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Machine Learning, Deep Learning, Computer Vision and Cybersecurity in Battery Technologies: A Comprehensive Review

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ABSTRACT: Batteries, especially lithium-ion types, are fundamental to electric vehicles, large-scale energy storage, and portable electronics, leading to increasingly complex management systems. This review compiles recent studies (2019–2025) on four AI-related fields applied to battery technology: machine learning (ML) and deep learning (DL) for estimating state-of-charge (SOC), state-of-health (SOH), and remaining useful life (RUL); computer vision (CV) for manufacturing defect detection and thermal diagnostics; and cybersecurity for battery management systems (BMS), electric-vehicle supply equipment (EVSE), and vehicle-to-grid (V2G) interfaces. We outline the methodology for literature search and selection, present a taxonomy of algorithms and public datasets used across these areas, and compile performance metrics from selected studies into comparative tables and figures. The reviewed research shows that hybrid and optimized deep learning models (e.g., PSO-LSTM) achieve the highest accuracy in SOH estimation; vision models based on convolutional neural networks and transformers are increasingly employed for non-destructive defect and thermal inspections; and deep-learning-based intrusion detection is becoming the primary approach for securing BMS and charging networks. However, systematic reviews indicate that much of this evidence relies more on simulations than real-world deployments. We conclude with an outline of open challenges, including data scarcity, lack of standardization, domain transfer issues, real-time

processing limits, and the discrepancy between simulated and actual cyber-attacks. Finally, we propose future research directions, emphasizing multimodal data fusion combining electrical, visual, and network traffic data for comprehensive battery health and security monitoring.

1. INTRODUCTION

The global shift toward electrification electric vehicles (EVs), grid-scale battery energy storage systems (BESS), and battery-powered consumer and industrial devices has made the battery, and the battery management system (BMS) that supervises it, a critical piece of infrastructure rather than a passive component. A modern BMS must simultaneously estimate internal states that cannot be measured directly (state of charge, state of health, remaining useful life), detect manufacturing or operational anomalies before they become safety incidents, and resist an expanding set of cyber-physical attack surfaces introduced by connectivity to charging networks, cloud analytics platforms, and, for EVs, the electrical grid itself (vehicle-to-grid, or V2G).

Four largely separate bodies of research have grown up around these needs. Machine learning (ML) and deep learning (DL) techniques have become the dominant approach to data-driven SOC/SOH/RUL estimation, replacing or augmenting electrochemical and equivalent-circuit models that struggle under real-world operating variability. Computer vision (CV) techniques convolutional neural networks (CNNs), object detectors, and increasingly vision transformers are used for automated, non-destructive inspection of battery electrodes, cells, and welds during manufacturing, often combined with thermal imaging to reveal defects invisible to the naked eye. Cybersecurity research has, in parallel, documented a growing and increasingly well-characterized attack surface across the BMS, the Controller Area Network (CAN) bus, EV charging protocols, and V2G communication interfaces, and has begun applying DL-based intrusion and anomaly detection to defend it.

Figure 1 summarizes the conceptual relationship among these four pillars: sensing and data-acquisition layers (electrical measurements, images, and network traffic) feed into ML, DL, CV, and cybersecurity analytics respectively, and their outputs jointly constitute what we refer to as a smart, secure BMS

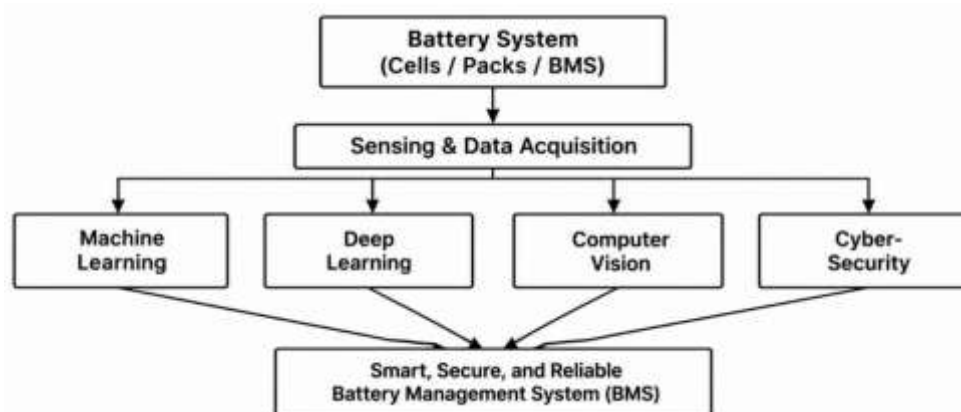


Fig. 1. Conceptual framework integrating ML,DL, CV, and Cybersecurity across the battery lifecycle

