Data-Driven Diagnosis of Electrified Vehicles: Results from a Structured Literature Review

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Abstract

Traditional onboard vehicle diagnostics are rapidly evolving concomitant to the rise of electrified powertrains, digital transformation, and intelligent technologies for advanced system management. The big data now available in modern vehicles offers unprecedented opportunities for condition monitoring and prognosis, but also presents challenges in scaling and integrating multimodal sensor data across components with varying timescale dynamics. Machine learning techniques have proven particularly effective in implementing diagnostic functions within electrified vehicle powertrains. This study systematically reviews intelligent, data-driven techniques for health monitoring and prognosis of electrified powertrains. We categorize existing research based on diagnostic functions and machine learning methods, with a focus on approaches that do not require prior knowledge of faulty operational states. Our findings indicate that deep learning methods are state-of-the-art across several diagnostic functions, fault modes, system levels, and multimodal sensor integration.

2012 ACM Subject Classification Computing methodologies → Machine learning algorithms; Hardware → Safety critical systems; Hardware → Failure recovery, maintenance and self-repair

Keywords and phrases Diagnostic functions, Machine Learning, Powertrain, Electrified vehicles

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1 Introduction

The digital transformation within the transport system is rapidly changing the landscape of automotive engineering processes for developing, operating, and managing the end-of-life of vehicles. One of the primary motivations for the electrification of powertrains is to reduce their ecological footprint by increasing energy transformation efficiency and moving towards zero CO_2 emissions [22]. At the same time, this transformation aims to improve transportation safety. Active safety systems (ASSs) engage transiently in the event of detection of internal or external hazards, they react timely providing warnings, adjusting the parameters or control of the vehicle, yet without assuming the responsibility and role of the

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human driver [44]. On the other hand, Advanced Driver Assistance Systems (ADASs) are expected to engage continuously as they increase the level of *driving automation* defined in the SAE J3016 standard [43]. At level 5, vehicle decision-making is fully automated, requiring of more comprehensive health awareness capabilities. Vehicle powertrain electrification brings unprecedented possibilities regarding vehicle control, eco-driving, real-time health monitoring, and predictive maintenance. Data transmission and storage are scaling rapidly in speed and bandwidth to accommodate the volume of information generated by the many digital sensors available in the intra-vehicle networks connecting the different components of an electrified powertrain (EP). The traditional component-based onboard diagnostics, prescribed in the *On-Board Diagnostics* (OBD-II) and the ISO 14229-1 *Unified Diagnostic Services* (UDS) standards, are expected to transition to hierarchical intelligent health management systems.

Diagnostic solutions can be developed using different conceptual frameworks. In the case of motors, but equally appropriate for other components of the EP, Chen et al. [5] classifies the approaches into *model-based*, *signal-based*, and *data-driven*. Within model-based methods, the classification can be refined into analytical mathematical models, magnetic equivalent circuits (MECs), and digital simulation models [2]. The choice of the kind of model is driven by accuracy, computational complexity, and in many cases the type of faults to consider. As for signal-based diagnosis techniques, they are mainly concerned with characterizing the different fault signatures. They rely on feature extraction techniques that operate in the time, spectral, or time-frequency domains. Because of its sound theoretical foundations, these techniques are often incorporated in data-driven approaches. Data-driven diagnosis is primarily enabled by machine learning (ML) and artificial intelligence (AI) models.

In this paper, we review the current research landscape of data-driven Intelligent Diagnostic Systems (IDSs) for EPs and present the first installment of a comprehensive literature survey currently in the making. Section 2 details the methodology of our research, including research questions (Section 2.1), search criteria (Section 2.2), inclusion criteria (Section 2.3), and our data processing approach (Section 2.4). Bibliometric facts are presented in Section 3. In Section 4, we discuss the present answers to the research questions. Section 5 interprets and discusses our findings. Finally, Section 6 offers some concluding remarks.

2 Methodology

The methodology of this study is summarized in Figure 1. We start by formulating our research questions. Then we define a search string to query pertinent scientific databases. Various inclusion criteria were defined to narrow down the relevant articles, resulting in a subset of articles that undergo a pre-screening process. This curation step ensures that the selected articles align with the predefined scope and objectives. Finally, we conduct a manual review of the articles to collect our insights and findings regarding various DFs, components and machine learning methods.

