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A Systematic Review of AI-Driven DC Arc Fault Detection Methods for High-Voltage Electric Vehicle Systems: Techniques, Challenges, and Future Directions

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ABSTRACT

Direct current (DC) arc faults are serious safety hazards in high-voltage electric vehicle (EV) systems. Sustained high-energy discharges can cause thermal runaway and fires. Conventional detection methods often underperform in the dynamic environments of EVs. This paper reviews artificial intelligence (AI)-based detection techniques for EVs, assesses methods from photovoltaic (PV) systems, and defines deployability criteria such as inference time and hardware needs. We analyzed 72 peer-reviewed studies published between 2018 and 2025, sourced from IEEE Xplore, ScienceDirect, Web of Science, SpringerLink, and Wiley Online Library after a strict quality assessment. Hybrid AI models achieve high accuracy (97-99.99%) but face real-time deployment challenges, with inference times from 4 ms to 200 ms depending on hardware. Deep learning needs large, labeled datasets. Variable-frequency traction inverters produce electromagnetic interference, creating unique EV challenges. Key deployment barriers include sensor integration costs, limited automotive ECU computation, and a lack of standardized validation protocols. Future research should focus on explainable AI for safety certification and federated learning to address data scarcity, offering practical guidance for robust detection systems.

1. Introduction

In recent years, the transition from internal combustion engines to electric vehicles (EVs) represents a major advancement in sustainable transportation, driven by growing evidence of climate change and the imperative to reduce fossil fuel consumption [1], [2]. As shown in Fig. 1, the global EV market has experienced substantial growth, rising from $112.9 billion in 2018 to an estimated $906.7 billion by 2028 [3]-[5]. Advances in battery technology, expansion of charging infrastructure, and the enactment of supportive government policies have enabled this transformation [6]. Nevertheless, the accelerated adoption of EVs presents new challenges, particularly regarding the safety and reliability of high-voltage electrical systems. DC arc faults pose significant hazards due to their ability to sustain high-energy discharges in the absence of natural zero crossings [7]-[9]. Such

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faults can lead to fires, component damage, and catastrophic system failures, thereby presenting serious risks to vehicle occupants and emergency responders, as illustrated in Fig. 2. Consequently, arc fault detection and mitigation are governed by stringent regulations established by regulatory authorities and automotive standards, including ISO 6469, SAE J2344, and UL 1699B. Despite these guidelines, the dynamic and complex nature of electric vehicle (EV) power networks continues to present challenges in developing robust and reliable detection systems [9]-[12].

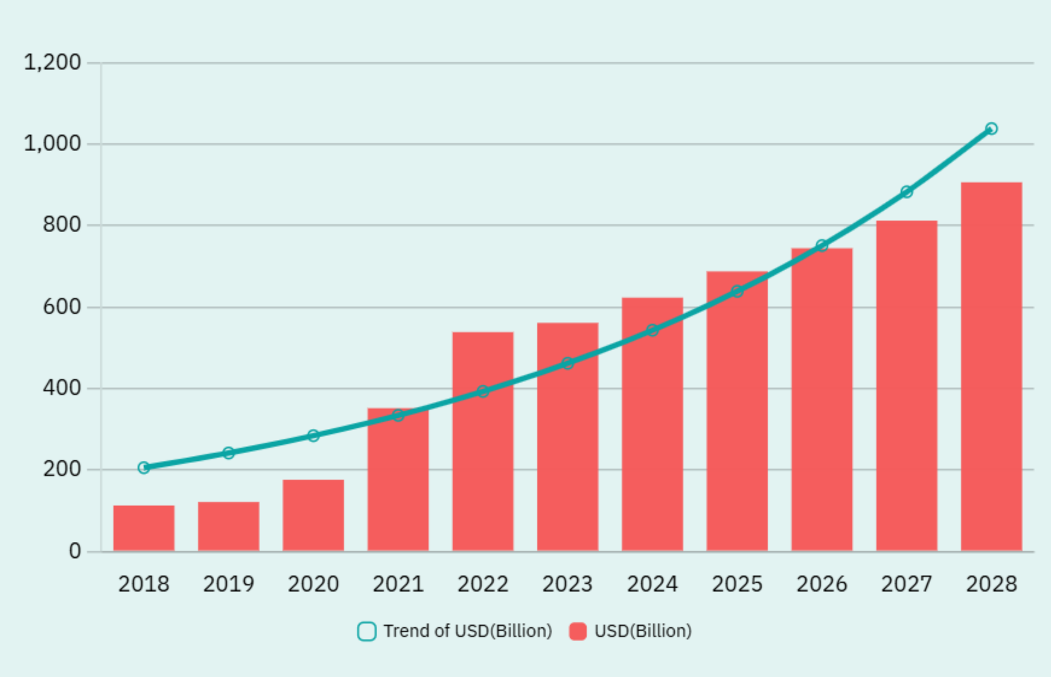

Fig. 1. Shows the exponential growth of the global EV market from 2018-2028 [2]

Traditional detection methods that monitor current and voltage thresholds are straightforward to implement; however, they are susceptible to false positives caused by electrical transients and load fluctuations [13]. These false positives can result in unnecessary system shutdowns, reducing vehicle availability and eroding user confidence. Advanced signal processing techniques, including the Fast Fourier Transform (FFT) and wavelet transforms, have been utilized to analyze frequency-domain characteristics and improve detection accuracy. However, these methods generally require substantial computational resources, limiting their applicability in real-time embedded systems for electric vehicles. This challenge underscores the need to balance analytical precision with practical system constraints [14]. The development of artificial intelligence (AI) and machine learning (ML) has facilitated data-driven methods for intelligent arc-fault detection. Although supervised and unsupervised learning models demonstrate high accuracy in classifying fault patterns [15], [16], their integration into electric vehicles is hindered by processing limitations, latency constraints, and the requirement for adaptability to diverse operating conditions [17].

A major challenge in this field is the limited literature addressing DC arc faults in production electric vehicle (EV) power systems. Most foundational research on advanced detection algorithms, including artificial intelligence (AI) and machine learning (ML), has focused on photovoltaic (PV) systems and other DC microgrids. While these systems share high-voltage DC architectures, their operational environments differ significantly. Electric vehicle systems are subject to dynamic load profiles, mechanical vibrations, variable switching frequencies from traction inverters, and complex electromagnetic interference, all of which can modify arc signatures and affect detection feasibility [18], [19]. This gap is significant because detection methods developed for stationary PV systems may not be directly applicable to the demanding and mobile EV environment without substantial adaptation.