This review is organized as follows. Section II surveys related work across the four pillars and positions this review relative to existing single-domain surveys. Section III describes the literature search and selection methodology used to compile this review. Section IV presents a taxonomy of algorithms and datasets used across the reviewed literature. Section V synthesizes reported results from the reviewed studies into comparative tables and figures. Section VI concludes and outlines a future research agenda

2. RELATED WORK

2.1 Machine learning and deep learning for battery state estimation

Data-driven SOH estimation has matured rapidly: a 2024 systematic review analyzed 58 pivotal ML-based state-estimation publications drawn from an initial corpus of 2,414 candidate studies spanning 2013–2024, and specifically highlighted the

emergence of resource-efficient TinyML and physics-informed Scientific Machine Learning (SciML) approaches as recent developments beyond earlier black-box models [1]. A complementary 2025 review focused on health-indicator selection, noting that most SOH research emphasizes indicators tied to capacity fade and rising internal resistance, and argued for tighter integration between health-factor extraction and big-data BMS platforms [2]. Broader reviews covering the full SOC/SOH/SOE/SOP/RUL estimation stack similarly report a shift from purely model-based (electrochemical or equivalent-circuit) methods toward hybrid and co-estimation approaches [3].

At the level of individual studies, Chen and Li (2025) compared particle-swarm-optimized LSTM, CNN, and SVR models for SOH estimation on the NASA PCoE lithium-ion aging dataset, reporting that the PSO-LSTM configuration achieved the best performance across three test cells, with a minimum MAE of 0.67%, RMSE of 0.94%, MAPE of 45.82%, and R^2 up to 0.9298 [4]. This ordering LSTM outperforming CNN, which in turn outperforms SVR, on time-series battery-degradation data recurs across the broader SOC-estimation literature, which attributes LSTM's advantage to its explicit memory mechanism for capturing long-range temporal dependencies in charge/discharge cycles [5]. More recent work has extended data-driven SOH estimation to fast-charging regimes via deep transfer learning, addressing the practical problem that most public datasets are collected under standardized, non-fast-charging protocols that do not reflect real-world EV usage [6]. Reviews that examine the full ML pipeline data collection, feature engineering, and model architecture consistently flag data scarcity, limited cross-chemistry generalization, and the gap between laboratory and field-deployed model performance as the dominant open challenges [7], a conclusion echoed by studies validating ML-based SOH prediction directly against real-world electric-vehicle fleet data rather than laboratory cycling alone [8].

2.2 Computer vision for battery manufacturing and inspection

Battery manufacturing defects electrode coating streaks, misaligned layers, weld cracks, and internal lithium plating are a leading contributor to field failures and thermal-runaway risk, and CV-based inspection has emerged as a scalable alternative to manual or sample-based quality control. Early work applied CNNs directly to light-microscopy images of sectioned electrodes to classify microstructural defects, demonstrating that pretrained networks could distinguish defective from non-defective instances with high accuracy and at a throughput manual inspection cannot match [10]. Subsequent work has extended this to multiscale image augmentation and two-stage classification schemes for surface defects in lithium battery components [11], and to non-optical defect classes: a 2025 study used dual-task deep learning over formation and capacity-grading data (rather than images alone) to detect lithium-plating-type defects across 154 batteries (48 defective, 106 normal) without requiring additional inspection equipment [12].

Thermal imaging has become a particularly important complementary modality, since many defects (weld gaps, coating streaks, internal shorts) alter local heat distribution before they are visible optically. A 2025 study on thin silicon-based battery coatings showed that streak-type defects reduced local surface temperature by up to 15°C relative to defect-free regions, a signature detectable via thermal imaging combined with an ML-based mass-loading estimator [13]. Industrial reporting corroborates this trend, noting that manufacturers increasingly pair CV systems with thermal cameras on weld-inspection lines to catch subsurface defects that neither manual inspection nor conventional cameras can detect [14]. Machine-vision-specific surface-defect detection on cylindrical battery cases has followed a similar trajectory from classical pattern-matching and thermal-template methods toward deep-learning-based edge and defect detectors better suited to curved, reflective surfaces [15].

