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Review on Intelligent Approaches for Estimation and Monitoring of the BMS

Prathibha D[1] and Mohan N[2]
[1]Lecturer and HoD, Dept of Electrical and Electronics Engineering, JSS Polytechnic, Mysuru, India
Email: Prathi.soni@gmail.com
[2]Associate Professor, Dept of Electrical and Electronics Engineering, JSS S&STU, Mysuru, India
Email: mohann.eee@jssstuniv.in

***Abstract*— The global energy sector is undergoing transformation to reduce carbon emissions and combat climate change, driven by the rapid advancement of alternative energy sources and the rapid adoption of lithium-ion (Li-ion) batteries. These batteries are essential across multiple industries necessitating advancement in Battery Management Systems (BMS) to ensure their safe and efficient operation. This article provides a detailed review of recent advancements in BMS. The review encompasses various ML algorithms such as feed forward neural networks (FFNN), radial basis function neural networks (RBFNN), extreme learning machines (ELM), support vector machines (SVM), recurrent neural networks (RNN), and Bayesian networks (BN), among others. The discussion covers underlying principles, advantages, and applicability is discussed, along with comparisons of their performance in SOC and SOH estimation. Furthermore, the paper addresses challenges in data acquisition, model training, and algorithm validation, emphasizing the importance of high-quality datasets and computational efficiency. The review concludes by highlighting future research directions to improve the efficiency and applicability of machine learning-based BMS for electrified vehicle applications**

***Index Terms*— Electrical vehicles (EV), BMS (Battery management system), ML (Machine Learning), SOH (state of health), and SOC (state of charge)..**

I. INTRODUCTION

To address carbon emissions and address environmental shifts and power deficits, the global energy landscape is undergoing transformation. This shift is propelled by the widespread advancement of nonconventional energy sources such, leading a gradual reduction in fossil fuel usage. One key enable of this transition is the widespread adoption of Lithium-ion batteries, renowned for their high energy capacity and output, superior efficiency and prolonged lifespan. These batteries find applications across diverse sectors, including transportation, mobile electronics and ESS. Given their pivotal role, ensuring the safe, reliable, and economically feasible function of Li-ion batteries is paramount. However, like all energy storage devices, they experience performance degradation over prolonged usage, necessitating continuous monitoring of their SOC and SOH to sustain optimal functionality. The structure of the paper is as follows Section II provides review on the BMS, Section III discusses on AI in BMS, Section IV presents an overview of ML approaches in SOC, Section V explore the overview of ML approaches in SOH, Section VI comparisons of SOC and SOH methods, Section VII Conclusion and Recommendations.

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II. REVIEW ON THE BMS

The rise of next generation hybrid and electric vehicles signifies a major shift in the automotive industry from traditional fuel vehicles towards electric alternatives. Central to these vehicles is the BMS, essential in both electric transportation and sustainable energy storage. [1] This article explores battery technologies, focusing on challenges, concerns, and solutions related to BMS, contains battery simulation, condition assessment and charging methodologies. It provides detailed examination different types of battery models: electrical, thermal, and electro-thermal and discusses SOC and SOH, along with diverse charging strategies and optimization methods. The BMS is highlighted for its comprehensive role in managing handling data, current, voltage, assessing charging and discharging, balancing and safe guarding batteries, regulating temperature, different cell balancing circuits, considering their impact on current and voltage stability, regulation dependability, energy dissipation and performance outlining the advantages and disadvantages of each. Additionally, the paper identifies existing research gaps, suggesting areas for future exploration and innovation in BMS.

Li-ion battery powered Electrical Vehicles are becoming more popular as an eco-friendly option to reduce fossil fuel impact. Precise tracking of state of charge and state of health is crucial for the battery management system in these batteries. [2]This article explores the use of AI, specifically deep learning algorithms such as Long Short-Term Memory (LSTM) and bidirectional LSTM (BiLSTM), to forecast lithium ion battery SOC and SOH. Different gradient descent optimization algorithms with various learning rates were tested to determine their effect on root mean squared error (RMSE) and mean absolute error (MAE). Using the Panasonic 18650PF Li-ion dataset, LSTM and BiLSTM models with four hidden layers of 128 units were developed. Results showed the choice of algorithm significantly affects accuracy, with BiLSTM generally enhancing performance but at a higher computational cost. The study also addressed over fitting issues and noted that an optimized LSTM model achieved very low MAE and RMSE during both training and testing phases. Additionally, the model was successfully implemented on FPGA PYNQ Z2 hardware, showing promising results for energy-efficient AI applications in battery management.