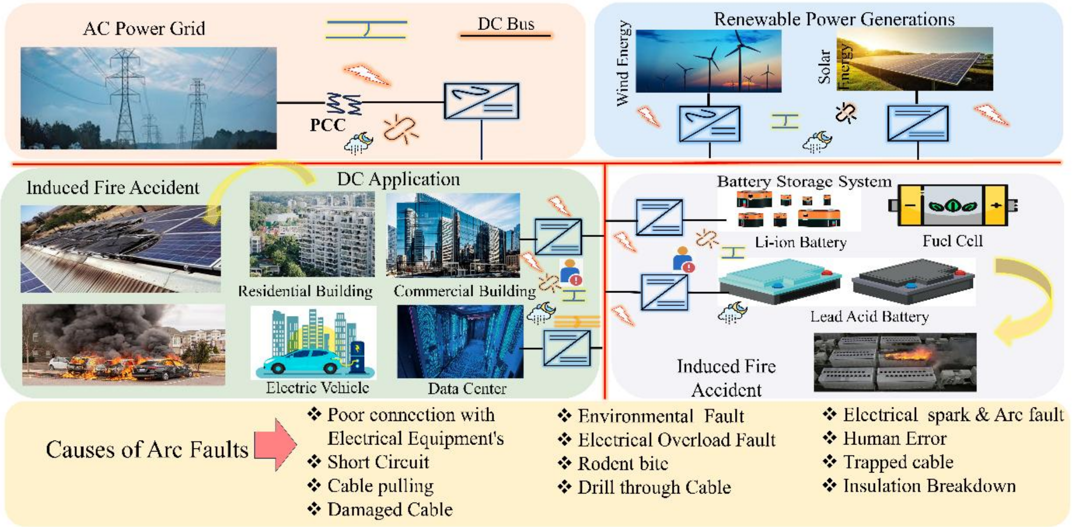

Fig. 2. illustrates the potential safety hazards caused by DC arc faults in EV systems, including thermal runaway and fire risks that endanger occupants and first responders [1]

This review employs a systematic and pragmatic approach to analyze studies on electric vehicle (EV) systems, integrating key research from photovoltaic (PV) and general direct current (DC) applications. The analysis critically assesses the suitability of these methods for the complex, noisy, and dynamic environments typical of electric vehicles, with particular attention to system-specific variations in capacitance, inductance, and noise signatures. The primary contribution of this paper is a comprehensive systematic review that: (1) offers a focused evaluation of detection methods within the context of automotive safety standards and operational constraints, (2) establishes a structured taxonomy and comparative assessment of method transferability from PV to EV contexts, (3) identifies major challenges and future research directions, emphasizing real-time deployment and certification, and (4) presents a detailed comparison framework that incorporates inference time and hardware platform requirements to evaluate practical deployability.

2. Review Methodology

This systematic literature review (SLR) was conducted in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor, transparency, and reproducibility [20]. The complete PRISMA 2020 checklist is provided as Supplementary Material S1. The review process comprised four sequential phases: formulation of research questions, systematic literature search and selection, quality assessment and risk of bias evaluation, and data extraction and synthesis [21], [22]. The early stage of research on electric vehicle (EV)-specific DC arc-faults, a pragmatic, domain-informed approach was adopted. The analysis focuses on studies within the EV context and strategically incorporates seminal and high-impact research from photovoltaic (PV) systems and DC microgrids, where detection methodologies are more mature. The applicability and transferability of these cross-domain methods to the EV environment are critically evaluated in Section 4 and Section 5, with explicit consideration of architectural and operational differences.

2.1. Research Questions

This study, formulated four research questions (RQs) to guide the review:

- RQ1: Which signal processing and artificial intelligence techniques are most frequently utilized for DC arc-fault detection, and what performance metrics have been reported for these methods?
- RQ2: To what extent can detection methods originally developed for photovoltaic (PV) systems and other DC microgrids be effectively transferred and adapted to electric vehicle (EV) power systems, given the differences in noise profiles, load dynamics, and operating conditions?

- RQ3: What are the major practical challenges that hinder the transition of laboratory-validated detection methods to implementation in large-scale, mass-produced EV applications?
- RQ4: What emerging trends and critical research gaps shape the development of next-generation, robust, and certifiable arc-fault detection systems for electric vehicles?

2.2. Literature Search and Selection

A comprehensive literature search was conducted on July 31, 2025, using five major academic databases: IEEE Xplore, ScienceDirect, Web of Science, SpringerLink, and Wiley Online Library. Only peer-reviewed articles and conference proceedings published in English from January 1, 2018, to July 31, 2025, were considered.

The primary search string employed was as follows: ("DC arc fault" OR "arc fault detection") AND ("electric vehicle" OR "EV" OR "automotive" OR "photovoltaic" OR "PV" OR "DC microgrid") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "AI" OR "hybrid model") AND ("detection" OR "diagnosis" OR "protection")

Inclusion criteria were as follows: (1) studies focusing on DC arc faults; (2) demonstration of application to EV systems or proposal of novel methodologies from PV or DC microgrids with clear adaptation potential; (3) proposal or validation of a novel detection method; and (4) reporting of quantitative performance metrics, such as accuracy or response time.

Exclusion criteria included: (1) studies focusing exclusively on AC systems; (2) publications not in English; (3) patents, books, or non-peer-reviewed literature; and (4) duplicate publications.

Screening Process: A total of 505 unique records were screened by title and abstract, resulting in the exclusion of 378 records. The remaining 127 full-text articles were assessed for eligibility. Of these, 41 were excluded for the following reasons: absence of quantitative metrics (n=18), exclusive AC focus (n=12), lack of EV relevance (n=8), and duplicate data (n=3). Consequently, 72 studies proceeded to quality assessment. The complete selection process is depicted in the PRISMA 2020 flow diagram (Fig. 3).

2.3. Quality Assessment

A formal quality assessment was performed using a structured 10-point rubric adapted from established protocols [22], [23]. Two independent reviewers assessed each of the 86 studies across five dimensions: clarity of experimental design (0-2), dataset realism and comprehensiveness (0-2), reporting of performance metrics (0-2), comparative analysis (0-2), and acknowledgment of limitations (0-2).

Inter-reviewer agreement was substantial (Cohen's κ = 0.87), and discrepancies were resolved through discussion. Studies scoring below 6 out of 10 were classified as high risk of bias and excluded from synthesis. Fourteen studies were excluded due to low quality scores, leaving 72 included in the final qualitative synthesis. The results are presented in Table 1.

Table 1. Summary of quality assessment results

QA Score Range	Category	Number of Studies	Handling in Synthesis
9-10	Excellent	18	Fully included; high weight in analysis
7-8	Good	32	Fully included
6	Fair	22	Included, limitations noted
0-5	High Risk of Bias	14	Excluded from synthesis

2.4. Data Extraction and Synthesis

Data from the 72 included studies were systematically extracted into a standardized template. Key extracted information included: detection method, classification, application context, performance metrics, inference time, and hardware platform, dataset description, and author-identified limitations.

