Machine Learning for Distributed Acoustic and Fibre-Optic Sensing in Infrastructure Monitoring: A Systematic Review (2015-2025)

Abd Rahim Saidin, Illani Mohd Nawi
Department of Electrical and Electronic Engineering, Universiti Teknologi PETRONAS, 32610 Seri Iskandar, Perak, Malaysia

***Abstract*—Distributed acoustic sensing (DAS), together with broader distributed fibre-optic sensing (DFOS), has emerged over the past decade as a candidate technology for large-scale infrastructure monitoring, while machine learning (ML) is increasingly used to interpret its high-throughput data. This study presents a PRISMA 2020-guided bibliometric and systematic-mapping review of this convergence. A structured search of Web of Science, Scopus, and IEEE Xplore returned 291 records published between 2015 and 2025; after duplicate removal and two stages of screening, a final analytical corpus of 31 publications was established, of which 16 are primary DAS-with-ML infrastructure studies. Publication output rises sharply to seven papers in 2024 and twelve in 2025. Among the primary studies, convolutional neural networks (CNNs), recurrent models, and CNN-LSTM hybrids are prominent, with more recent use of few-shot learning, graph neural networks (GNNs), generative models, and self-supervised learning. Perimeter security is the most represented application domain, followed by traffic, railway, and structural-health monitoring. Critical synthesis shows that the apparent dominance of CNNs is partly explained by the natural two-dimensional spatiotemporal representation of DAS data and by mature, reusable CNN pipelines, rather than evidence of universal superiority. Cross-study comparison remains limited by heterogeneous sensing environments, inconsistent acquisition and label reporting, non-uniform evaluation protocols, sparse computational reporting, and minimal long-term robustness evaluation. Five research gaps are identified: cross-infrastructure generalisation, standardised benchmarks and open datasets, physics-data-driven integration, interpretability and uncertainty, and operationally robust edge deployment.**

Keywords*—Bibliometric analysis; convolutional neural network; deep learning; distributed acoustic sensing; distributed fibre-optic sensing; infrastructure monitoring; machine learning; phase-sensitive OTDR; structural health monitoring; systematic review

I. Introduction

Distributed acoustic sensing (DAS) converts a standard optical fibre into a long, densely sampled array of vibration sensors by analysing Rayleigh-scattered light produced as laser pulses travel along the fibre. Because it can interrogate tens of kilometres of fibre with metre-scale spatial resolution and high sampling rates, DAS, together with related distributed fibre-optic sensing (DFOS) techniques, has attracted growing interest for transport, energy, and civil-infrastructure monitoring [23], [24], [30]. A single buried or surface-mounted cable can simultaneously capture intrusion, traffic, seismic, and structural signatures, making the technology attractive where conventional point sensors would be costly or impractical [1].

The volume and complexity of DAS data exceed what manual or rule-based analysis can handle efficiently. This has motivated ML and, increasingly, deep learning to automate event detection, classification, signal enhancement, and condition assessment [6], [10]. Convolutional and recurrent architectures, along with meta-learning and graph-based models, have been applied to traffic, railway, urban, structural, and perimeter-monitoring tasks [11], [22], [28]. Despite this activity, the field still lacks a consolidated picture of how the DAS-ML intersection has developed, how evidence quality varies, and which apparent research gaps remain robust after accounting for a small and heterogeneous corpus.

This review addresses that need through a PRISMA-guided bibliometric and systematic-mapping analysis of literature published from 2015 to 2025. The three research questions are: (RQ1) How have publication trends and thematic developments in DAS-ML research evolved? (RQ2) Which authors, venues, and countries are most active, and how are they connected through co-authorship and shared topics? (RQ3) What research gaps and future opportunities are supported by the available evidence for infrastructure and smart-infrastructure applications?

The corresponding objectives are to quantify publication and methodological trends (RO1); map geographical, venue, co-authorship, and keyword structures (RO2); and critically synthesise the 16 primary DAS-with-ML studies through study-quality assessment, ML-application mapping, cross-study comparability analysis, and evidence-grounded research gaps (RO3).

