior accuracy compared to traditional estimation algorithms, laying a foundation for autonomous EV diagnostics.

[4] M. Ahwiadi.(2025) The authors reviewed existing RUL prediction technologies, emphasizing deep learning models such as CNN and GRU architectures. They proposed a hybrid approach integrating empirical degradation data with real-time sensing for reliable lifecycle prediction.

[5] WN. Vasavi.(2025) This paper explored multiple machine learning algorithms (SVM, Random Forest, and XGBoost) for EV battery lifespan prediction. The results demonstrated that tree-based ensemble methods provided better generalization with limited datasets.

[6] M. Cavus. (2025) The paper introduced a deep learning model for large EV fleet management within smart grids. It highlighted how predictive maintenance of batteries enhances grid resilience and reduces downtime through proactive scheduling.

[7] S. Gu.(2025) This study applied reinforcement learning to optimize EV charging and discharging strategies while considering battery health degradation. The safe RL approach ensures operational safety and extends battery lifetime through adaptive policy learning.

[8] Y. Wang.(2022) The authors released a benchmark dataset for battery capacity estimation and degradation prediction. The dataset has become a key enabler for developing and validating advanced ML models for SoH and SoC estimation.

[9] K. R. Lin.(2023) This paper analyzed misconceptions and errors in interpreting SoH values within the EV industry. The authors proposed visualization and explainable AI techniques to improve user understanding of battery health metrics.

[10] H. R. Hasan.(2025) A foundational paper on using composable NFTs and blockchain to create digital battery passports. The proposed framework ensures sustainability, traceability, and ownership verification throughout the battery lifecycle.

[11] SA. Pohlmann.(2025) This study identified stakeholder requirements for developing digital product passports (DPPs). It emphasized compliance with EU circular economy regulations and integration with sustainable supply chain systems.

[12] A. Ali.(2025) A comparative analysis of EV battery recycling frameworks in China and the USA. It highlighted the role of regulatory standards and digital traceability tools in managing end-of-life batteries effectively.

[13] M. Popowicz.(2025) This work explored how DPPs can increase consumer transparency regarding material sourcing, battery health, and carbon footprint. It linked DPP adoption to enhanced consumer trust and sustainability awareness.

[14] Q. Li.(2025) The authors compared Decision Trees, SVM, XGBoost, and Random Forest for complex data analysis. Their findings informed optimal algorithm selection for SoH and lifespan prediction tasks in EV battery datasets.

[15] T. Champahom. (2025) The study compared deep learning and gradient boosting methods for energy demand prediction. Results indicated that LSTM excelled in temporal dependencies, while XGBoost performed better with tabular degradation data, suggesting a hybrid approach for battery modeling.

III. Summary

These 15 reviewed studies collectively highlight the rapid progress in applying deep learning, hybrid machine learning models, reinforcement learning, and digital passport frameworks for EV battery health prediction and lifecycle management. Most works employed advanced architectures such as LSTM, CNN, GRU, and cascaded hybrid models for SoC, SoH, and RUL estimation, while ensemble techniques like Random Forest, XGBoost, and Decision Trees improved robustness with limited or noisy datasets. Several studies also contributed benchmark datasets and explainable AI mechanisms to enhance interpretability, while emerging approaches such as safe reinforcement learning for charging optimization and blockchain enabled digital battery passports expanded the scope of battery traceability and sustainability. Typical datasets included real world degradation curves, capacity fade benchmarks, and BMS generated operational data, with consistent improvements in accuracy and reliability across varying conditions. Despite these advancements, common limitations persist, including restricted dataset diversity, insufficient real world validation, high computational demands for deep models, limited interpretability, and challenges related to interoperability, privacy, and regulatory integration in digital passports. Overall, LSTM based architectures, tree based ensemble methods, and hybrid deep learning ML frameworks emerged as the most effective solutions, offering a balanced mix of accuracy, generalization, and practical feasibility for next generation EV battery health forecasting and digital lifecycle management.