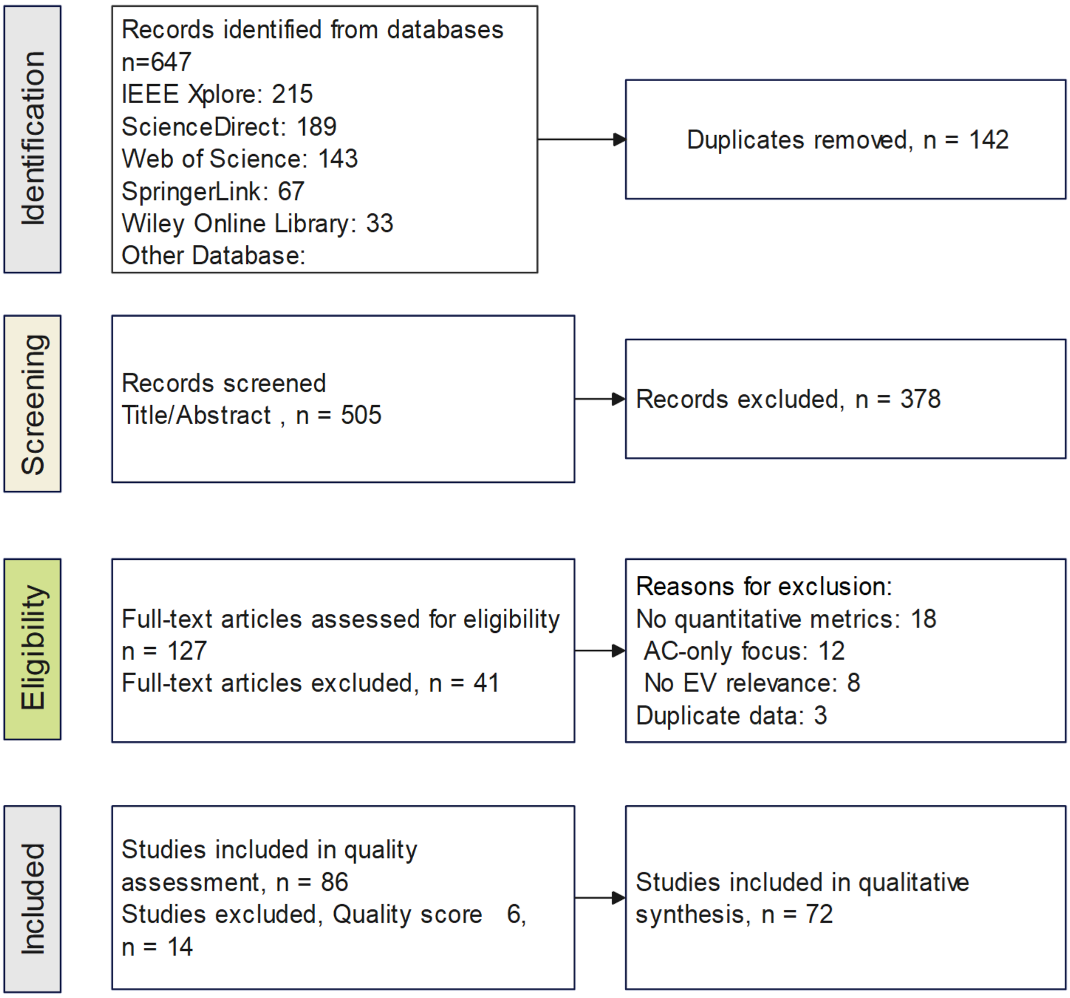

Fig. 3. PRISMA flow diagram illustrating the literature selection process [20]

A narrative and thematic approach was used for synthesis. Studies were grouped by methodological family, and findings were compared to identify patterns, contradictions, and trends over time. Performance metrics, particularly inference-time accuracy and hardware requirements, were tabulated (Table 1, Section 4) to assess practical deployability. The synthesis explicitly distinguished between findings specific to electric vehicles and those from photovoltaic or direct current microgrid studies.

2.5. Acknowledgment of Review Limitations

Key limitations are acknowledged to ensure transparency:

- Domain Heterogeneity: The inclusion of photovoltaic and microgrid studies introduces heterogeneity, and quantitative cross-domain comparisons should therefore be interpreted with caution.
- Publication Bias: There is a potential bias toward studies that report positive results.
- Evolving Field: As the field is rapidly advancing, newer techniques may have emerged after the search was conducted (July 2025).
- Language Bias: The review was restricted to English-language publications.
- These limitations are taken into account when interpreting the results and formulating conclusions.

3. Fundamentals of DC Arc Faults

3.1. Nature, Causes, and Impacts of DC Arc Faults

DC arc faults are sustained plasma discharges in high-voltage electric vehicle (EV) systems that maintain current continuity through ionized paths when natural current zero-crossings are absent [1], [8]. Fig. 4 illustrates that these faults can occur at multiple locations within EV power systems, including both onboard and offboard components. The schematic in Fig. 4 identifies potential DC arc-fault locations and highlights vulnerable points in the high-voltage system [24], [25].

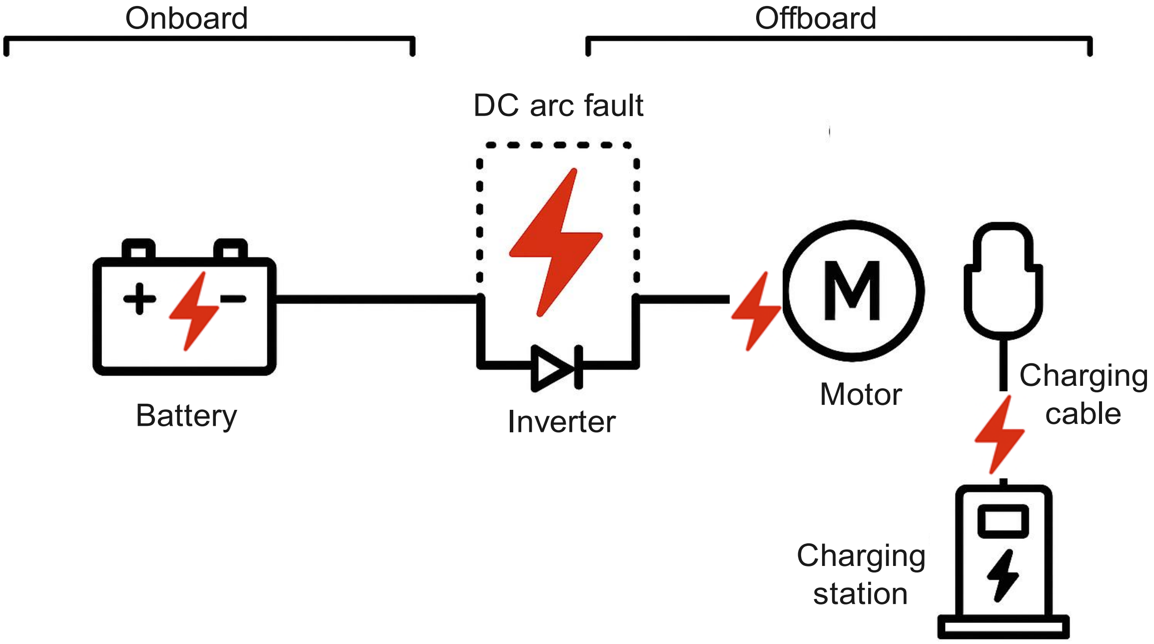

Fig. 4. Schematic of DC arc fault location in an electric vehicle

Initiation mechanisms primarily consist of insulation breakdown, connector degradation, mechanical damage to high-voltage cables, and manufacturing defects in battery systems. Arc plasma exhibits extreme thermal properties, with temperatures exceeding 10,000 K, nonlinear voltage-current (V-I) characteristics, and broadband electromagnetic emissions. As shown in Fig. 5 (a) and (b), fault classification differentiates between series arcs, which occur when broken conductors continue to carry current, and parallel arcs, which result from short circuits between conductors or to ground [26].