The contributions are: 1) a PRISMA 2020-compliant search and screening protocol yielding a reproducible corpus of 31 publications; 2) quantitative bibliometric characterisation of publication, geographical, venue, collaboration, and keyword patterns; 3) a five-criterion quality assessment of the 16 primary studies; 4) a two-dimensional mapping of ML families to application domains, interpreted explicitly as corpus-level coverage rather than proof of field-wide absence; and 5) a critical synthesis of dataset heterogeneity, evaluation comparability, computational reporting, data quality, and long-term deployment challenges, leading to five evidence-mapped research directions.

II. Literature Review

The literature reflects a progression from deterministic signal processing towards data-driven analysis. Early and parallel work focused on signal fidelity, phase-noise compensation, sensing-system design, and measurement quality [4], [7]. Classical ML then appeared in traffic, railway, and structural settings through support-vector machines, ensemble classifiers, and principal-component-based methods [13], [15], [16], [21].

Deep learning subsequently became prominent. CNNs have been applied directly to phase-sensitive optical time-domain reflectometry (phi-OTDR) spatiotemporal matrices for event recognition [10], while recurrent and hybrid CNN-LSTM models capture temporal dependencies in compromised-data and railway-condition monitoring [2], [22]. Autoencoder-based self-supervised learning has been explored for traffic and perimeter applications [6], [12]; meta-learning addresses limited labelled data in urban monitoring [11]; and graph-diffusion modelling explicitly represents spatial sensor topology for anomaly detection [28]. Signal separation using recurrent architectures provides a further example of task-specific model development [27].

Several adjacent sensing studies highlight acquisition and data-quality constraints that directly influence ML reliability. Optical vibration-monitoring systems demonstrate dependence on sensing configuration and signal conditioning [7]; embedded distributed optical-fibre networks show the need to distinguish thermal effects from mechanical strain [8]; and distributed fibre processing in axially loaded precast piles illustrates the importance of installation and load-transfer conditions [9]. Related low-SNR noise-removal work [17], DAS optimisation studies [18], and output-only sensor fusion using distributed optical-fibre measurements [20] reinforce the point that model performance cannot be interpreted independently of measurement quality. At the systems level, cloud-computing and storage considerations in seismology [25] and multiparameter distributed sensing [26] also motivate scalable and calibration-aware deployment strategies.

Application-oriented work spans pipeline and geotechnical monitoring [19], hydrogen-pressure-vessel and composite structural-health monitoring [29], open DAS event datasets [5], and synthetic DAS data generation [14]. Recent reviews survey DAS for seismology, intelligent event perception, and the wider technology landscape [23], [24], [30]. The present review differs by combining PRISMA screening, bibliometrics, quality assessment, primary-versus-adjacent study separation, ML-application mapping, and a critical comparability/deployment synthesis. Table I positions these contributions against the closest prior reviews.

TABLE I. Positioning of the Present Study Against Closely Related Reviews

Study	Technology scope	Review method	ML/DL	Period	Application focus	PRISMA	Bibliometric	Quality	Gaps
Markom et al. (2025) [30]	DAS/DFOS broadly	Systematic review	Partial	N/R	Seismology, perimeter, traffic	Partial	No	No	Partial
Rashid et al. (2025) [23]	DAS for seismology	Narrative survey	Partial	N/R	Seismology	No	No	No	Partial
Wu et al. (2025) [24]	DAS event perception	Narrative review	Yes	N/R	General event detection	No	No	No	Yes
Present study	DAS + DFOS + ML for infrastructure	PRISMA bibliometric/systematic map	Yes	2015-2025	Pipeline, railway, SHM, traffic, security, urban	Yes	Yes	Yes	Yes

[a] N/R = not reported. “Partial” indicates that the feature is discussed but is not the primary analytical layer.

III. Methodology

This review applies a bibliometric and systematic-mapping methodology, with study selection reported in accordance with PRISMA 2020 [31]. Web of Science, Scopus, and IEEE Xplore were searched.