We center our study on the Motor Systems (MSs) of EPs. Attending to the fact that healthy behavior data is easier to obtain than faulty behavior data, we also focus on unsupervised machine-learning methods, suitable to work without knowledge nor data from faulty behavior of the system. We aim to shed light on how these methods can deliver effective and reliable EP IDSs. In the following, we provide details about the research questions, search schema, acceptance criteria, and data processing pipeline.

[2] A detailed account of the different approaches and classifications found in the literature can be found in Usman et al. [53]. Usman's taxonomy refers to these classes as electrical equivalent circuit, magnetic equivalent circuit, and numerical methods.

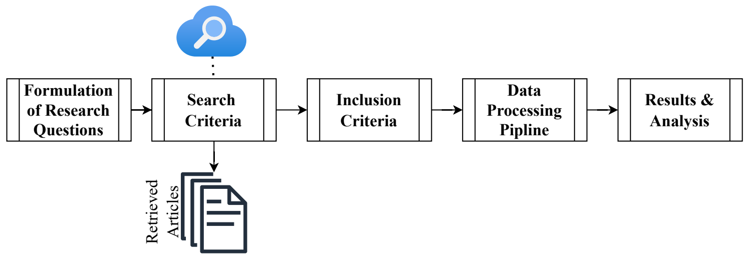


Figure 1 Survey methodology overview.

2.1 Research Questions

1. What are the DFs covered in the research?
2. What components of the EP are considered?
3. What anomalies or faults were included in the study?
4. What are the AI techniques applied to implement the DFs?
5. To what extent is it feasible to develop DFs implemented with unsupervised ML techniques that rely exclusively on unlabeled data corresponding with the healthy behavior of the system?

2.2 Search Criteria

2.2.1 Scientific Portals

Searches performed in: (1) SAE Mobilus, (2) Scopus, (3) IEEE Xplore, (4) TU Graz Library Search, (5) Wiley Online Library, (6) ProQuest, (7) ScienceDirect, and (8) Web of Science.

2.2.2 Search Query

Logic based: "electric vehicle" AND "motor" AND ("machine learning" OR "artificial intelligence") AND ("fault detection" OR "anomaly detection" OR "diagnosis" OR "condition monitoring" OR "predictive maintenance").

2.3 Inclusion and Exclusion Criteria

Papers written in languages other than English, articles to which our institution has no access, empty, incomplete, or untraceable records, retracted articles, papers older than 2018, only abstracts, and all non-peer-review publications were excluded from the survey. All battery-subsystem-only, software-only, and cybersecurity-related papers were considered out of scope for this review. The curation step is explained in Section 2.3.1.

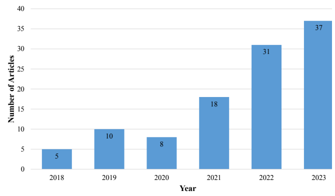
2.3.1 Prescreening Criteria

1. At least one of the following: fault detection, anomaly detection, diagnosis, condition monitoring, or predictive maintenance.
2. At least one of the following: DC link, motor, inverter, and reducer.
3. At least one intelligent data-driven approach.
4. At least one research question is addressed.
5. literature review with at least one work satisfying one or more of the previous criteria.

Selected works either satisfy criteria 1, 2, 3, and 4 simultaneously or they satisfy 5.

Science Portal	Hits	Included (✓)		Excluded (✗)	
		Research	Review	Access	No access
SAE Mobilus	42	1	1	39	1
Scopus	38	16	4	16	2
IEEE Xplore	17	13	0	4	0
TU Graz Library Search	31	15	5	11	0
Wiley Online Library	46	4	2	40	0
ScienceDirect	110	8	1	101	0
ProQuest	506	47	12	447	0
Web of Science	12	8	2	1	1
Total	804	112	27	659	4
Unique	754	86	23	642	3

(a) Summary of results of the prescreening process.



(b) Yearly published articles (RC).

Figure 2 Bibliometric results.

2.3.2 Collections

After the prescreening procedure, the selected works are identified as the *Reference Collection* (RC). In addition, by inspecting each work within the RC we identify additional papers that fulfill our acceptance criteria. These works are referred to as *Extended Collection* (EC). Finally, references preceding 2018 that are relevant constitute the *Baseline Collection* (BC).