Detecting series faults in automotive systems presents significant challenges because normal operating currents often mask their signatures. In contrast, parallel faults may result in dangerously elevated current levels. The accumulation of thermal energy introduces substantial safety risks, such as thermal runaway in lithium-ion batteries, which can initiate localized heating cascades. Fig. 5 (c) illustrates the limitations of conventional protection schemes, showing that traditional overcurrent devices frequently respond inadequately to series arcs and exhibit delayed responses to parallel faults [27]. These failures may lead to damage to power electronics, carbonization of insulation, and complete failure of the propulsion system, thereby posing serious hazards to vehicle occupants and emergency responders [28].

The automotive environment poses distinct detection challenges, including intermittent connections caused by mechanical vibrations and thermal cycling. High-frequency converter noise further obscures arc signatures [29]. Moreover, modern 400V and 800V architectures increase detection complexity due to reduced breakdown thresholds and elevated fault energy.

Achieving compliance with standards such as ISO 6469-3 and SAE J2344 is particularly challenging in complex electromagnetic environments characterized by dynamic load profiles, switching noise, and stringent electromagnetic compatibility (EMC) requirements [30]. The adoption of wide-bandgap semiconductors, including silicon carbide (SiC) and gallium nitride (GaN), further complicates detection by altering arc formation dynamics and increasing high-frequency spectral interference [31]. Detection systems should address the entire vehicle lifecycle, including factors such as component aging and the accumulation of micro arcing damage. Overcoming these challenges necessitates advanced detection methods that are compatible with automotive-grade hardware constraints and ensure reliability across diverse operational scenarios [32], [33].

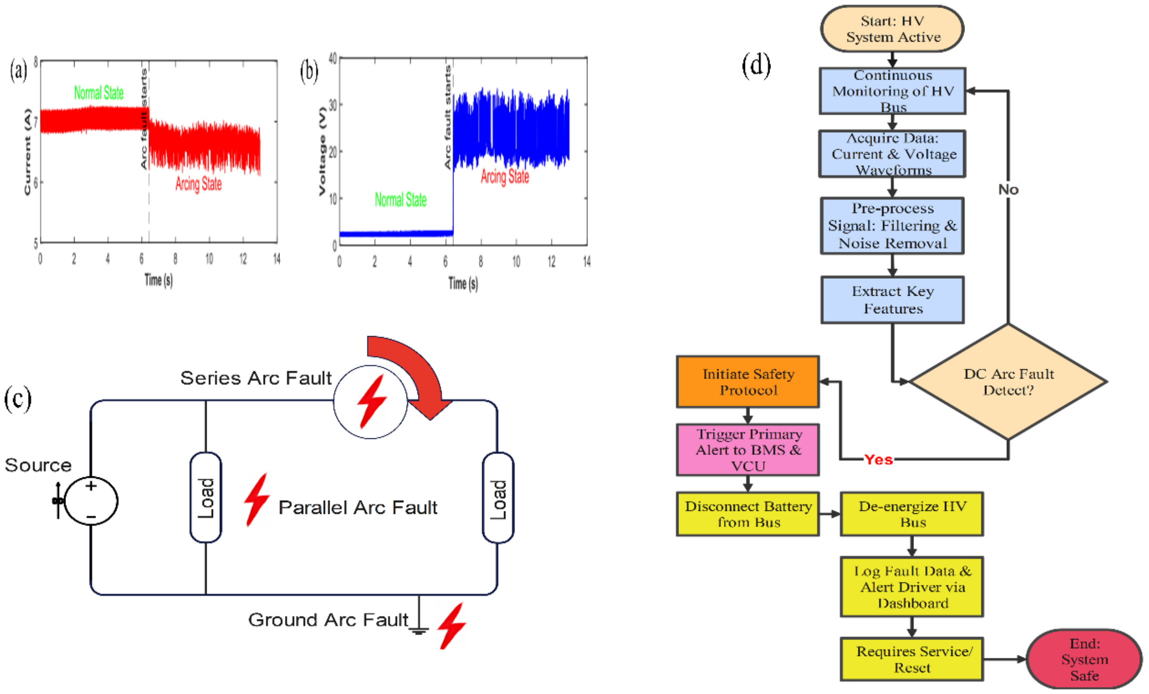

Fig. 5. (a) Current and (b) Voltage characteristics during DC arc fault initiation (c) Various type of arc fault equivalent circuit [34] (d) Typical flowchart for AI-based EV arc fault protection system

4. DC Arc Fault Detection Methods

Detecting DC arc faults is particularly challenging because arcs can persist for extended periods in direct current circuits due to the absence of natural zero-crossings for extinguishment [1]. The field now encompasses a broad spectrum of detection techniques, from foundational hardware-based approaches to advanced data-driven algorithms. Fig. 6 presents a systematic classification of the principal detection methodologies reported in the literature, organized within a comprehensive taxonomy. This taxonomy enables researchers and practitioners to better understand, evaluate, and select suitable methods. Subsequent sections examine each category in detail, addressing both traditional and AI-based strategies, which offer significant potential to enhance detection accuracy and reliability. Nevertheless, practical implementation in electric vehicle (EV) systems necessitates careful consideration of computational limitations and environmental adaptability.

4.1. Traditional DC Arc Fault Detection Methods

Traditional methods for detecting DC arc faults involve analyzing circuit electrical properties, such as current and voltage, to identify patterns indicative of arcing events. These methods are generally classified into time-domain and frequency-domain analyses, with time-frequency approaches bridging both domains. Fig. 7 illustrates these categories within the broader framework of arc-fault detection methodologies, highlighting their relationships and typical applications in EV systems.