Intelligent Automation (IA) combines artificial intelligence and robotic process automation in the automotive sector, driving the digital transformation of autonomous vehicles and potentially eliminating the need for human involvement, thus enhancing safety and vehicle intelligence. [3]This study examines and compares the use of AI, ML and IoT in developing electrical vehicles, emphasizing the shift from manual processes to automate and the importance of understanding risk mitigation. It addresses safety standards and challenges in object detection, cyber security, and vehicle-to-everything (V2X) privacy, and discusses the risks and benefits of autonomous technologies. The survey also reviews design techniques for AI and IoT-based tools and frameworks tailored to autonomous vehicles and their functionalities and applications. The paper covers advancements in using ML, DL, RL and statistical techniques in this field and concludes the future research directions to further enhance electrical vehicle technology. Li-ion batteries are crucial for energy storage, electric transportation and portable electronics, making accurate state of health (SOH) assessments vital for their longevity and safety.ML is increasingly used to analyze these complex nonlinear systems, enhanced by big data and cloud computing. [4]In this paper reviews and explains five important studied ML algorithms for SOH estimation, including their principles, advantages, and applicability, using standardized flowcharts. It evaluates these methods across three dimensions: algorithm performance on five metrics, trends from a decade of research publications, and training approaches including feature extraction and selection. Key findings indicate that SVM and ANN are prominent in research, deep learning showing great potential for complex conditions given sufficient data. Ensemble learning is noted for its balance between data requirements and accuracy.

Recent advancements in AI and ML have greatly advanced research in estimating states of EV batteries, particularly through data handling ML approaches. [5]This paper surveys various ML techniques for estimating battery SOC and SOH, including FFNNs, RNNs, SVM, RBF and Hamming networks. It evaluates these based on inputs, outputs, data quality, test conditions, battery types, and accuracy. The study also experiments with FNN and LSTM, RNN architectures over fifty training sessions of 3000 epochs each, noting performance variations due to random parameter initialization, which underscores the importance of repeated trials for optimal results. Furthermore, the paper emphasizes the need for comparable network parameters and consistent datasets in ML experiments to ensure valid conclusions.

With digitalization and improved data access, AI has become key in solving complex computational challenges. Artificial Neural Networks (ANNs) are useful in digital signal processing but often underperform due to their high processing and memory demands. To enhance AI application performance, hardware accelerators like GPUs, FPGAs and ASICs. FPGAs are particularly valued for their speed, low power use, and reprogrammability, outperforming central processors and GPUs.

In electric vehicle technology, BMS are important for maximizing the efficiency of LiBs, which are nonlinear and vary over time. This complexity makes estimating battery states like SoC, SoH and Remaining Useful Life (RUL) challenging. [6] In this paper reviews AI-driven data approaches and hardware accelerators for predicting these states in LiBs, aiming to develop an advanced AI BMS to improve the efficiency of Electric Mobility (E-Mobility).

III. ARTIFICIAL INTELLIGENCE (AI) IN BMS

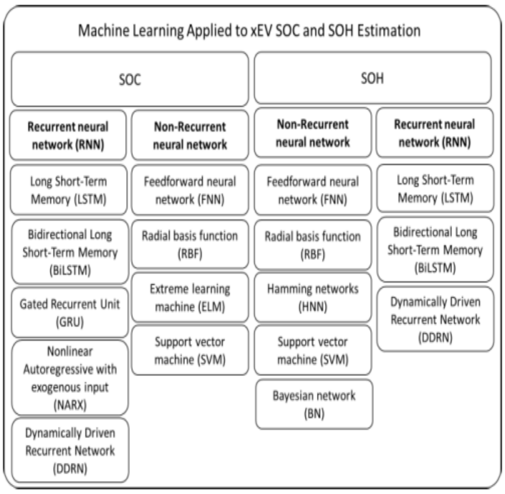

Figure 1: Summary of the ML Methods [8]

This survey paper focuses on the state-of-the-art ML methods for estimating SOC and SOH in electrified vehicles (xEVs), situated within the broader realm of AI and extending across all subfields of ML. Figure 1 shows summary of the SOC and SOH estimation techniques discussed in this paper.