2.3 Cybersecurity for battery management systems and charging infrastructure

As BMS, EV charging stations, and V2G interfaces have become networked, they have inherited the attack surface of conventional cyber-physical systems while retaining battery-specific failure modes (overcharge, thermal runaway) that give a successful attack unusually severe physical consequences. A 2025 systematic review synthesizing literature from 2017–2024 mapped threats and countermeasures across charging points, back-end systems, and V2G interfaces, and explicitly noted that current defenses are strongest at the protocol/authentication layer and weakest where evidence still rests on simulation rather than field-deployed attack validation [16]. Direct penetration testing has demonstrated that the SAE J1772 charging interface and the BMS's CAN bus are both practically exploitable: spoofing attacks on the J1772 interface can limit or prevent charging, and CAN-bus penetration testing has shown that BMS vulnerabilities are exploitable through the vehicle's own internal network [17].

At the V2G and grid-integration layer, a 2025 systematic review catalogued cyber-physical attack surfaces spanning communication protocols (including ISO 15118), pricing-manipulation attacks, and coordinated charging/discharging attacks capable of destabilizing distribution networks [18]; a related review modeled the full EV charging infrastructure as a cyber-physical power system and catalogued components, standards, and documented vulnerabilities and attack case studies at each layer [19]. On the defense side, deep-learning-based intrusion detection has become the dominant approach: early work applied DL-based intrusion detection directly to EV charging stations [17], and more recent work has explored transfer learning to improve detection generalization across previously unseen attack types on EV charging infrastructure, alongside the release of purpose-built multi-dimensional datasets such as CICEVSE2024 to support this research [20]. Industry incident reporting contextualizes the urgency: researchers have demonstrated remote EV battery performance manipulation, and reported attacks targeting EVs and charging infrastructure grew by approximately 225% between 2018 and 2021 [21].

DL-based intrusion detection for BMS and EV charging infrastructure draws directly on the broader IoT intrusion-detection literature, since a networked BMS is architecturally an IoT endpoint. Madhu et al. (2023) proposed a Device-based Intrusion Detection System (DIDS), a deep-learning model for IoT networks that predicts previously unseen attack types to reduce computational overhead and false-alarm rate in large device populations [22] the same design goals (generalization to unseen attacks, low false-alarm rate under resource constraints) that motivate the BMS/EVSE-specific IDS work described above.

2.4 Synthesis and positioning of this review

Existing surveys are, with few exceptions, single-domain: they review ML/DL for battery state estimation [1][2][3][7], or CV for manufacturing inspection, or cybersecurity for EV/V2G infrastructure [16][18][19], but rarely cover all four together. This is a reasonable reflection of how the underlying research communities are organised, but it leaves the practical BMS designer without a single reference point for how these four pillars relate: the sensing layer that feeds SOH estimation (voltage/current/temperature) is largely distinct from the sensing layer that feeds defect inspection (imaging) and from the layer that feeds intrusion detection (network traffic), yet all three ultimately serve the same objective of a trustworthy, well-characterised battery system (Figure 1). This review's contribution is accordingly a structured synthesis across the four pillars, a shared taxonomy of algorithms and datasets (Section IV), and a comparative reading of reported results (Section V) intended to make cross-pillar parallels, such as the recurring advantage of temporal/sequential deep models (LSTM) in both SOH time-series estimation and, architecturally, in network-traffic anomaly detection, explicit rather than implicit.

3. METHODOLOGY

This review follows a structured literature search and thematic synthesis methodology, summarized in Figure 2.