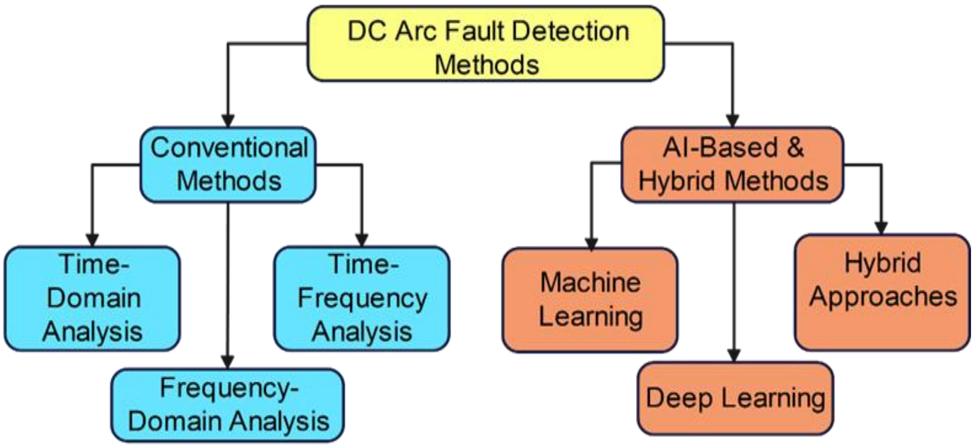

Fig. 6. Presents a comprehensive taxonomy of DC arc fault detection methods for electric vehicle systems, organizing approaches into traditional and AI-based categories with their respective sub-classifications

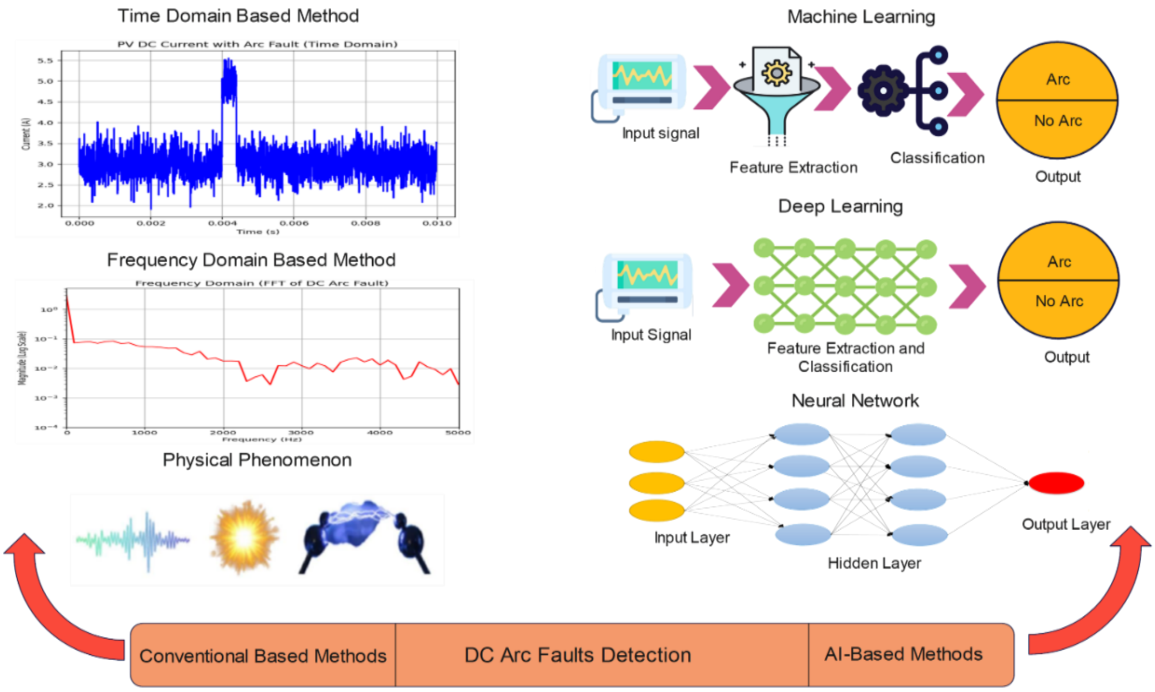

Fig. 7. DC arc fault detection: conventional methods and AI-based approaches

4.1.1. DC Arc Fault Detection Methods Based on Time Domain

Time-domain analysis methods for DC arc-fault detection evaluate electrical signals, such as voltage and current, over time to detect anomalies indicative of arc faults. These methods utilize deviations in current and voltage waveforms from standard operating conditions to enhance fault-detection accuracy. Statistical features such as Root Mean Square (RMS), variance, skewness, and kurtosis are commonly extracted from time-domain signals to detect behavioral changes associated with arc faults. While time-domain-based detection methods are seldom used independently, they serve as a foundational component for arc detection. Numerous studies have assessed the effectiveness of time-domain methodologies for identifying DC arc faults in electrical systems [34].

For instance, Li et al. [35] introduced a high-frequency arc-detection technique utilizing information entropy, kurtosis, and skewness to distinguish and assess arc-fault levels in DC systems. This method differentiates between arc faults and load changes, and evaluates fault severity based on arc distance. Georgijevic et al. [36] developed a series arc-fault detection algorithm for photovoltaic systems that employs modified Tsallis entropy to distinguish between chaotic (arc state) and ordered (no-arc state) current variations, enabling detection without prior system information and demonstrating both sensitivity and robustness. This approach identified both sustained and minor sparking arcs in a real photovoltaic system, achieving high sensitivity and avoiding false detections from regular operational changes. Zhang et al. [37] proposed a method for detecting DC arc faults in photovoltaic systems using time-domain features, specifically the rate of change of the mean current and the difference between the maximum and minimum current values, thereby improving detection accuracy. However, the feature set in this study is limited for comprehensive fault identification, potentially limiting its ability to detect a broad range of fault scenarios. Seo et al. [38] developed a DC arc-fault detection method based on statistical analysis, achieving 99.999% accuracy. Fitrianto et al. [39] designed a series of DC arc-fault detectors that integrate a microcontroller and a Fast Fourier Transform (FFT). Additional advancements include preprocessing data with singular value decomposition, sample entropy, and high-order cumulants to improve detection [40], as well as monitoring the fractal dimensions of current and voltage waveforms to identify sustained arcs in networks and electric vehicles [41].

Despite their simplicity and utility, time-domain methods have notable limitations. They are vulnerable to noise interference and may generate false positives due to switching events or load fluctuations. These methods often struggle to distinguish between different types of disturbances occurring simultaneously. Although time-domain analysis is effective for detecting rapid changes, it may not offer a comprehensive assessment of fault origin or cross-type interference, especially when multiple disturbances overlap or when faults develop gradually. Additionally, these methods typically require threshold tuning and may not adapt effectively to the dynamic operating conditions of electric vehicles without ongoing recalibration.

