International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 17, No. 4, December 2026, pp. 2353~2362
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v17.i4.pp2353-2362

Integration of digital twin models for intelligent fault detection in EV drive systems

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Article Info

Article history:

Received Dec 31, 2025
Revised Sep 17, 2026
Accepted Oct 4, 2026

Keywords:

AI/ML
Digital twin
Edge computing
Electric vehicles
Fault diagnosis
Internet of things
Predictive maintenance

ABSTRACT

The adoption of digital twin technology is on the rise for predictive maintenance and health monitoring in electric vehicles, facilitating real-time fault diagnosis, system optimization, and informed decision-making. This study offers an in-depth assessment of the latest developments in digital twin architectures aimed at fault detection within electric drive systems, classifying current methodologies into model-based, data-driven, and hybrid frameworks. The investigation centers on the diagnostic functionalities pertaining to frequently observed faults, such as inverter malfunctions, motor winding anomalies, and bearing deterioration. This study examines the integration of digital twins with enabling technologies, such as the internet of things (IoT), edge and cloud computing, and artificial intelligence and machine learning techniques, to enhance real-time execution and predictive capabilities. Significant challenges concerning computational efficiency, interoperability, and model fidelity have been recognized as critical research hurdles. This study emphasizes existing research deficiencies and proposes future pathways, intending to assist researchers and practitioners in creating scalable and intelligent diagnostic solutions for advanced electrified transportation systems.

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1. INTRODUCTION

Sustainable transport must reduce fossil fuel use and greenhouse gas emissions. Low carbon emissions, operational expenses, and energy efficiency make EVs crucial to sustainable mobility. As electric vehicle (EV) adoption rises, user confidence depends on system performance, reliability, and safety. EV dynamics, energy management, and propulsion are controlled by power electronic converters, electric machines, battery packs, control units, and communication interfaces. EV components' complexity renders them susceptible to insulation failure, inter-turn short circuit (ITSC), inverter switch degradation, thermal overload, encoder malfunction, and sensor drift [1], [2]. Issues like fire and traction loss can affect performance, dependability, and safety. Real-world load variations, variable road conditions, and weather changes challenge offline testing, threshold-based and model-based observers, and signal analysis [3]. In complex multi-component systems, transient fault detection and prediction are limited. Digital twin technology creates a real-time digital replica of the physical system for intelligent fault diagnosis to overcome these limits. Simulate failures, optimize control, and monitor system degradation with physics-based modelling, data analytics, and AI to improve prediction and proactive system-health management [4]. DTs can detect inverter insulated-gate bipolar transistor (IGBT) faults [5], traction-motor bearing degradation, battery management system (BMS) imbalances, and electric mobility system interconnectivity

and communication difficulties. Historical data and simulation results enable DT systems to diagnose early, decrease false positives, and adapt to changing conditions. Edge computing, IoT frameworks, cloud services, and machine learning algorithms, along with digital twins, can power smart, connected electric vehicle systems.

Figure 1 illustrates that from 2025 to 2029, the automotive and electric vehicle industries will invest billions in Digital Twin technology, growing across applications. More people are using digital twins to monitor, improve, and anticipate vehicle-subsystem operation. Increased electrification and health monitoring are rapidly changing battery management and powertrain architecture. Rising production and supply chain utilization, predictive maintenance, and charging infrastructure are developing more quickly despite their smaller proportions. Table 1 shows anticipated annual trends through 2029. The growing deployment of digital twins emphasizes electric drive-system dependability and economy. DT-based fault diagnosis models include three:

i) Model-based digital twins: These require physics-based system behavior models. Real-world dynamics are replicated using analytical models and simulation tools like ANSYS and MATLAB/Simulink, which require exact parameter identification and real-time model updates [6].
ii) Data-driven digital twins: These methods train machine learning or deep learning models to identify and classify issues using historical and current data. Flexibility is high, although it depends on labelled data quality and quantity [7].
iii) Hybrid digital twins: Hybrid digital twins use physical modelling and data analytics to discover and adapt to faults. To circumvent model- or data-based restrictions, dynamic recalibration uses expert knowledge and real-time measurements [8].