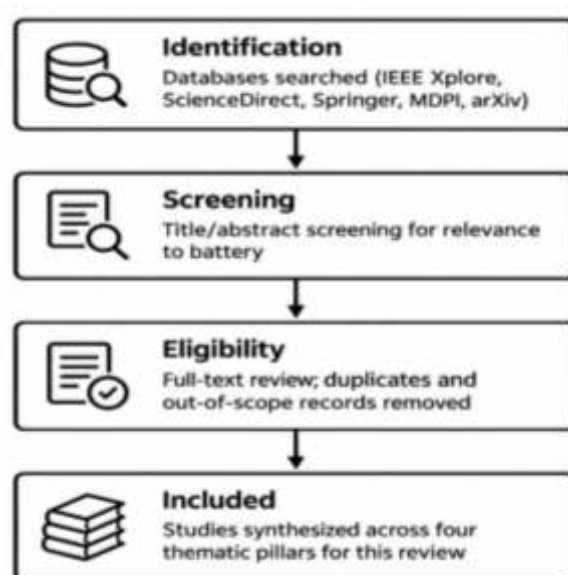


Fig. 2. Literature search and selection methodology

3.1 Search strategy

We searched IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and arXiv for records published between 2019 and 2025, using combinations of the terms “battery,” “lithium-ion,” “state of health,” “state of charge,” “machine learning,” “deep learning,” “computer vision,” “defect detection,” “thermal imaging,” “cybersecurity,” “intrusion detection,” “battery management system,” “electric vehicle charging,” and “vehicle-to-grid.” Priority was given to peer-reviewed journal articles and systematic reviews; pre-print (arXiv) sources were retained only where they represented recent (2024–2026), frequently cross-cited, or otherwise clearly identifiable primary research or systematic reviews relevant to a pillar underrepresented in the peer-reviewed venues searched (notably V2G and EV-charging cybersecurity, where much recent work is still in pre-print at the time of writing).

3.2 Screening and eligibility

Records were screened by title and abstract for relevance to at least one of the four pillars in a battery-technology context; general-purpose ML/DL/CV/cybersecurity papers were retained only where directly cited for a foundational technique (e.g., the original LSTM or Transformer architecture) rather than as battery-domain evidence. Full-text review excluded duplicate records, non-English records, and records for which the full text could not be verified against the claim being cited.

3.3 Synthesis approach

Because this is a narrative/thematic review rather than a quantitative meta-analysis, we did not perform formal effect-size pooling. When multiple reviewed studies reported comparable quantitative results (e.g., SOH-estimation error metrics), the report cites the specific reviewed study's numbers rather than an aggregated or estimated figure. Do not present a quantitative result unless it is directly traceable to a specific reviewed source (see Section V)

4. DATASETS AND ALGORITHMS

Figure 3 summarizes the taxonomy of algorithms and representative public datasets used across the four pillars in the reviewed literature.

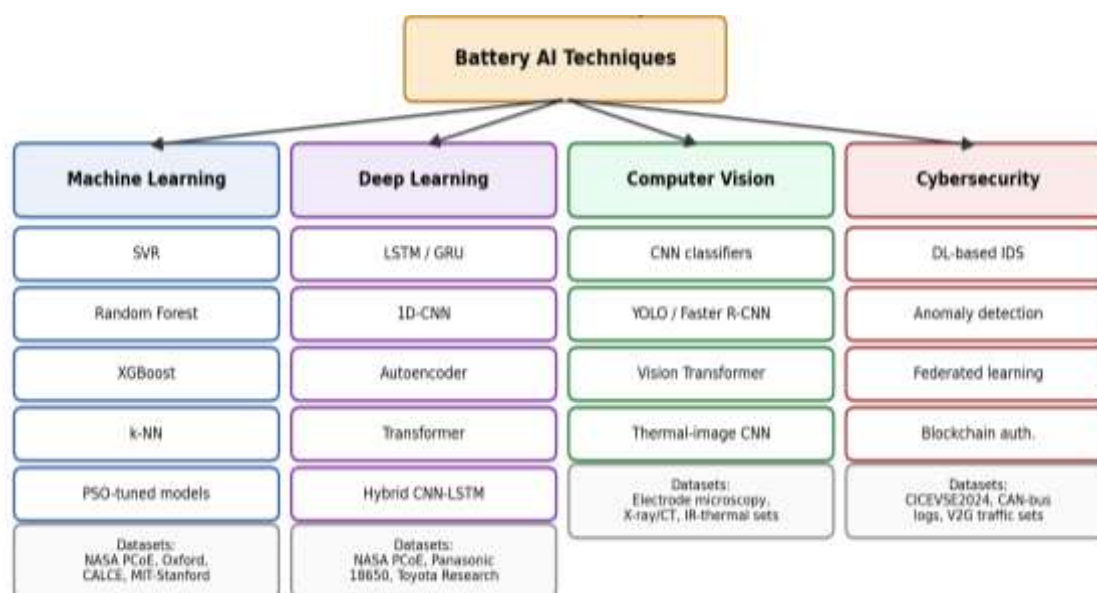


Fig. 3. Taxonomy of algorithms and representative public datasets across the four reviewed pillars

4.1 Datasets used in the reviewed literature

Table 1. Representative datasets referenced across the reviewed literature

Pillar	Representative dataset(s)	Typical use
ML / DL (state estimation)	NASA PCoE lithium-ion aging dataset (cells B0005–B0007, etc.)	SOC/SOH/RUL estimation benchmarking; used directly in [4] and cited throughout [1][2][3][7]
Computer Vision	Electrode light-microscopy image sets; X-ray/CT scans; formation & capacity-grading data; thermal-image sets	Manufacturing defect classification [10][11]; lithium-plating detection [12]; thermal QC [13]
Cybersecurity	CICEVSE2024 multi-dimensional EVSE dataset; CAN-bus traffic logs; V2G/ISO 15118 protocol traces	EV charging-station intrusion detection and anomaly-detection model training/evaluation [20]