4.1.2. DC Arc Fault Detection Methods Based on Frequency Domain

Frequency analysis-based DC arc-fault detection methods play a critical role in ensuring the safety and reliability of electric vehicle (EV) systems. These methods exploit the distinct frequency characteristics of signal patterns associated with arc faults to distinguish between fault conditions and normal operation. Multiple techniques have been developed to analyze the spectral components of current or voltage signals for arc-fault identification [42]. Frequency-domain approaches, including the Fourier Transform and harmonic analysis, complement time-domain techniques by providing insights into the spectral content of signals. Arc faults generate irregularities in current, resulting in unique harmonics and high-frequency noise that are detectable through spectral analysis.

For example, Dong et al. [43] applied the Fourier Transform to current signals to extract spectral features and improve detection accuracy. Liu et al. [7] used a wavelet transform combined with a two-stage filter to preprocess weak-current signals, achieving 99% accuracy within 150 ms. Wang et al. [44] isolated arc-induced common-mode current and voltage (CMCV) signals through frequency-selection circuits. Nashrulloh et al. [45] employed the Fast Fourier Transform (FFT) to identify high-frequency disturbances in EV systems. Bachache et al. [46] utilized the Discrete Wavelet Transform (DWT) for arc-fault detection in photovoltaic systems.

Despite their advantages, frequency-domain methods encounter significant challenges in EV applications. In contrast to stationary photovoltaic (PV) systems with fixed-frequency inverters, EV traction inverters operate at variable switching frequencies that fluctuate with motor speed, generating broadband noise that can obscure arc signatures. This dynamic noise environment requires adaptive filtering techniques or advanced transforms, such as wavelet packets, to differentiate arc-induced harmonics from switching noise. The applicability of PV-based frequency-domain methods to EVs is further hindered by differences in system capacitance and inductance profiles. EV systems exhibit distinct impedance characteristics due to traction motors and variable-frequency drives, which influence arc signature propagation and frequency response compared to stationary PV systems. Furthermore, the computational complexity of these methods may restrict real-time implementation, limiting their practicality in resource-constrained automotive electronic control units (ECUs).

4.1.3. DC Arc Fault Detection Methods Based on Time-Frequency Analysis

Time-frequency analysis-based methods play a critical role in ensuring the safety and reliability of electric vehicle (EV) systems by enabling accurate DC arc-fault detection. These methods analyze arc-fault signals in both time and frequency domains, thereby enhancing the precision of fault detection and identification [47], [48]. Time-frequency analysis techniques are particularly effective for capturing the transient and non-stationary characteristics of arc-fault signals. By converting measured current or voltage signals into a domain that simultaneously represents time and frequency, these approaches allow for detailed characterization of spectral content over time [47]. This process enables the identification of distinctive arc-fault signatures, including high-frequency noise and transient fluctuations.

Several time-frequency analysis techniques are widely employed in DC arc-fault detection. The Short-Time Fourier Transform (STFT) analyzes signal segments to determine their frequency components. Ukil et al. [49] demonstrate that STFT is effective for transient-state detection in DC networks, achieving high fault-detection accuracy. While STFT is primarily utilized in high-voltage DC transmission systems, its underlying principles are applicable to DC arc-fault detection in EV systems. However, STFT is limited by its fixed window size, which prevents it from simultaneously capturing high-frequency transients and low-frequency components. The Wavelet Transform (WT) addresses this limitation by using variable-sized windows, thereby providing improved time-frequency localization. This characteristic makes WT suitable for detecting transient events and analyzing non-stationary signals. Panpaliya & Ali et al. [50] demonstrate that wavelet transformation can effectively distinguish between arc and non-arcing signals. This approach preserves time-domain information and enhances both real-time detection and confidence in arc event identification. The Hilbert-Huang Transform (HHT) is an adaptive technique that decomposes signals into intrinsic mode functions (IMFs) and applies the Hilbert transform to obtain instantaneous frequency information. Zhang et al. [51] report that HHT can extract features from current waveforms across various loads, thereby improving the accuracy of distinguishing between normal and fault-arc states. This method is also applicable to DC arc-fault detection in EV systems.

Guo et al. [52] examine the application of Variational Mode Decomposition (VMD) for detecting DC arc faults in photovoltaic systems, demonstrating that VMD can extract both time and frequency-domain features to improve fault detection and localization. Similarly, Liu et al. [53] apply VMD to photovoltaic arrays, enhancing fault-detection accuracy by analyzing both time and time-frequency domains. Although VMD exhibits significant potential for DC arc-fault detection, challenges persist in adapting the method to diverse operational environments and maintaining robustness under varying load conditions. Future research should prioritize optimizing VMD parameters to enable broader application in EV systems. Thomas et al. [42] introduce a real-time arc-fault detection strategy for DC systems in More Electric Aircraft, utilizing time-frequency-domain features analyzed by a feed-forward Artificial Neural Network to address issues such as dynamic loading and system stability.

4.2. AI-Based and Hybrid Approaches for DC Arc Fault Detection Methods

Artificial intelligence-based methodologies have significantly advanced DC arc-fault detection in electric vehicle (EV) systems. These data-driven approaches, including machine learning (ML) and deep learning (DL) [54], [55], facilitate real-time analysis of complex, high-frequency signals from high-voltage DC buses to identify hazardous arc signatures [56]. Key advantages of these models include enhanced discrimination between fault transients and normal load variations, reduced response times, and compatibility with existing battery management and power electronics systems [57], [58]. However, implementation within automotive-grade electronic control units (ECUs) remains challenging due to the substantial computational resources required by neural networks.

Furthermore, the scarcity of high-fidelity, real-world arc-fault datasets from operational EVs limits model development. These systems are also susceptible to missed or false detections in electrically noisy environments [59]. The typical workflow, as illustrated in Fig. 5 (d), comprises signal acquisition, noise-reduction preprocessing, feature extraction, and model inference. This structured methodology enhances detection robustness.

4.2.1. Machine Learning and Deep Learning for DC Arc Fault Detection

Machine learning techniques constitute a foundational layer for intelligent fault detection. Supervised models, such as Support Vector Machines (SVMs), have been directly applied; for instance, Sabeena et al. [58] reported 95% accuracy in fault detection for electric vehicle (EV) systems. Performance improvements are frequently achieved through advanced feature engineering. Xia et al. [59] integrated wavelet entropy features with SVM and logistic regression for serial arc detection in EV power systems, resulting in high accuracy and low false-positive rates. Yin et al. [60] proposed a multi-stage methodology that utilized fractional wavelet energy entropy for feature extraction, random forest for feature selection, and a kernel extreme learning machine (KELM) for final classification, achieving 99.82% diagnostic accuracy for DC series arcs. Additional applications include machine learning classifiers for EV charger fault detection (94.59% accuracy) [63] and CatBoost models for drive motor fault classification (94.1% accuracy) [64], although these approaches address broader system faults rather than exclusively arcing faults. Xia et al. [63] further applied a windowed Fourier transform in conjunction with SVM to improve data quality and reduce false detections in EV systems.