IV. OVERVIEW OF ML APPROACHES IN BATTERY STATE OF CHARGE ESTIMATION

In this part, we delve into research context concerning utilization of ML techniques for estimating battery SOC. The SOC function as the electric vehicle's counterpart to a fuel gauge in conventional gasoline vehicles. However, the direct measurement provided by a fuel gauge, determining the percentage of remaining usable energy within the battery necessitates an indirect approach via estimation. This involves different types of techniques utilizing quantifiable indicators. The nonlinear behavior of batteries adds complexity to this task. Yet, achieving accurate SOC estimation is paramount for enhancing vehicle functionality, ensuring safe operation, optimizing passenger requirements and minimizing costs of design or oversizing.
In subsequent sections, we explore various machine learning SOC estimation methods drawn from recent literature.

A. The Feedforward Neural Network (FNN)

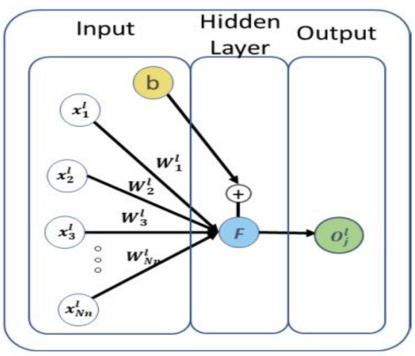

Figure 2: A basic structure of FNN

A FNN is a basic neural network that can handle more number of inputs and outputs through nonlinear mappings. These typically include a simple structure with one hidden layer, more inputs and a single output. Training a FNN involves adjusting the biases (b) and weights (W) of the perceptron to minimize sum-of-squared-error loss function using the back propagation algorithm. This algorithm updates the biases and weights iteratively depend on the error's partial derivatives to reduce the loss. Training usually continues for a predetermined number of repeatedly over the dataset, known as epochs, and may also incorporate other stopping criteria depends on the rate of error improvement.

B. The Radial Basis Function (RBF) Neural Network

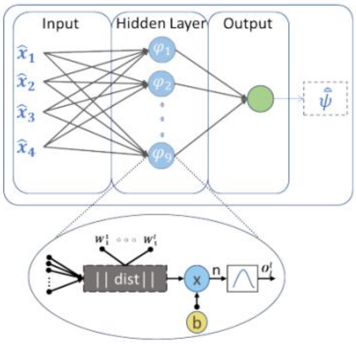

Figure 3: The structure of Radial basis function

The RBFNN is a method of feedforward neural network. Unlike typical feedforward networks with single-valued activation functions, RBFNNs use Gaussian kernels to process the scaled Euclidean distance computed by neurons in the hidden layer. RBFNNs are known for quick training and effective interpolation. In RBFNNs have been applied in various scenarios, like online SOC estimation in battery cells using methods such as extended Kalman filter (EKF) for both lead-acid and Li-ion batteries. These models capture battery dynamics and use previous data like SOC and terminal voltage along with environmental conditions like temperature. Other examples include using RBFNNs with different Kalman filters to improve SOC estimation accuracy and robustness in dynamic conditions, such as in lithium polymer batteries. The networks help in establishing system uncertainty bounds and enhancing voltage estimation across battery cells by quantifying variances, which supports more accurate tracking of battery dynamics using an adaptive AEKF for SOC estimations for multi-cell packs.

C. The Extreme learning machine (ELM)

The ELM is type of FNN but differs in its training algorithm, utilizing the Moore-Penrose pseudoinverse matrix instead of traditional back propagation. ELM has been applied to Lithium ion battery modeling, with subsequent SOC estimation using Kalman filters (KF). Compared to radial basis function (RBF) methods, ELM offers superior SOC estimation accuracy with lower computational burden. Various KF algorithms were assessed, and ELM, particularly with adaptive unscented Kalman filter (AUKF), demonstrated enhanced accuracy and reduced computational demands. Additionally, in optimizing ELM's hidden layer neurons, researchers used the gravitational search algorithm (GSA) across different drive cycles and temperatures. However, their validation approach's limitations call for further investigation into the efficiency of this method for xEV applications.