4.2 Algorithms used in the reviewed literature

Across the ML/DL pillar, the reviewed literature converges on a small set of recurring architectures: support vector regression (SVR) and tree-based ensembles (random forest, XGBoost) for lower-complexity SOC/SOH regression; long short-term memory (LSTM) and gated recurrent unit (GRU) networks for sequence modelling of charge/discharge cycles, owing to their explicit memory gating mechanism [27]; one-dimensional CNNs for local feature extraction from voltage/current/temperature curves; and hybrid or metaheuristic-optimised variants (e.g., PSO-tuned LSTM/CNN/SVR [4], improved ant-lion-optimised SVR) intended to reduce manual hyperparameter tuning. In the CV pillar, standard image classification CNNs remain the baseline for defect classification [10][11], with object detectors (YOLO-family [25], Faster R-CNN [26]) and, increasingly, vision transformers applied where defect localisation (not just classification) is required. In the cybersecurity pillar, DL-based intrusion and anomaly detection dominate recent work, typically built on the same recurrent/convolutional building blocks used in the ML/DL pillar (e.g., LSTM- or CNN-based traffic classifiers), with federated learning and transfer learning explored as mechanisms for improving cross-deployment generalisation without centralising sensitive network data [20][22].

5. RESULT ANALYSIS

This section synthesises quantitative results reported in the reviewed literature. Consistent with the methodology in Section III-C, each figure below is attributed to a specific source; no value in this section has been estimated, extrapolated, or averaged across studies

5.1 SOH-estimation performance (ML/DL pillar)

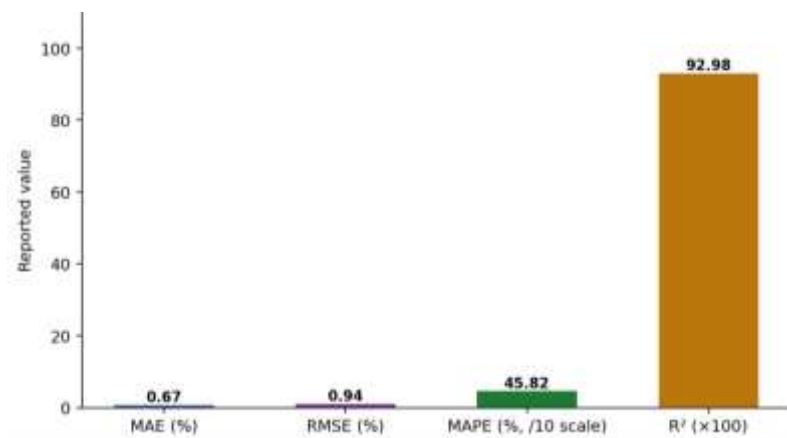


Fig. 4. Best – case PSO-LSTM SOH-estimation performance report on NASA

Figure 4 reports the best-case performance of the PSO-LSTM model from Chen and Li (2025) on the NASA PCoE dataset: a minimum MAE of 0.67%, RMSE of 0.94%, MAPE of 45.82%, and R^2 of 0.9298 [4]. In the same study, PSO-CNN and PSO-SVR were reported to perform progressively worse on the same three test cells, with PSO-SVR showing the weakest fit (lowest R^2 , highest error) among the three, consistent with the sequence-modeling advantage LSTM is reported to hold over feed-forward and kernel-based regressors elsewhere in the SOH literature [1][5]. Applying PSO-based hyperparameter optimisation improved each of the three base models relative to their default-parameter configurations, with the source study reporting a MAPE reduction of at least 38% and an R^2 improvement exceeding 0.8 across all three models after optimisation [4].