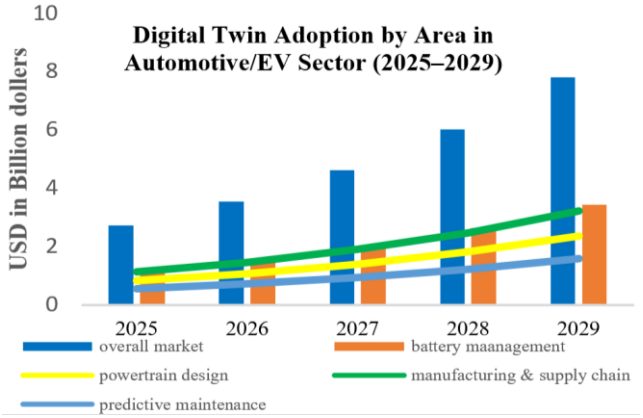

Figure 1. Digital twin adoption trends in automotive and EV applications (2025-2029)

Table 1. Year-wise market growth of digital twin applications in the automotive and EV

Year	Overall market	Battery management	Powertrain design	Mfg. supply chain	Predictive maintenance & charging infra
2025	2.73	1.20	0.82	1.12	0.55
2026	3.55	1.56	1.07	1.46	0.72
2027	4.62	2.03	1.38	1.90	0.94
2028	6.01	2.64	1.81	2.47	1.22
2029	7.81	3.44	2.35	3.21	1.59

Despite substantial difficulties, digital twin foundations seem promising. Computational overhead, platform standardization, data interoperability, cybersecurity, and model correctness under uncertainty are important issues. DT-AI/ML integration creates labelling, overfitting, interpretability, and real-time inference difficulties. We must overcome these limits to provide scalable, sophisticated diagnostic tools for real-world EVs. Instead of the electric drive system, many digital twin studies focus on EV subsystems. Comparisons are difficult due to differences in DT designs, diagnostic methods, data requirements, real-time implementation, fault coverage, processing abilities, and deployment feasibility. Integrating AI/ML requires a systematic review of data, interpretability, complexity, cybersecurity, and interoperability to consolidate gains, evaluate methods, identify challenges, and determine future research goals.

This review explores digital twin technologies for intelligent fault identification and diagnostics in electric vehicle drive systems and their real-time and system performance limits. DT techniques for electric

drives, converters, and Battery Management Systems are assessed for architecture, integration, and fault coverage. Model-centric, data-oriented, and hybrid DT designs are assessed for diagnostic ability. The latest case studies and applications are examined to uncover enabling technologies, difficulties, and research opportunities. The results unify DT-driven fault detection and diagnosis (FDD) and its potential to increase EV drive systems' intelligence, safety, dependability, and sustainability. This review's relevance is in furnishing a unified reference for researchers and EV technology innovators to comprehend the existing landscape of DT-enabled FDD, select fitting diagnostic structures, pinpoint implementation difficulties, and prioritize forthcoming research endeavors. From a utilitarian standpoint, the outcomes can aid in formulating trustworthy condition-monitoring and predictive-maintenance tactics for electric drive systems, consequently boosting system availability, safety, and operational performance.

A digital twin approach is used to detect and diagnose faults in electric vehicle drive systems in this organized research study. “IEEE Xplore” and other open access sources were searched for “Digital Twin”, “EV”, “electric drive”, “fault detection”, and “diagnosis studies”. These studies were examined for fault coverage, diagnostic capability, data demands, real-time application, computational complexity, and validation conditions for EV subsystems, fault types, DT architectures, diagnostic methods, AI/ML techniques, and validation approaches. This method can identify research constraints, needs, and directions. Since public literature did not involve humans or personal data, ethical approval was not needed.

2. ELECTRIC VEHICLE DRIVE SYSTEMS: ARCHITECTURE & FAULT LANDSCAPE

Electric vehicles use an electric drive system to transform electrical energy into mechanical force. The drive system encompasses various vital parts responsible for energy conversion, power oversight, and torque provision [9]. These components are represented in Figure 2.