Summary Table
SUMMARY OF REVIEWED RESEARCH PAPERS ON BATTERY HEALTH AND PASSPORT

Ref. No.	Authors	Focus Area	Key Technique / Model	Outcome	Relevance to Battery Passport
1	Pourbunthidkul et al.	SoC & voltage prediction under dynamic driving conditions; multi-cell behavior modeling	LSTM (Cascaded)	Improved real-time cell prediction; better temporal capture of voltage drift	Enables dynamic SoC tracking and supports real-time health estimation
2	Gong et al.	SoH modeling review; comparison of electrochemical vs ML-based health indicators	Literature synthesis	Foundational knowledge for modeling; identifies data gaps and evaluation issues	Framework comparison aids selection of reliable SoH indicators for passports
3	Mamidi et al.	AI-Enhanced BMS; integrated SoC, SoH, and fault analytics	Hybrid ML models	Accurate SoC/SoH/Fault diagnosis across varying loads	Health data integration supports digital battery identity development
4	Ahwiadi & Wang	RUL prediction; degradation path estimation	CNN, GRU	Lifecycle prediction accuracy; captures long-term aging patterns	Lifecycle data logging improves traceability for passports
5	Vasavi et al.	Lifespan prediction for EV batteries with limited datasets	XGBoost, RF	High accuracy on limited data; robust against noise	Supports long-term degradation profiling required for circular economy compliance
6	Cavus & Bell	Smart grid resilience; fleet-level battery coordination	Deep learning	Predictive maintenance; reduces downtime across fleets	Fleet-level data sharing integrates large-scale operational insights into battery passports
7	Gu et al.	Charging optimization; health-aware charging/discharging cycles	Reinforcement Learning	Health-aware scheduling; reduced battery stress	Energy & degradation log adds operational transparency to passports
8	Wang et al.	Dataset creation; large-scale EV usage and degradation dataset	EVBattery dataset	Benchmark dataset; high-quality temporal performance data	Training Passport AI models with standardized large-scale data
9	Lin et al.	SoH interpretation; user misinterpretations; explainability	Explainable AI	Improved user understanding; reduces SoH confusion	Enhances transparency and trust in Battery Passport health metrics
10	Hasan et al.	Battery Passport; digital identity; traceability and ownership	Blockchain + NFT	Digital identity; tamper-proof lifecycle records	Core blockchain layer for secure and verifiable battery passport implementation
11	Pohlmann et al.	DPP for EV batteries; stakeholder analysis	Stakeholder study	Circular economy integration; identifies industrial requirements	Compliance and standards alignment ensures global passport interoperability
12	Ali et al.	Recycling frameworks; policy comparison across regions	Comparative policy	Sustainable recycling; identifies bottlenecks in current recycling models	End-of-life traceability supports complete lifecycle documentation
13	Popowicz et al.	Consumer transparency; user-centric product passport features	DPP framework	User-centric traceability; interface-level insights	User interface integration improves accessibility of Battery Passport data
14	Li & Zhou	ML comparison for battery datasets; performance benchmarking	XGBoost, RF, SVM	Algorithm benchmarking; identifies best models for structured data	Model selection for Passport AI ensures consistent health predictions
15	Champahom et al.	Energy forecasting; battery load prediction for transport systems	LSTM vs XGBoost	Hybrid potential; strong temporal + tabular performance	Predictive passport analytics enhances long-term battery usage forecasting

IV. Future Work

Future research must first address the major limitation of dataset scarcity and lack of real world diversity observed across existing studies. Most battery health prediction models are trained on controlled laboratory datasets or small-scale operational records, restricting their ability to generalize across different climates, driving behaviors, battery chemistries, and OEMs. Expanding benchmarking datasets, integrating multi chemistry data (LiFePO, NMC, NCA), and adopting privacy preserving data sharing frameworks such as federated learning will be essential for enhancing model robustness. Large scale real world datasets will also support better validation and reduce the performance gap between laboratory models and real vehicle conditions.

Another key area for future work lies in improving the efficiency, deployability, and interpretability of battery health prediction models. Current deep learning architectures such as LSTM, CNN, and GRU often require high computational resources, making real time deployment on embedded BMS hardware difficult. Research into lightweight model optimization—pruning, quantization, knowledge distillation, and edge AI integration will enable fast and accurate on-vehicle predictions. At the same time, incorporating explainable AI (XAI) and uncertainty estimation techniques will enhance transparency, user trust, and regulatory acceptance, particularly for safety-critical parameters like SoH and RUL.

Ensuring interoperability, standardization, and cybersecurity within digital battery passport systems represents another important direction. Current passport architectures lack unified data formats, cross-platform compatibility, and secure communication standards. Future efforts should align with emerging global regulations such as the EU Battery Passport mandate, implement standardized protocols like ISO/IEC and OPC-UA, and incorporate strong cybersecurity mechanisms including cryptographic hashing, distributed ledgers, and AI based anomaly detection. These improvements will support tamper proof lifecycle tracking and reliable data exchange across manufacturers, service providers, and recyclers.

Finally, integrating comprehensive circular economy and sustainability indicators into both prediction models and battery passport frameworks will be crucial. Most existing research overlooks second life performance modeling, recycling metrics, carbon footprint estimation, and environmental impact assessments. Future systems should incorporate these parameters to support full lifecycle optimization, improve material recovery strategies, and enable transparent environmental reporting. Embedding such sustainability focused insights into Battery Passports will strengthen their role in guiding responsible EV battery manufacturing, usage, and end of life decision making.

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