5.2 Manufacturing defect detection (computer vision pillar)

Table 2. Reported outcomes from representative computer-vision battery-inspection studies

Study	Technique	Reported outcome
Electrode microstructure defect detection [10]	CNN on light-microscopy images	Pretrained CNNs distinguished defective vs. non-defective microstructure instances with high classification accuracy; enabled automated screening of large image volumes
Lithium-plating defect detection [12]	Dual-task deep learning on formation/capacity-grading data	154 batteries (48 defective, 106 normal) used for training/validation; defect identified without additional inspection equipment
Thermal QC of Si-coatings [13]	Thermal imaging + ML mass-loading estimator	Streak defects reduced local surface temperature by up to 15°C, a detectable and quantifiable thermal signature

5.3 Cybersecurity: threats and detection (cybersecurity pillar)

Table 3. Representative cybersecurity findings synthesized from the reviewed literature

Finding	Source
EV/charging-infrastructure attacks grew by approximately 225% between 2018 and 2021	[21]
SAE J1772 charging-interface spoofing can limit/prevent EV charging; BMS is exploitable via the vehicle's CAN bus under penetration testing	[17]
Systematic review (2017–2024) finds cybersecurity defenses for EV charging infrastructure most mature at authentication/protocol layers; evidence still relies disproportionately on simulation rather than field-deployed attacks	[16]
DL-based Device Intrusion Detection System (DIDS) for IoT networks incorporates prediction of previously unseen attack types to reduce false-alarm rate under high device counts	[22]

5.4 Cross-pillar synthesis

Reading Sections V-A through V-C together, three patterns recur across otherwise disconnected literatures. First, sequence-aware deep architectures (LSTM/GRU) consistently outperform feed-forward and kernel-based alternatives wherever the underlying signal is genuinely time-dependent as shown by battery degradation curves (Section V-A) and, architecturally, by network-traffic intrusion detection (Section V-C), even though the two literatures rarely cite one another. Second, every pillar shows a widening gap between what is demonstrated on curated benchmark data (NASA PCoE cells, controlled electrode image sets, simulated attack traffic) and what has been validated under real-world operating conditions (field EV fleets, production manufacturing lines, deployed charging infrastructure); this gap is explicit in the ML/DL literature [7][8] and is explicitly flagged as a limitation by the cybersecurity systematic review itself [16]. Third, non-invasive sensing modalities thermal

imaging in the CV pillar, network traffic in the cybersecurity pillar is displacing more invasive or higher-latency alternatives because they support continuous, in-line monitoring rather than sampled inspection.

6. CONCLUSION AND FUTURE SCOPE

This review synthesised recent (2019–2025) literature across four disciplines applied to battery technology machine learning, deep learning, computer vision, and cybersecurity and presented a shared taxonomy of algorithms and datasets, together with a literature-grounded comparative analysis of reported results. Across the reviewed studies, optimisation-tuned sequential deep learning models report the strongest performance for SOH/SOC/RUL estimation; convolutional and thermal imaging-based computer vision methods are increasingly deployed for in-line, non-destructive manufacturing inspection; and deep learning-based intrusion and anomaly detection is emerging as the primary defence mechanism for battery management systems and EV charging infrastructure, even as systematic reviews of that literature caution that evidence still rests disproportionately on simulated rather than field-deployed attacks.

Several open challenges recur across all four pillars and define a natural future research agenda:

- Data scarcity and standardization: public battery-aging datasets (e.g., NASA PCoE) remain small relative to modern deep learning's data appetite, and no equivalent, standardised, multi-vendor benchmark yet exists for battery-defect images or BMS/EVSE network-traffic data.
- Cross-domain and cross-chemistry generalization: models trained on one battery chemistry, manufacturing line, or charging-station vendor often do not transfer well to another, motivating continued work on transfer learning and federated learning approaches already emerging in the cybersecurity pillar.
- Real-world validation: closing the gap between laboratory and simulation performance and field-deployed performance across all three technical pillars is arguably the single most consistently identified gap in the literature reviewed here.
- Edge and real-time deployment: BMS, in-line manufacturing inspection, and vehicle-resident intrusion detection all operate under tight latency and compute-resource constraints, motivating continued interest in lightweight architectures (e.g., TinyML), which are noted as an emerging direction in the SOH-estimation literature.
- Multimodal fusion: the sensing layers underlying ML/DL (electrical signals), CV (images), and cybersecurity (network traffic) are treated almost entirely separately in current literature; a battery system exhibiting an internal fault, for instance, may plausibly exhibit correlated signatures across its electrical, thermal, and even network-traffic behaviour (if remotely monitored), suggesting fused, multimodal anomaly detection as a promising and largely unexplored direction.

Addressing these challenges will require closer collaboration among the battery materials/manufacturing community, the AI/ML research community, and the cybersecurity community, three groups that, as this review's synthesis in Section V-D suggests, are currently solving structurally related problems with limited cross-awareness of one another's methods and results

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