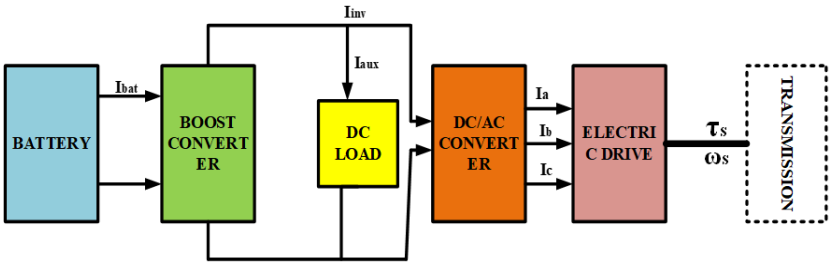

Figure 2. Generalized architecture of an electric vehicle drive system

2.1. Key components of the EV drive system

EVs are powered, controlled, and monitored by the electric drive system. According to voltage and switching frequency, the inverter switches DC power from the batteries to the traction motor utilizing IGBTs or MOSFETs for optimal conversion and thermal efficiency. Performance, cost, and material availability determine the traction motor: PMSM or IM. In contrast to PMSMs, IMs are cheap, durable, and rare-earth element-free without compromising efficiency or torque density [10]. In high-to-low and low-to-high voltage systems, the DC-DC converter controls auxiliary electronics, supercapacitors, and energy-recovery circuits. BMS measures cell voltage and temperature, manages charging and discharging, protects against failures, and balances lithium-ion cells for battery health, safety, and system reliability [11].

2.2. Common faults in EV drive systems

EV drive systems are vulnerable to various electrical, mechanical, and power electronics faults. These faults can occur due to thermal stress, vibrations, overvoltages, and aging. Table 2 summarizes the key faults and their impact [12], [13].

2.3. Impact of faults

EV drive-system faults can impact safety, performance, and dependability. Battery thermal runaway, inverter shoot-through, and rapid torque loss might disable control and cause danger [14]. If motors, inverters, and battery modules have undetected flaws, they degrade faster, lower working life, and raise lifecycle costs. Accidental downtime from faults can reduce fleet capacity and profitability. To maintain EV drive-system safety and sustainability, real-time fault identification and predictive maintenance are needed [15].

Table 2. Fault classification in EV drive systems

S. No	Fault category	Component	Typical faults	Impact
1	Electrical	PMSM/IM	Inter-turn short circuit, open-phase	Reduced torque, increased losses, vibration, demagnetization
2	Mechanical	Bearings, rotor	Bearing wear, rotor eccentricity (static/dynamic)	Acoustic noise, unbalanced torque, long-term damage
3	Power electronics	Inverter (IGBT/MOSFET)	Shoot-through, gate failure, open switch	Overcurrent, phase loss, system shutdown
4	Energy conversion	DC–DC converter	Transformer faults, diode failure	Power loss, voltage instability
5	Energy storage	BMS/battery	Sensor drift, thermal runaway, cell imbalance	Reduced range, safety hazards, degradation

2.4. Need for real-time fault monitoring

Safety and efficiency of electric vehicles require real-time monitoring. Electric vehicle drive systems need rapid fault identification in dynamic settings to avoid serious faults that could impair vehicle safety and reliability [16]. Real-time diagnostics streamline fleet access and increase safety and enable predictive maintenance. With new driver-assistance and autonomous capabilities, onboard diagnostics must be robust, adaptive, and rapid. Constantly monitoring health can improve control systems, save energy, and extend inverter, motor, and battery life [17]. Standardized fault detection methods using offline analysis lack flexibility, scalability, and real-time response. Advanced solutions like digital twin frameworks, which give real-time, precise, and proactive system health data, are needed due to these limits.

3. DIGITAL TWIN TECHNOLOGY: FUNDAMENTALS AND RELEVANCE

Diagnostics and predictive maintenance boost fleet availability and stability. For safety, autonomous electric vehicles with advanced driver-assistance technology need strong, adaptive, and reactive onboard diagnostic systems. Monitoring component health improves controller performance. Highly accurate digital twins replicate asset behavior, condition, and evolution. Figure 3: 2003-2025 AI benefits from digital twins. Basic research, communication, and the Internet of Things have advanced aviation and industry. Simulation has helped smart manufacturing. Better city-scale digital twin monitoring and decision-making with BIM, AI, and real-time analytics [18].