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), facilitate automatic feature extraction from raw or preprocessed temporal and time-frequency signal representations [55]. Liu et al. [13] applied the VGG16 architecture to series arc identification in EV charging systems, achieving over 98% recognition accuracy, though high-frequency noise remained a challenge. Recent research emphasizes the development of computationally efficient, lightweight models suitable for embedded deployment. Wang et al. [64] and Paul et al. [65] designed lightweight CNNs for photovoltaic (PV) systems, achieving up to 98.81% and over 98.15% accuracy, respectively, with the latter reporting an interruption time of 25 ms. Lu et al. [66] implemented a neural network-based online detector for PV systems, achieving 99.5% accuracy with a detection latency of 4 ms. To address the scarcity of real fault data, Transfer learning has also been employed to enhance performance; Choi et al. [67] used a feature-fusion model with transfer learning to achieve 99.99% accuracy across diverse loads. Further architectural innovations include Deep Neural Networks for general electronic arc faults (99.95% accuracy) [68], 1D-CNNs for detection within fractions of a current cycle [69], and hybrid CNN-LSTM networks for simultaneous fault diagnosis and circuit behavior prediction (98.43% accuracy) [70]. Practical deployment is demonstrated by Chen et al. [71], who implemented a lightweight, Adam-optimized BP neural network on an STM32 microcontroller, achieving 99.27% accuracy and tripping times of 72-201 ms.

Despite these advancements, significant challenges persist in mitigating background noise, achieving real-time detection, and managing computational complexity. Addressing these issues requires further research to improve noise immunity, enhance real-time detection capabilities, and develop lightweight models suitable for embedded hardware.

4.2.2. Hybrid Detection Methods for DC Arc Fault Detection

Hybrid detection methods combine signal processing techniques with artificial intelligence models to improve accuracy, robustness, and computational efficiency. These methods often employ advanced transformations to extract optimal features before classification. For instance, Yin and Xiao et al. [72] applied Wavelet Packet Transform (WPT) for time-frequency decomposition, a Residual Convolutional Neural Network (RCNN) for deep feature learning, and a Support Vector Machine (SVM) for classification, achieving 99.72% accuracy with detection times below 100 ms. Zhang et al. [73] integrated an Improved Empirical Wavelet Transform (EWT) with Singular Value Decomposition (SVD) to reduce noise and fuse features in photovoltaic (PV) systems, reporting 99.47% accuracy and a 56.7% increase in computational speed. To capture long-term temporal dependencies in fault signals, Omran et al. [74] combined a Multilayer Perceptron (MLP) with a Bi-Directional Long Short-Term Memory (Bi-LSTM) network, processing both spatial and temporal features to achieve 99% accuracy. Other hybrid strategies include combining time- and frequency-domain features with decision trees or K-Nearest Neighbors (KNN) to enhance noise resilience [75], and applying Empirical Mode Decomposition (EMD) with an SVM to reduce interference from power-electronics switching [76]. In electric vehicle (EV) applications, Liu and Pan et al. [77] developed a hybrid LSTM-Transformer model that utilizes both voltage and current signal characteristics, achieving a 97% fault recognition rate with improved resistance to environmental noise.

A significant limitation of these advanced hybrid models is their increased architectural complexity, which can impede real-time implementation on automotive electronic control units (ECUs) and complicate generalization across different EV platforms and operating conditions. Models that achieve high accuracy but exhibit excessive latency or require high-end GPUs may not be suitable for automotive-grade ECUs, which are subject to strict real-time constraints and cost limitations. Table 2 provides a comprehensive comparison of the AI-based detection methods discussed in this section, including their accuracy, inference time, and hardware requirements.

Table 2. Comparison of DC arc fault detection models

Study	Model / Method	Accuracy	Inference Time	Hardware/Software
[58]	SVM	95%	-	Python/CPU
[59]	Wavelet Entropy +SVM/Logistic Regression	99.08%	-	TMS320F28069
[78]	Windowed Fourier Transform + SVM	99.25%	-	TMS320F28069
[60]	Fractional Wavelet Energy Entropy + Random Forest + Kernel ELM	99.82%	110 ms	CPU
[71]	Pulse Signal Number + Adam-optimized BP Neural Network	99.27%	45 ms	STM32F401RCT6
[61]	Machine Learning Classification Algorithm	94.59%	-	MATLAB Simulink
[79]	Ensemble Machine Learning	99.95%	37 ms to 69 ms	Microcontroller
[62]	CatBoost	94.1%	-	MATLAB Simulink
[13]	VGG16 (Deep CNN)	98%	-	Python
[64]	Lightweight CNN with Attention Mechanism	98.81%	48–60 ms	CompactRIO-9030
[65]	Lightweight CNN	98.15%	25 ms	STM32H743ZI2
[66]	Neural Network-based Online Detector	99.5%	1.26 ms	TMS320F280049
[67]	Transfer Learning-based Feature Fusion	99.99%	-	Raspberry Pi 4
[68]	Deep Neural Network (DNN)	99.95%	28 ms	Raspberry Pi 3
[69]	1D Convolutional Neural Network	99.908%	-	Python
[80]	Phase Space Reconstruction + CNN	99.00%	-	Pyhton
[70]	CNN + Long Short-Term Memory (LSTM)	98.43%	-	MATLAB
[81]	Temporal CNN + Single Layer NN	99.88%	154 ms	Quad-core ARM-A57
[83]	Transfer Learning + 1D-CNN & LSTM (TL–LEDarcNet)	95.8%	23.11 ms	NVIDIA Jetson Nano
[56]	Optimized Detection Model (Visualization)	97.95%	-	MATLAB /Python
[82]	WPT + Residual CNN + SVM	99.72%	-	STM32
[73]	Improved Empirical WPT + Singular Value Decomposition	99.47%	-	MATLAB /Python
[74]	Multilayer Perceptron + Bi-Directional LSTM	99%	-	Python
[77]	LSTM + Transformer	97%	-	Python
[76]	Empirical Mode Decomposition + SVM	High Accuracy	70.8 ms	FPGA

4.3. Critical Analysis of Transferability from PV to EV Systems

A key finding of this review is that methods originally developed for photovoltaic (PV) systems require substantial modification before they can be effectively applied to electric vehicle (EV) applications. Although both domains employ high-voltage DC architectures, three fundamental differences prevent direct transfer between them.

- Noise Environment: PV systems generally employ fixed-frequency inverters, resulting in predictable noise profiles. In contrast, electric vehicle traction inverters operate with variable switching frequencies that depend on motor speed, generating broadband, non-stationary noise that can obscure arc signatures. Consequently, frequency-domain methods that are effective in PV systems may not perform adequately in EVs unless adaptive filtering is implemented.
- System Impedance Characteristics: Electric vehicle systems exhibit markedly different capacitance and inductance profiles due to traction motors, extended cable harnesses, and variable-frequency drives. These characteristics modify the propagation of the arc signature and the frequency response relative to stationary PV systems.
- Operational Dynamics: Electric vehicles are subject to rapid load changes, such as those caused by acceleration and regenerative braking, as well as mechanical vibrations and broad temperature variations. These conditions, which are uncommon in PV systems, generate electrical transients that may cause false positives in detection algorithms calibrated for the stable operation of PV systems.