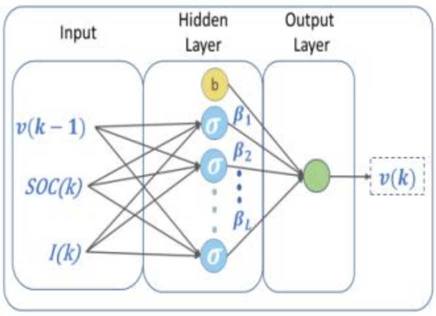

Figure 4: ELM structure

D. The Support vector machine (SVM)

Initially developed for different tasks, SVM required adaptation for battery SOC estimation, often employing support vector regression (SVR) for non-linear data. SVR simplifies optimization using quadratic programming with linear constraints, incorporating an error tolerance margin to improve stability. In a study, 60Ah LFP battery using to estimate SOC by applied SVM for the RBF kernel and kernel computation for support vector derivation. Optimal performance was achieved with 903 support vectors in a high-dimensional space, utilizing battery data including current, voltage and temperature profiles. Same research group was conducted similar work on a 100Ah cell.

E. The Recurrent neural network (RNN)

The RNN utilizes previous data in a self contained cycle, facing challenges with long-term dependencies suitable for tasks with short-term sequence dependencies but, like in battery data. Training may encounter the "exploding" or “vanishing” gradient problem, where errors diminish or escalate. Variants like the long short-term memory (LSTM) network, bidirectional LSTM (BiLSTM), and gated recurrent unit (GRU) address this by incorporating gating mechanisms to retain and propagate past temporal dependencies effectively [11]. These architectures excel at handling time series tasks or lengthy sequential data including speech recognition and battery SOC estimation.

V. Overview of ML approaches in Battery SOH

Battery aging involves degradation of active materials in the anode/cathode and the depletion of Li-ion inventory due to intricate physical or chemical side reactions within the battery, including electrolyte exfoliation, graphite loss and SEI film formation. This aging result in capacity fade, reducing electric vehicle range and power fade, limiting system power capability and efficiency. Capacity and resistance are crucial parameters defining battery performance, with the SOH typically associated with one or both, depending on the application. In energy-intensive applications like electric vehicles, SOH correlates with capacity, while in power-focused applications such as grid support, SOH relates to resistance.

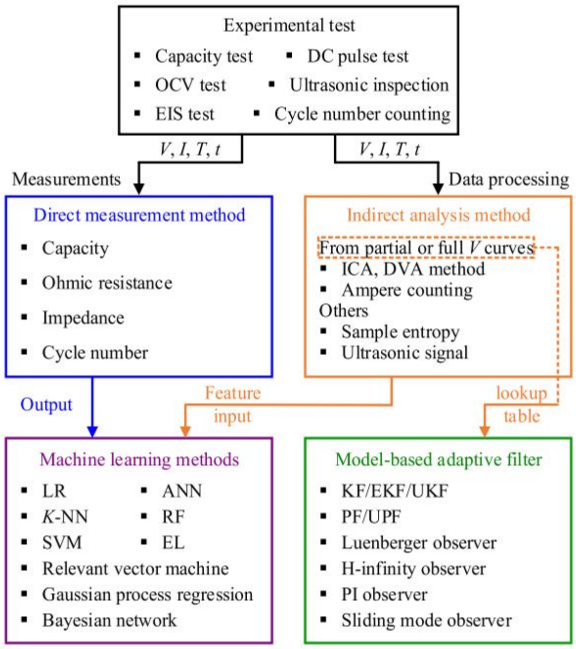

Figure 5: Classification of SOH estimation methods

Developing efficient battery models are challenging due to the critical internal dynamics and operational conditions.ML technologies such as SVM, ANN and others, have gained traction in their adaptability and independence from predefined models. These methods estimate SOH by analyzing patterns between battery data features (e.g., voltage, current, temperature) and SOH indicators (e.g., capacity, resistance), leveraging data from aging experimental tests. Big data technology enhances real-time monitoring and SOH estimation accuracy while reducing microprocessor requirements. Researchers primarily validate algorithms using publicly available datasets, including those from NASA, CALCE. Machine Learning algorithms for battery state estimation can be non-probabilistic (e.g., SVM, ANN, random forest) or probabilistic (e.g., Gaussian process regression, Bayesian network), with the former favored for SOH estimation. Thus, this paper focuses solely on reviewing non-probabilistic algorithms.