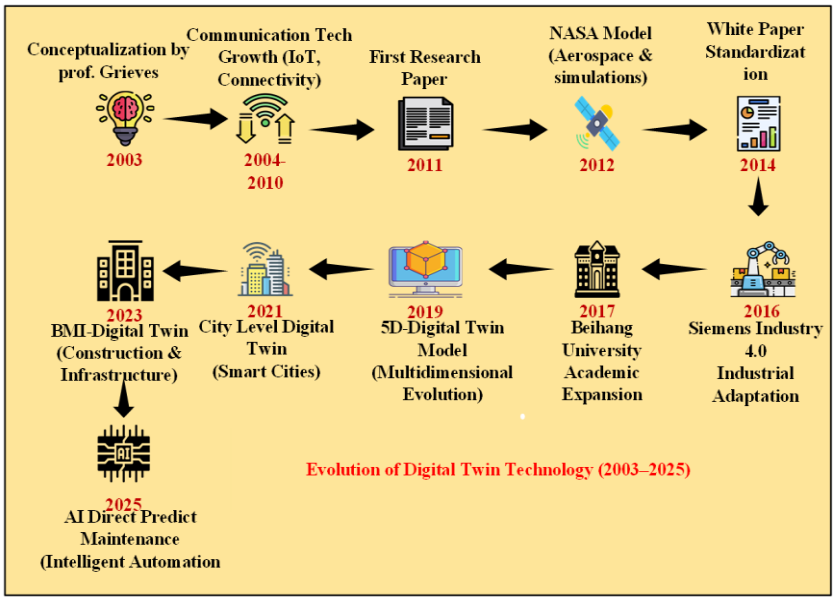

Figure 3. The progression of digital twin technology from 2003-2025

Application granularity classifies component-level twins (e.g., permanent magnet synchronous motor or battery cell models), system-level twins (e.g., EV drivetrain), and process-level twins. Predictive twins predict motor bearing wear, descriptive twins monitor structural and behavioral dynamics (e.g., SOC tracking), and prescriptive twins optimize control actions [19], [20]. DTs simulate and assess component

performance (ANSYS motor efficiency study), enable live tracking via embedded sensors, detect real-time anomalies (e.g., battery cell imbalance), and predict crucial component RUL [21]. Unlike simulation or control models, dynamic, bidirectional digital twins continuously update the virtual model with physical feedback for real-time decision support. Simulink-Speedgoat HIL validates motor control, whereas ANSYS-modelled PMSM twins detect winding faults and anticipate degradation trends using real-time current and heat data [22]. MATLAB or Siemens Xcelerator predictive battery twins enable advanced heat control and degradation prediction. Based on Nvidia Omniverse, complicated vehicle digital twins may simulate autonomous electric vehicle performance in challenging circumstances. Predictive maintenance, control performance optimization, savings on research and testing, and system safety by forecasting failure scenarios such as battery thermal runaway are transforming the electric car industry [23]. Digital twin scope, functionality, and life cycle for EV drive systems. Classify digital twins by component, system, process, descriptive, predictive, and prescriptive. Additionally, they develop, monitor, diagnose, and prognose. Table 3 lists classes and EV usage.

Table 3. Fault classification in EV drive systems

Classification criterion	Type of DT	Functional objective	Representative EV application
By scope [24]	Component-level DT	Represents a single part (e.g., motor, battery cell).	Digital twin of an electric motor for predictive maintenance.
	System-level DT	Simulates an entire subsystem (e.g., EV powertrain, BMS).	Digital twin of a full battery pack with thermal modelling.
	Process-level DT	Simulates an entire subsystem (e.g., EV powertrain, BMS).	Fleet management system optimizing charging schedules.
By functionality (intelligence level) [25]	Descriptive twin	Real-time monitoring (passive data visualization).	Live dashboard showing battery temperature & voltage.
	Predictive twin	Uses AI/ML to forecast failures (e.g., remaining battery life).	AI model predicting motor bearing wear.
	Prescriptive twin	Recommends actions (e.g., optimal charging strategy).	Suggesting battery cooling adjustments.
By lifecycle stage [26]	Design	Virtual prototyping before manufacturing.	Simulating aerodynamics in ANSYS.
	Monitoring	Real-time tracking of performance	IoT sensors tracking battery health.
	Diagnosis	Identifying faults (e.g., battery cell imbalance).	AI detecting abnormal motor vibrations.
	Prognosis	Predicting future failures (e.g., battery degradation rate).	Estimating remaining battery lifespan.