2.4 Data Processing

A total of 804 references (754 unique) were prescreened independently using the criteria described in Section 2.3.1. We classified the papers as original research papers or as literature reviews. Being a partial installment, this paper coverage is restricted to 15 IEEE Xplore papers and all publications within the RC between 2018, and 2020, and parts of 2021.

3 Bibliometric Facts

All bibliometric facts are based on the RC exclusively. Table 2a summarizes the classification obtained after the screening procedure. ProQuest portal contributed the highest volume of accepted papers: 42 research papers and 12 review papers (59 in total, or 54% of the final collection), SAE Mobilus the lowest by volume, 1 research paper and 1 review paper (2 in total, or 1.83% of the final collection). On the other hand, the precision of the search engines differs significantly. IEEE Xplore provided only a moderate number of hits (17), yet the prescreening process resulted in an acceptance rate of 76.4%. In contrast, the accuracy of ProQuest was only 11.66%. Figure 2b illustrates the yearly distribution of selected published articles, revealing a growing acceptance of data-driven techniques.

4 Results

What are the DFs covered in the research?

Table 1 summarizes the classification of research papers according to different diagnostic functions. It can be seen that most research items focus on the FD and Diag categories. We classify a work as Diag if at least two different types of faults are included.

Table 1 Publications according to diagnostic function.

Code	Diagnostic function	RC	EC	BC
ADiag	active diagnosis	[27] [38]		
CM	condition monitoring	[30]		
Diag	diagnosis	[1] [34] [35] [38] [49] [50] [52] [55] [61] [63] [64] [65]	[16] [19] [28] [36] [37] [51] [56]	[6] [8] [23] [32] [47] [62]
DTBHM	digital-twin-based health monitoring	[54]		
DTBP	digital-twin-based prognostics	[54]		
FD	fault detection	[2] [4] [13] [17] [29] [31] [33] [40] [48] [57] [58] [59] [60]	[18] [51]	[6] [10] [11] [20] [21] [24] [32] [39] [41] [42] [45] [46] [47] [62] [66]
FE	fault excitation	[27]		
FI	fault isolation	[27]		
FL	fault localization	[2]	[18]	[20] [39] [41] [42] [46]
RA	risk assessment	[25]		
SA	severity assessment	[4] [13] [17] [48] [63]	[9] [16] [28] [56]	[6] [10] [11] [20] [39] [42] [45] [46] [66]
UAD	(unidentified) anomaly detection	[15]		

Table 2 Publications according to EP component.

Code	Component	RC	EC	BC
Agnos	agnostic	[15] [25] [31]		
Inv	inverter	[2] [4] [40] [48]		
HVDCL	high voltage DC line	[57] [58] [59]		
GB	gearbox	[65]	[37]	
Mot	motor	[1] [7] [12] [13] [14] [17] [30] [33] [34] [35] [49] [50] [52] [54] [55] [60] [61] [63] [64]	[9] [16] [18] [19] [28] [36] [37] [51] [56]	[6] [8] [10] [11] [20] [21] [24] [32] [39] [41] [42] [45] [46] [47] [66]
MotS	motor system	[38]		
Sen	sensor	[3] [48] [64]		[62]
PEC	power electronic circuit	[23]		

What components of the EP are considered?

Table 2 shows the coverage of papers per powertrain component. The bias towards motor components is likely a consequence of our search query (see Section 2.2.2).

What anomalies or faults were included in the study?

Table 3 summarizes our findings regarding the types of faults for EPs. There is good coverage of mechanical and electrical faults.

What are the AI techniques applied to implement the DFs?

Table 4 identifies the AI techniques performing intelligent diagnostic functions. It is a common practice to perform multi-technique benchmarks. It can be seen from the frequency of entries alone that among the classic ML techniques, those related to the decision tree

Table 3 Publications according to fault types.