Battery SOH serves as an indicator of battery degradation relative to its initial state, providing crucial insights for the vehicle energy management system to maintain optimal performance and safety thresholds. Numerous methodologies exist to measure and estimate the SOH of xEV battery, with latest studies primarily focusing on assessing either capacity loss (SOHc) or internal resistance increase (SOHr). In this section, conventional ML techniques for SOH estimation are categorized into the subsequent types.

A. The Feedforward Neural Network (FNN)

In [20], created a real-time approach employing a FNN to estimate capacity loss (SOHc), leveraging historical data from 18650 form factor cells over a year of testing. The approach analyzed distributions of battery current, voltage, and temperature, evolving with aging and capacity changes. A k-means algorithm determined optimal sub-region volumes, simplifying FNN pattern classification.FNN, with 80 inputs, an 80 neurons hidden layer, and a single output for SOHc, was trained using histograms of counts in each sub-region, outperforming two SVM approaches. Challenges include adjusting to cell differences within a pack and continual updating of histogram distributions. In [21], a SNN computed SOH by estimating internal variables of a battery EC model, tailored to any existing battery model structure. Feature inputs included SOC and its polynomial powers, allowing 4th order polynomials in the SNN design structure. Data from a Mercedes Benz S400 Hybrid vehicle over 174,000 km trained and validated the SNN, showing computational speed and memory efficiency advantages over Extended Kalman Filter.

In [22], an ITDNN estimated SOHc using time-lagged input data, improving battery dynamics and memory effects modeling. Dataset milestones, from starting of life to ending of life, were generated for an LFP 20 Ah cell at varying ambient temperatures and currents. A 20 seconds optimal time-delay for voltage and current signals defined ITDNN structure, comprising input, two hidden and output layers [23].

Similarly, employed an FNN with input time-delays, studying capacity estimation errors' impact on SOC estimation. Meanwhile, correlated battery terminal voltage variations to internal resistance increase (SOHr) using a geometric approaches, achieving accurate SOH estimation with around 1% Error.

B. The Recurrent neural network(RNN)

Estimating SOH involves monitoring a battery's aging process through dynamic signals and memory, making recurrent neural networks (RNN) logical for SOH estimation.

In [26], the Dynamically Driven Recurrent Network (DDRN) was constructed to estimate both SOC and SOH for two Li-ion batteries. DDRN utilized current, voltage, temperature, and delayed inputs of current and voltage, reducing data requirements through an associative memory feature. While promising, further investigation is recommended for integrating SOC and SOH estimations. In [27], a Long Short-Term Memory (LSTM) layers used to determine SOHc by considering current and voltage snapshots during charging cycles. Empirical validation showed high accuracy in SOH estimation. Similarly, [28] employed LSTM for SOHc estimation using simulated data correlated with cell capacity variation, resulting in accurate predictions validated by experimental datasets. In [29], an LSTM-based model simultaneously estimated SOC and battery internal resistance (SOHr) using various inputs, demonstrating improved performance compared to other ML models. Lastly, an RNN was developed using parameters correlated with Li-ion SOC to predict battery SOH based on capacity fade and increase in equivalent series resistance, achieving accurate predictions validated by experimental datasets. These approaches underscore the effectiveness of neural network models, particularly RNNs and LSTMs, for accurate and reliable battery SOH estimation.

C. The Radial basis function (RBF) neural network

In [30], researchers utilized Sparse Bayesian Predictive Modeling (SBPM) to unveil nonlinear relationships between battery voltage and capacity sequence sample entropy. SBPM employing radial basis functions, Hybrid Pulse Power Characterization (HPPC) procedure was tailored to assess these relationships using a battery cell pack. Sample entropy, averaging across the entire time-series, revealed patterns in battery terminal voltage dynamics. The Panasonic UR14650P model, trained and validated on data from NMC Li-ion cells at varying surrounding temperatures, demonstrated performance compared to Support Vector Machine (SVM). Results showed that as sample entropy increased, battery capacity tended to decrease.