The variable-switching-frequency characteristic of modern electric vehicle inverters poses a significant challenge for frequency-domain analysis methods. As motor speed varies, the inverter switching frequency also shifts, resulting in a dynamic noise spectrum that may coincide with arc-induced harmonics. Addressing this issue requires either adaptive filtering techniques that track the switching frequency or time-frequency methods with higher resolution than conventional FFT-based approaches. Wavelet transforms and empirical mode decomposition are particularly promising for EV applications, as they can more effectively localize both frequency and temporal information in non-stationary signals.

5. Challenges in DC Arc Fault Detection in Electric Vehicles

A range of technical and practical challenges inherent to the automotive environment impede the deployment of reliable DC arc-fault detection in electric vehicles. These obstacles include signal-level interference, system-wide integration issues, and economic constraints. Addressing these challenges is essential for enabling solutions that progress from laboratory validation to certified automotive deployment.

- **Dynamic and Noisy Operational Environment:** Electric vehicle (EV) power networks are subject to rapid load fluctuations, mechanical vibrations, and wide temperature variations, all of which generate electrical transients that resemble arc signatures and result in high false-positive rates [28]. In contrast to photovoltaic (PV) systems that use fixed-frequency inverters, EV traction inverters operate at variable switching frequencies that depend on motor speed, producing broadband noise that masks arc signatures and complicates the adaptation of PV-based detection methods. Additionally, widespread electromagnetic interference (EMI) from power electronics further impedes accurate fault detection.
- **Sensitivity-Reliability Trade-off:** High-sensitivity detection systems can identify low-energy arcs but are prone to false alarms from benign transients, which diminishes user confidence [13]. In contrast, systems with lower sensitivity may fail to detect developing series arcs, increasing the risk of thermal hazards [25]. Achieving both high sensitivity and low false-positive rates requires advanced feature extraction techniques that surpass conventional threshold-based methods.
- **Computational and Data Constraints:** Advanced artificial intelligence (AI) models require computational resources beyond the capabilities of standard automotive electronic control units (ECUs). Achieving real-time inference within 100 to 200 milliseconds remains challenging [64], and high-accuracy models frequently depend on costly hardware accelerators such as graphics processing units (GPUs) or field-programmable gate arrays (FPGAs). Furthermore, essential performance metrics, such as false-positive rates and latency, are often omitted from published

studies. The scarcity of authentic arc-fault data further restricts the development and training of robust, generalizable models [59].

- **System Integration and Standardization:** The integration of detection systems with battery management systems (BMS), inverters, and charging hardware presents significant complexity. The lack of standardized communication protocols and the prevalence of proprietary original equipment manufacturer (OEM) architectures hinder the development of universal solutions. In contrast to PV systems, there is a notable lack of EV-specific validation benchmarks and standards [17].
- **Economic Viability:** The automotive industry's emphasis on cost efficiency conflicts with the requirements for specialized hardware, such as high-speed sensors and advanced processing units, as well as the development of artificial intelligence (AI) solutions. Many high-accuracy models that rely on field-programmable gate arrays (FPGAs) or graphics processing units (GPUs) are not economically viable for large-scale production [31].

Addressing these challenges requires algorithmic innovation, system-level co-design, standardized validation procedures, and cost-effective hardware to enable the transition from laboratory validation to certified automotive deployment.

6. Future Trends in DC Arc Fault Detection for EVs

The development of DC arc fault detection in electric vehicles is increasingly influenced by advances in artificial intelligence, sophisticated sensing technologies, and edge computing. As EV architectures become more complex and operate at higher voltages, future protection systems must address existing limitations in reliability, computational efficiency, and adaptability to real-world conditions. This section highlights key emerging trends expected to shape the field's future, prioritized by their potential to address the challenges outlined in Section 5 and their relevance to automotive industry requirements.

- **Multi-Modal Sensing and Sensor Fusion:** Future systems are expected to integrate electromagnetic, thermal, and acoustic sensors with fiber-optic technology to achieve electromagnetic interference immunity. Data fusion algorithms are anticipated to reduce false positives; however, challenges such as sensor miniaturization and cost remain significant.
- **Embedded AI and Edge Computing:** Deploying lightweight neural networks on automotive electronic control units or hardware accelerators is essential for achieving detection times below 100 milliseconds. Model compression techniques, such as quantization and pruning, enable 80-90% size reduction with minimal accuracy loss [56], [64].
- **Explainable AI (XAI) for Certification:** Techniques such as SHAP and LIME are critical for ISO 26262 certification because they provide transparency in fault diagnosis decisions. Real-time XAI methods are required for validation in safety-critical applications [45].
- **Federated Learning for Fleet Intelligence:** Federated learning enables collaborative model training across vehicle fleets while preserving data privacy, thereby addressing data scarcity [59]. Key challenges include managing heterogeneous data and minimizing communication overhead.
- **Hybrid and Physics-Informed AI Models:** Integrating physical knowledge, such as through Physics-Informed Neural Networks, enhances model generalizability and ensures physically plausible predictions when data are limited [41].
- **Standardization and Co-Design:** EV-specific standards for validation protocols are urgently needed, unlike established PV standards (UL 1699B). Co-design with vehicle subsystems

(BMS, VCU) and collaboration between developers, OEMs, and certification bodies are essential for integrated safety architectures.

Advancement of these interconnected trends is required in parallel, with standardization and co-design as foundational priorities, to enable the development of certifiable, economically viable detection systems for autonomous electric mobility.

7. Conclusion

This systematic review, conducted in accordance with PRISMA 2020 guidelines, examines 72 peer-reviewed studies (2018-2025) on AI-driven DC arc-fault detection in electric vehicle (EV) systems. The results indicate a shift from traditional detection methods to AI-based and hybrid approaches, with reported accuracies reaching up to 99.99%. Nevertheless, significant barriers to practical deployment remain, including computational limitations of automotive electronic control units (ECUs), insufficient data availability, and certification challenges related to ISO 26262.

The limitations of this review include domain heterogeneity resulting from the inclusion of photovoltaic (PV) studies, publication bias favoring positive outcomes, and the rapid evolution of AI methodologies.

Future research priorities include: (1) developing standardized, EV-specific datasets and validation protocols; (2) advancing federated learning and explainable artificial intelligence (XAI) to support certification; (3) exploring multimodal sensor fusion and physics-informed neural networks; and (4) investigating transformer-based architectures [72] and advanced optimization techniques [71].

Effective practical implementation necessitates co-design with automotive system architectures and collaboration among academic institutions, original equipment manufacturers (OEMs), and standards organizations. Such cooperation is essential to bridge the gap between laboratory validation and cost-effective, certifiable deployment in operational EV systems.

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