Code	Fault type	RC	EC	BC
AWBF	abrasive wear (BF)		[28]	
BallF	ball fault (BF)	[7] [34] [35] [63] [65]	[19] [37] [51] [56]	[47]
BCD	bearing cage defect			[24]
BiasSF	bias sensor fault	[64]		[62]
BF	bearing fault	[7] [12] [52] [55]	[51]	[6] [21] [47]
BRBF	broken rotor bar fault	[7] [13] [50]	[16] [51]	[32]
BRF	bowed rotor bar	[14]	[51]	
ChpTooth	chipped tooth		[37]	
CompF	component level fault	[25]		
CrkToothR	crack in tooth root		[37]	
CycSF	cyclic sensor fault			[62]
DCSAF	DC serial arc fault	[57] [58] [59]		
ErrSF	erratic sensor fault			[62]
MisTooth	missing tooth		[37]	
WrnTooth	worn tooth	[37]		
FRSC	faulty ring of squirrel-cage		[16]	
GFOS	gain fault on sensor	[48]		
IDF	irreversive demagnetization fault	[52]	[9] [28]	
ITSF	inter-turn short-circuit fault	[17] [33] [49]	[18] [36]	[8] [10] [20] [39] [41] [42] [45] [46] [66]
IRF	inner raceway fault (BF)	[7] [34] [35] [63] [65]	[28] [37] [51] [56]	[6]
IOSF	intermittent open-switch (OSF)	[4]		
MIF	model inductance fault (MPF)	[27]		
MotF	motor failure	[38] [61]		
MPF	model parameter fault	[31]		
MRF	model resistance fault (MPF)	[1] [27] [49]		
PGSF	phase to ground short-circuit fault	[50]	[36]	[8]
PPSF	phase to phase short-circuit fault	[1] [49] [50]		[8]
OCF	open circuit fault	[2] [29]		[23]
OCPF	open circuit of phase fault	[1]	[36]	
OSF	open switch fault	[40]		
ORF	outer raceway fault (BF)	[7] [34] [35] [60] [63] [65]	[19] [37] [51] [56]	[6] [47]
REF	rotor eccentricity fault	[12] [14]		
RMA	rotor misalignment	[7]	[51]	
RU	rotor unbalance	[34]	[51]	
SCF	short circuit fault	[29]		[23]
SEF	static eccentricity fault			[11] [20]
SM	shaft misalignment	[34]		
SOF	sensor omission fault	[3]		
StckSF	stuck sensor fault			[62]
ApkSF	spike sensor fault			[62]
UA	unidentified anomaly	[15]		

family are often preferred, in particular, if strengthened by ensemble methods. SVM, remains a reference model, the community praises the good performance and low computational cost provided the volume of data is limited; yet another reason for its application. Deep learning techniques have also recently populated the field. The tried-and-true CNN family is the natural choice, whether in their 1-D or 2-D variants. Its application is further facilitated by the availability of public pre-trained models over which transfer learning techniques can be applied. The autoencoder family and deep stacking models are also present. Despite our partial coverage, the diversity of models and methodologies is already apparent.

Table 4 Publications according to AI technique included in the study.

Code	AI technique	RC	EC	BC
ABOD	angle-based outlier detector	[15]		
ADCNN	adaptive deep CNN		[56]	[24]
AE	deep autoencoder	[15]		
AEOD	autoencoder for outlier detection	[15]		
CNN	convolutional neural network	[7] [30] [34] [38] [52] [63] [65]	[28] [56] [19]	
DBN	deep belief network	[25]		[6]
DBNHDN	DBN-based hierarchical diagnosis network		[56]	
DCAE	deep coupling autoencoder		[37]	
DCTLN	deep convolutional transfer learning network		[19]	
DFC	decision forest classifier	[1] [12] [13] [14] [61]		
DJC	decision jungle classifier	[12] [13] [14]		
DTC	decision tree classifier	[1] [3] [12] [17] [38] [50]		
DTR	decision tree regressor	[48]		
EBTC	ensemble bagged trees classifier	[17]		
ESC	ensemble subspace classifier	[17]		
FuzzyL	fuzzy logic	[54]		[21] [46]
FSVM	fuzzy support vector machine			[23]
GBRBM	Gaussian Bernoulli restricted Boltzmann machine		[37]	
GMODBN	Gaussian mixture output dynamic Bayesian network	[60]		
GB	Gradient boosting	[1]		
IN	inception network	[34]		
IDDAN	inferable deep distilled attention network	[63]		
KMC	K-means clustering	[40]		
KNNC	K-nearest neighbor classifier	[1] [3] [17] [50]	[16]	[10] [20]
KNNOD	K-nearest neighbor outlier detector		[15]	
KPCA	kernel PCA			[6]
LLE	locally linear embedding			[6]
LR	logistic regression	[13] [14] [48] [57] [58]	[19] [37]	
MLP	multilayer perceptron	[1] [2] [13] [14] [25] [30] [40] [48] [49] [54] [65]	[16]	[11] [24] [39] [62] [66]
NPE	neighborhood preserving embedding			[6]
TLNN	time-lagged neural network			[42]
OCSVM	one-class SVM			[32]
PDSRC	part dictionary sparse representation classification			[47]
PCA	principal component analysis	[3] [4] [12] [17] [50]	[18]	
PN	prototypical network	[55]		
PSO	particle swarm optimization			[21] [42] [47]
QDA	quadratic discriminant analysis	[52]		
RBFN	radial basis function network			[24]
RBM	restricted Boltzmann machine		[37]	[6]
RNN	recurrent neural network			[41] [45]
ResNN	residual neural network	[34]		
SAE	sparse deep autoencoder		[28] [51]	[6]
SF	sparse filtering		[56]	
SOM	self-organizing map	[40]		[8]
Sperc	simple perceptron	[25]		
SVM	support vector machine	[1] [3] [17] [33] [35] [40] [50] [52] [55] [57] [58] [59] [63] [64]	[51] [56]	[21] [23] [32] [47]
SVR	support vector regression	[30]	[9]	
WCBC	word-code-based classification		[16]	
WDCNN	deep CNN with wide first-layer kernel	[55]		
WPNF	wavelet-prototypical network based on fusion of time and frequency domain	[55]		