D. The Hamming networks (HNN)

In [31], a Hamming Neural Network (HNN), known for binary pattern recognition, was combined with equivalent circuit modeling and Dual Extended Kalman Filter (DEKF) used to estimate SOC, Capacity (SOHc), and Resistance (SOHr) of batteries .The HNN estimated charge/discharge voltage variations and capacity patterns, which were then inputted into a DEKF for state and parameter estimation. Experimental data from 20 Li-ion batteries 0f model Samsung 18650 categorized into 15 distinct classes were transformed into binary arrays for HNN processing. The FFL computed internal structure with input pattern data, while the recurrent layer utilized the winner-take-all principle to output the dominant response.

E. The Support vector machine (SVM)

In [32], the application of SVM for xEV SOH estimation is discussed, focusing on estimating both SOHc and SOHr using data from vehicle batteries. The SVM was trained using discharge pulses to compute SOHr and SOHc during full discharge or partial discharge profiles, with parameters including battery current, temperature, and SOC.SVM demonstrated efficiency of 6.2% RMSE for SOHr and 0.63% RMSE for SOHc, indicating potential onboard vehicular application viability.

Another study detailed in [34] combined an ECM with a SVM using a particle filter to estimate State of charge, State of health, and Remaining useful life of Li-ion batteries. The Relevance vector machine adjusted the Equivalent circuit model’s internal parameters as the battery aged, utilizing data from cycle-life tested Li-ion cells through EIS and various sensors. After training, the RVM along with PF produced a probability distribution over time to estimate SOH and RUL.

Additionally, [35] presented a novel approach merging SOC and SOH estimation using an adaptive sigma point Kalman filter and an SVM, acknowledging the interdependence of SOC and SOH.

In [36], an SVM-based model was developed for online SOHc estimation using battery voltage data during charging. The coefficient β was adjusted as the battery aged, the SVM updates SOHc accurately, demonstrated using experimental datasets from NMC cells cycled under varying conditions.

F. Bayesian Network (BN)

In [37], a Dynamic Bayesian Network (DBN) was employed to estimate battery SOH using observed battery terminal voltage. The Li-ion cells data was trained using DBN model from at various aging states and charging processes, achieving an error rate less than 5%.Similarly, in a study akin to [37], a Bayesian network (BN) was utilized to estimate SOH based on probabilistic distribution using steady current duration, voltage reduction and open circuit voltage after a charge cycle. Evaluated using data from 110 Li-ion batteries, the method achieved an average error of 0.28%.

VI. Comparison between SOC and SOH

The summary encompasses SOC estimation errors for various methods, including details such as training/testing data profiles, inputs/outputs, dataset quality, battery types, and temperatures investigated. Common inputs like voltage, current, and temperature are used, with some studies incorporating averaged or calculated values. Approximately 50% employ automotive-style drive cycles with fluctuating temperatures, whereas the rest use constant or pulsed current cycles with stable temperatures. Higher data quality generally enhances method accuracies. RBFs exhibit the highest error (average 2.2%), average errors of 0.7%, 0.5%, and 0.4% show by FNNs, RNNs, and other methods respectively. RNNs and FNNs perform well on multi-temperature datasets with automotive drive cycles, suggesting their effectiveness. Further exploration is suggested for methods like ELM, AUKF and SVM, especially for more demanding cycles, to gauge their strength. Regarding SOHc and SOHr estimation, nearly all methods demonstrate the ability to estimate resistance or capacity with an error of 1% or less. Drawing specific comparative conclusions is challenging due to variations in battery types, datasets, testing environments and evaluation criteria, highlighting the importance of data quality for ML models reliant on data-driven algorithms. While many studies utilize suitable datasets for preliminary studies, they may not suffice for comparing methods intended for xEV application.

VII. Conclusion and Recommendations

The research study concludes that various ML methodologies are appropriate for estimating battery SOC and SOH. However, many lack realistic xEV application dynamics in their data. Only three studies validated methods under negative ambient temperatures, crucial for challenging SOC and SOH estimation. Simplified comparisons suggest estimated with about 1% error for SOC and SOH. The overview is highlighting the complexity of collecting and preparing data, crucial for training algorithms. Months or years, Data required taking especially for SOH estimation. Despite growing data volume and ML advancements, utilization remains constrained by data quality and computational complexity. Future research should address this aspect consistently. Publications often use preliminary datasets, insufficient for xEV application comparisons. Additionally, inherent randomness in neural network training affects accuracy variations, as shown by repeated training. To ensure robustness in ML algorithm training and comparison, guidelines suggest using the same validation dataset, considering algorithm parameters, and repeating training processes.

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