A. Search Strategy

A Boolean query combined three concept blocks with the AND operator: 1) sensing technology (Distributed Acoustic Sensing, Distributed Optical Fiber/Fibre Sensing, Fiber/Fibre-Optic Sensing, Phase-sensitive OTDR, phi-OTDR, DAS, DOFS); 2) analytical layer (Machine Learning, Deep Learning, Signal Processing, Pattern Recognition, Neural Network*, Event Detection, Time-series Analysis); and 3) application domain (Infrastructure Monitoring, Structural Health Monitoring, Condition Monitoring, Smart Infrastructure, Smart Cities, Internet of Things, IoT, Cloud Computing). The query was adapted to each database, restricted to English-language publications from 2015 to 2025, and executed on 19 January 2026. The database-specific search parameters are summarised in Table II.

TABLE II. Search Parameters

Parameter	WoS	Scopus	IEEE Xplore
Years	2015-2025	2015-2025	2015-2025
Language	English	English	English
Search field	Full text	Full text	Full text
Records	172	65	54
Search date	19 Jan 2026	19 Jan 2026	19 Jan 2026

B. Screening and Eligibility

The search returned 291 records. After 64 duplicates were removed, 227 unique records underwent title-and-abstract screening, of which 123 were excluded. The remaining 104 records were assessed in full text; 73 were excluded for falling outside the declared scope, yielding a final analytical corpus of 31 publications (Fig. 1; Table III). The primary synthesis comprises 16 DAS-with-ML infrastructure studies. Screening was conducted by the lead author; borderline cases were reviewed independently by the second author and resolved by consensus discussion.

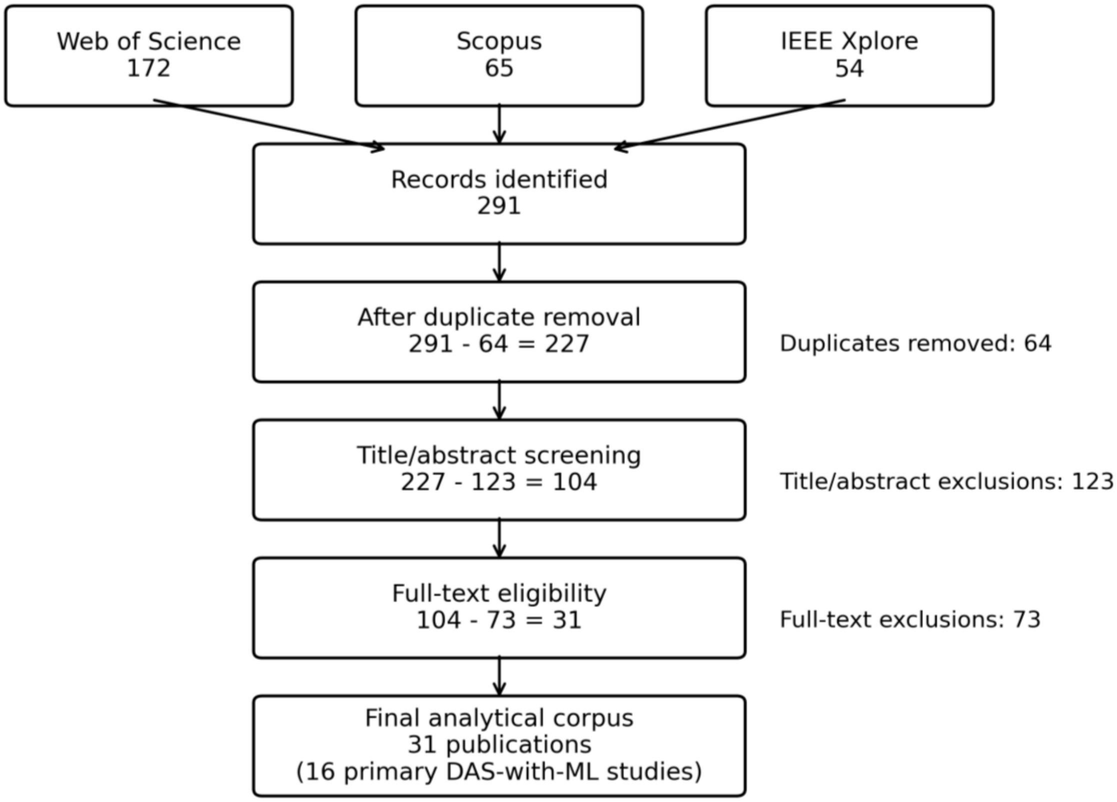

Fig. 1. PRISMA 2020 flow diagram of the study-selection process.