4. SOFTWARE TOOLS & ENVIRONMENTS FOR BUILDING DIGITAL TWINS

Modelling, simulation, IoT, real-time data, AI/ML, and predictive analytics enable EV system digital twin development using software tools and platforms. These enable component modelling, real-time monitoring, fleet management, and predictive maintenance. Significant digital twin platforms and their EV applications are listed in Table 4.

Digital twins in electric vehicles must balance accuracy, cost, and scalability. ANSYS is a costly system-level modelling tool. Control and component-level applications benefit from mid-range systems like MATLAB. AI-driven twins can be customized with cheap Python tools, but physical modelling is limited. Basic component-level digital twins are cheap but limiting. Accurate system-level digital twins cost more. Cloud-based digital twins like AWS and Azure reduce infrastructure costs and facilitate real-time IoT integration, while AI-driven ones like NVIDIA Omniverse provide predictive maintenance.

Table 4. Taxonomy of digital twin software platforms across simulation, IoT, and AI layers

Platform category	S. No	Digital twin software platform	Key capabilities	Application in EV systems
Simulation & modelling tools [27]	1	ANSYS Twin Builder	High-fidelity system-level DTs	Automotive, Aerospace
	2	MATLAB/Simulink	Control systems & component DTs.	EV motor/battery modeling
	3	Dassault systems (3DEXPERIENCE)	Full product lifecycle DTs.	Industrial EVs, smart factories
	4	Siemens NX & Simcenter	Predictive maintenance DTs.	Battery & drivetrain DTs
IoT & real-time data platforms [28]	5	NVIDIA omniverse	AI-driven, real-time DTs.	Autonomous EV simulation
	6	PTC ThingWorx	IoT-based DTs with AR integration.	Smart EV diagnostics
	7	AWS IoT TwinMaker	Cloud-based scalable DTs.	Fleet management DTs
	8	Microsoft Azure digital twins	Enterprise-scale DTs.	EV charging network optimization
AI/ML & predictive analytics tools [29]	9	DataRobot	AutoML for predictive DTs.	Battery failure prediction
	10	SAS analytics	Advanced prognostics & prescriptive DTs.	EV fleet optimization
	11	Python (TensorFlow/PyTorch)	Custom AI-driven DTs.	Research & custom EV DTs

Evaluated research is analyzed based on digital twin architecture, EV drive-system subsystem, fault type, diagnostic procedure, and validation method. Tables 3-5 provide a list of technologies, software, and defect detection and diagnosis approaches. They are compared in terms of diagnostic accuracy, data requirements, response time, real-time capabilities, complexity of computation, and validation conditions. DT-based problem detection and diagnostics for the practical applications of EV drive systems, as well as limits and research needs, are also discussed.

4.1. Fault detection and diagnosis methods

Reliability of EV driving systems requires fault identification and diagnosis. Due to their simplicity and low processing cost, motor current signature analysis (MCSA), vibration analysis, and model-based observers like Kalman filters and sliding mode observers are commonly employed [30]. Complex nonlinear faults cannot be solved with threshold-based techniques, which are simplistic, noise-sensitive, and inflexible. AI and ML can overcome these constraints. Convolutional neural networks (CNNs), long short-term memory (LSTM), and autoencoders (AEs) can analyze high-dimensional and multimodal data and automatically extract features from raw signals, while support vector machines (SVMs), random forest (RF), and XGBoost can reliably identify faults with moderate training data [31]. Vibration, current, and temperature data fusion improves diagnosis. Real-time fault detection is possible with online learning and edge computing for dynamic operating circumstances [32]. Diagnose accuracy, data, response speed, real-time capacity, and computing complexity distinguish classical, model-based, and AI/ML approaches. Threshold-based approaches, Kalman filter/state observers, vibration analysis, and MCSA can diagnose faults rapidly with less data compared to SVM, RF, XGBoost, CNN, LSTM, and autoencoders. Table 5 compares FDD approaches' accuracy, data requirements, response time, real-time capabilities, and computing complexity.