To what extent is it feasible to develop DFs implemented with unsupervised ML techniques that rely exclusively on unlabeled data corresponding with the healthy behavior of the system?

We found evidence of systems able to detect anomalies based on machine learning techniques that were trained purely on the healthy behavior of the system. In [15], Geglio et al. apply *reconstruction-based* anomaly detection. A reconstruction-based anomaly detector can be implemented on any signal corresponding to the healthy behavior of the system. They include several variants in their study, a fully convolutional autoencoder (AE CNN), a fully connected autoencoder for outlier detection (AEOD), an angle-based outlier detector (ABOD), and a K-nearest neighbor outlier detector (KNNOD). They also showed that these techniques can integrate the signals of 58 different sensors, that were available in the vehicle's powertrain network. In [37], Ma et al. applied a deep coupling autoencoder (DCAE) to integrate signals from different sensor modalities. The architecture stacked (1) Gaussian Bernoulli restricted Boltzmann machines (GBRBMs); (2) restricted Boltzmann machines (RBMs); (3) a coupling autoencoder (CAE) to integrate vibration and acoustic information; and a (4) multinomial logistic regression classifier taking as input the sparse representation computed by the DCAE architecture. This architecture effectively diagnosed several gearboxes (GB) defects, and BFs outperforming decision pathways based on DAEs operating with the single modalities and both modalities trained independently. By removing the multilayer regressor, reconstruction-based anomaly detection for multimodal signals is possible.

Some solutions are capable of multi-sensor fusion. Chen and Li in [6] apply sparse autoencoders (SAEs) to fuse simultaneously acquired vibration signals from three accelerometers monitoring a motor system. Their proposed method first computes a set of 15 time-based features and 3 frequency-based indicators per sensor. These are fed into a bank of 18 SAEs, each processing the individual features computed from the three vibration sensors. The stacked SAE layers first compute a sparse overcomplete representation, and then a single channel fusion. The 18 fused feature signals are then connected to a deep belief network (DBN) that diagnoses IRFs and ORFs of different magnitudes (slight, moderate, severe). Chen and Li benchmarked SAE-DBN architecture against PCA, KPCA, NPE, LLE, single SAE[3], and AE[4]. SAE-DBN outperformed all other ML models in the benchmark. In addition, it showed better generalization ability and robustness, requiring fewer training samples to achieve high accuracy across various operating points. The SAE stage in the model is an instance of a suitable candidate to be used in unsupervised learning scenarios.