As demonstrated in Table 5, both conventional and model-based methods are faster and require less data, whereas AI/ML-based methods are more diagnostic but require more data and computer resources. Use of multisensory data fusion for diagnostics increases system complexity. These results indicate that the choice of FDD is dependent on the trade-off between correctness, calculation expense, information access, and real-time capability.

Table 5. Comparison of traditional and AI/ML-Based FDD methods for EV drive systems

Method	Accuracy	Data requirement	Response time	Real-time capability	Complexity
MCSA	Medium	Low	Fast	Yes	Low
Vibration analysis	Medium–high	Medium	Medium	Yes	Medium
Kalman filter/SM Observer	High (model-dependent)	Medium	Fast	Yes	Medium–high
Threshold rules	Low–medium	Low	Very Fast	Yes	Low
SVM/RF/XGBoost	High	Medium	Fast	Limited (batch)	Medium
CNN/LSTM/AE	Very high	High	Moderate	Yes (with optimization)	High
Data fusion (multisensory)	Very high	High	Moderate	Yes	High

5. DIGITAL TWIN FOR FAULT DETECTION IN EV DRIVES

5.1. Architecture of DT-based FDD systems

Real-time data collection, virtual model synchronization, anomaly detection, and fault mitigation are part of electric vehicle drive closed-loop digital Twin fault detection and diagnosis systems. Motors, inverters, and battery systems provide sensor data to the DT via IoT or edge platforms. Deviation analysis allows early defect diagnosis in the virtual model's nominal and flawed system behavior [33]. Inverter DTs monitor thermal stress to prevent IGBT failures, while PMSM digital twins analyze stator current harmonics to detect inter-turn short circuits. The battery management system twins can predict cell imbalance or thermal runaway, boosting operational safety and durability [34].

5.2. Modelling approaches

DT modelling methods for FDD are physics-based, data-driven, or hybrid. FEM tools like ANSYS Motor-CAD and JMAG can accurately simulate electric machines and thermal systems [35]. Data-driven methodologies estimate system behavior using neural network-based surrogate models trained on historical and real-time data, improving computational efficiency and adaptability. In complex fault conditions, hybrid models like physics-informed neural networks and gray-box modelling combine domain expertise with data-driven learning to improve generalization, robustness, and interpretability [36].

5.3. Integration with intelligent algorithms

Modern algorithms increase fault detection in digital twin architectures. In the DT context, models like XGBoost, CNNs, and LSTM networks can detect fault patterns, forecast degradation trends, and improve decision-making. Closing-loop feedback techniques let the digital twin learn and adapt to new sensor data and operational results [37]. Using IoT infrastructure and cloud and edge computing platforms, electric vehicle fleets may scale digital twins for real-time defect analysis and remote diagnostics with reduced latency [38]. The intelligent defect detection and diagnostic ecosystem is shown in Figure 4 as a system-level block diagram of digital twins, machine learning algorithms, and edge/cloud infrastructure.

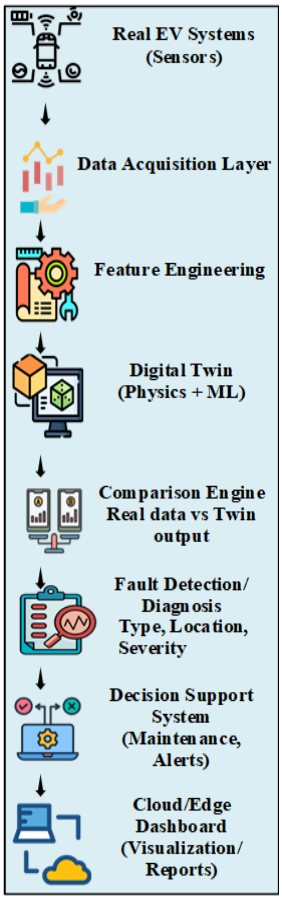

Figure 4. Integration of digital twins, machine learning algorithms, and edge/cloud infrastructure

5.4. Evaluation and benchmarking

Digital twin-based fault detection and diagnosis systems for electric vehicles must be benchmarked. Diagnostic accuracy, detection speed, resistance to noisy or missing data, flexibility to varied case types and operating conditions, and scalability for large electric vehicle fleets are essential. The Case Western Reserve University bearing dataset and real-world EV test benches provide motor and inverter diagnosis situations. Electric vehicle-specific fault-finding and diagnostic data are scarce due to controlled research [39]. Cost and complexity limit real-time method validation on simulation and HIL co-simulation platforms like Simulink with dSPACE, Speedgoat, and TwinCAT. Even with AI for digital twins, benchmarking and cross-platform validation are absent [40]. EV platform uptake and compatibility, open-access datasets, standardized benchmarking, and experimental validation are needed.

6. CHALLENGES AND OPEN ISSUES

Electric vehicle drive systems can benefit from digital twin-based fault diagnosis; however, various constraints prevent widespread use. Actual fault circumstances make machine learning model construction difficult due to limited annotated datasets and labelling difficulties [41]. Costly high-fidelity DT models

require many ANSYS or motor-CAD simulations and parameter modifications. High-speed real-time synchronization between physical systems and virtual twins is latency- and bandwidth-intensive [42]. Limited compatibility with ANSYS, MATLAB/Simulink, and Python-based ML frameworks makes multi-domain model integration challenging. As altered sensor data or system behavior might lead to false diagnoses or harmful control actions, cybersecurity concerns hamper DT implementation [43]. Furthermore, DT-FDD systems established for one architecture may need significant recalibration for other vehicle platforms and configurations, restricting applicability. Effective, scalable, and secure DT frameworks for intelligent fault detection in EV ecosystems must address these problems.

7. FUTURE RESEARCH DIRECTIONS

Several prospective research routes must be pursued to capitalize on digital twin-enabled fault detection and diagnostics in electric vehicle systems. PINNs combine the precision of physical modelling with the adaptability of data-driven learning to improve predictive performance and model interpretability [44]. Federated learning and edge AI have robust methods for privacy-preserving, real-time defect identification and diagnosis in dispersed electric car fleets without centralization. Interoperability, reusability, and cross-platform deployment require electric vehicle architecture-specific frameworks and ontologies. Autonomous self-healing drive systems, where digital twins can detect and analyze problems and begin adaptive control or maintenance procedures, are a new research topic. Integrating digital twins with vehicle-to-grid (V2G) technologies and smart mobility ecosystems improves fleet energy management, fault resilience, and intelligent transportation network performance [45]. DT-based diagnostics will evolve from component-level applications to intelligent EV ecosystems in these directions.

8. CONCLUSION

This article examines approaches for detecting and diagnosing failures in EV drive systems, including digital twins. This research classifies and compares model-based, data-driven, and hybrid digital twin electric vehicle problem detection methodologies. While digital twins provide simultaneous monitoring, anomaly detection, and predictive maintenance, traditional and AI/ML technologies are inaccurate, complex, and slow. Modelling allows physical interpretability, data-driven models allow complicated fault pattern navigation, and hybrid frameworks integrate both. DT-integrated FDD systems increase fault detection, reduce downtime, and improve safety with physics-based models, current algorithms, and cloud/edge infrastructure. To apply theoretical frameworks, data constraints, model correctness, tool compatibility, and cybersecurity must be addressed. Approach comparisons are limited by prior research datasets, validation criteria, and performance measurements. Using physics-informed neural networks, standardized digital twin frameworks, and empirical validation across electric vehicle platforms will advance hybrid modelling. Future research should focus on digital twin-based fault detection and diagnosis system real-time monitoring and interoperability. Digital fault diagnostics improves autonomous, intelligent, and resilient electric vehicle drive systems.

FUNDING INFORMATION

This study did not obtain any particular funding from public, commercial, or non-profit organizations.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest, whether financial or personal, that could have potentially influenced the research or findings presented in this paper.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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