Another example is given by [30], where Kaviya et al. implement condition monitoring (CM) for motors. Taking as inputs the DQ voltages and currents, coolant temperature, stator tooth temperature, temperature of the permanent magnet, motor speed, ambient temperature, and motor torque, they train an SVR to learn to predict a healthy motor's torque. Luo et al. [36] use the three-phase currents and rotor position as inputs to a LSTM network. The network is trained in unsupervised mode to predict the behavior of the healthy system. They show a qualitative confirmation of meaningful residuals that could be used for fault detection of OCPFs, PGSFs, and ITSFs under several operational conditions. There are instances of hybrid architectures that optimize the decisions, for example, in [41], Nyanteh et al. combine a recurrent neural network (RNN) with particle swarm optimization (PSO) to perform fault detection and fault localization. The RNN takes as inputs the three consecutive

[3] Referred to as SAE0 in the paper, is a single SAE, whose input was formed by concatenating the multi-sensor (3×18) features into a single vector.
[4] AE has the same architecture as SAE, but for the sparsity regularization term that is set to zero.

samples of the current phase A of the PMSM (1 input and 2 delays) and computes the current envelopes for each phase; the network being trained by a PSO algorithm having as its objective function an index that measures the ability of the RNN to compute an envelope to the input current along an operational cycle. A fault is detected when the differential current exceeds about three standard deviations from its mean value.

5 Discussion

Many works we have surveyed are instances of *diagnosis as classification*, where a ML model is trained in supervised mode with labeled faults. Often, ML model architectures are hybrids of several paradigms and/or architectures. For instance, the work of Zhang et al. [63] presents the inferable deep distilled attention network (IDDAN). It includes an attention mechanism implemented with a transformer encoder connected to a linear classifier. The authors use *data augmentation*, *knowledge distillation*, and *transfer learning.* A CNN (VGG-16) is trained as the teacher network and IDDAN as the student in the methodology of knowledge distillation. Transfer learning is applied by fine-tuning a multi-layer perception (MLP) fed by the distilled network transformer encoder.

We identify challenging circumstances regarding the setup of experimental platforms to gather data from physical plants that can simulate realistic driving cycles of EVs and excite the system sufficiently across its entire nominal envelope. In many cases, the community relies on public datasets and or synthetic data obtained from systematic simulations. As for simulation frameworks, a notable mention is the work of Meckel et al. [38]. In their study they developed a fault injection generic simulation framework for HEVs implemented in MATLAB/Simulink. Their framework incorporates several fault injection mechanisms allowing faults to manifest transiently, intermittently, or permanently.

Regarding distributed architectures, Jeong et al. [25] engineered an integrated self-diagnosis system (ISS) for autonomous vehicles. Their contribution is a distributed diagnostic solution that trains and optimizes diagnosis models in the cloud using the vehicle's operational data and deploys them at the edge (onboard the vehicle). It consists of three modules: the deep learning module (ODLM), the in-vehicle gateway module, and the edge computing-based self-diagnosis service. The first module performs diagnostics and risk assessment. The second optimizes the data transfer across the networks, collecting data from the vehicle sensors and top-down control signals and routing data to the OBD and actuators. The third informs diagnostic results to the cloud, infrastructure, and other vehicles.

Given the communication infrastructure of modern electrified vehicles, it seems essential to decompose diagnostic tasks into fine-grained computational graphs rather than relying on monolithic solutions. These graphs self-coordinate and coordinate with others, maintaining functionality even under severely degraded conditions. We refer again to the work of Meckel et al. [38] to illustrate two main aspects or requirements for IDS in our domain: (1) active diagnosis , and (2) explicit models of diagnostic procedures. They hypothesized the possibility of transforming a decision tree classifier (DTC) into a diagnosis model in the form of a *diagnostic directed acyclic graph* (DDAG). DDAGs can represent the orchestration of active and distributed processing and feature extraction tasks required in fault diagnosis. In [26], Jo et al. illustrate the use of DDAG for an abstract diagnosis model of the powertrain of an HEV, they showed how as nodes of the graph are executed they gather *evidence* to support a diagnosis decision. The outcome of some nodes (diagnostic tasks) can represent intermediate conclusions. Generally, several factors need to be considered to reach a diagnostic conclusion.

6 Concluding remarks

The landscape of data-driven intelligent diagnosis methods and architectures for EPs is diverse and blooming. In our first installment, of a comprehensive literature review still in the making, we have presented different views and classifications in the hope that they help the community to navigate the arena. The community could benefit from more open data repositories. The digital twin paradigm embraces the integration of multiple techniques, in particular model-based and data-driven approaches. Signal-based methods are already part of many feature-processing pipelines, often combined with deep learning models. Active diagnosis appears to be an essential function of IDSs.

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