TABLE III. INCLUSION AND EXCLUSION CRITERIA APPLIED DURING SCREENING

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed journal or conference articles, 2015-2025	Preprints, theses, book chapters, non-English publications
Technical focus	DAS/DFOS infrastructure sensing with ML/DL or directly relevant adjacent sensing-analysis context	Unrelated sensing modalities or hardware-only work without relevance to DAS/DFOS analysis
Application domain	Real-world or simulated infrastructure monitoring and closely related sensing contexts	Biomedical, downhole-reservoir-only, or clearly non-infrastructure applications
Methodology	Reports data acquisition, processing, model architecture, validation, or system characteristics used in the synthesis	Conceptual frameworks without empirical or analytical contribution
Data description	Provides sufficient sensing or experimental context for the intended synthesis	No meaningful description of sensing data or experimental setup

C. Data Extraction and Analysis

For each record, bibliographic metadata, authorship and country information, venue, sensing modality, ML category and technique, dataset type, deployment mode, maturity level, and reported validation characteristics were extracted into a structured master sheet. Author names and keywords were normalised before analysis. Bibliometric mapping was performed with VOSviewer, and descriptive statistics were computed from the master sheet. For the 16 primary studies, critical synthesis additionally considered whether the reported evidence permits comparison of sensing environments, acquisition characteristics, label quality/class balance, evaluation protocols, computational cost, and long-term operational robustness. Missing items were treated as reporting limitations rather than inferred.

IV. RESULTS

A. Bibliometric Overview

Annual output (Fig. 2) confirms a recent acceleration within the 31-publication corpus. After sparse activity through 2022, output rises to four papers in 2023, seven in 2024, and twelve in 2025. This pattern is consistent with growing adoption of deep-learning and data-driven methods in distributed sensing, although publication growth alone does not establish methodological maturity.

Venue concentration remains marked. Sensors contributes eleven of the 31 records and IEEE Access contributes two; the remaining 18 records are distributed across single-publication venues (Fig. 3). This concentration should not be read as venue dominance of the wider field because the result is sensitive to the search scope and small corpus size.

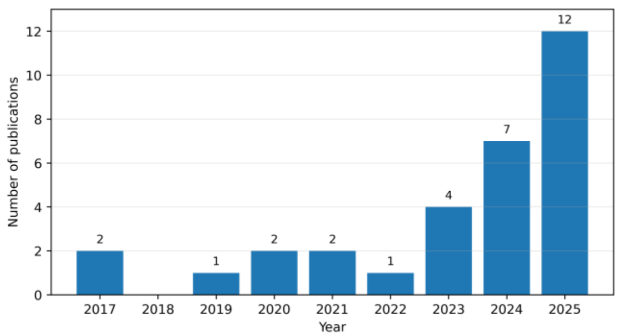

Fig. 2. Annual publication output of the reviewed corpus (n = 31).

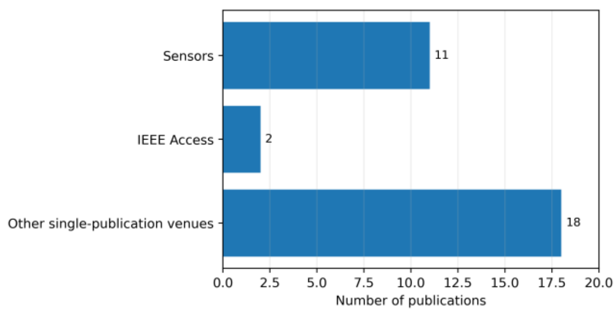

Fig. 3. Venue concentration in the reviewed corpus.

Geographically, China contributes seven papers, followed by the United States with four and Spain with three. Germany, Russia, Czechia, and Malaysia contribute two each; remaining country contributions are individually small (Fig. 4).

B. Collaboration and Thematic Structure

The co-authorship network (Fig. 5) is composed of several small, weakly connected clusters, indicating that collaboration is still concentrated within local research groups. The keyword co-occurrence map (Fig. 6) centres on distributed acoustic sensing and optical-fibre concepts, with linked clusters around deep learning, convolution, classification, signal processing, noise, traffic, and infrastructure monitoring.

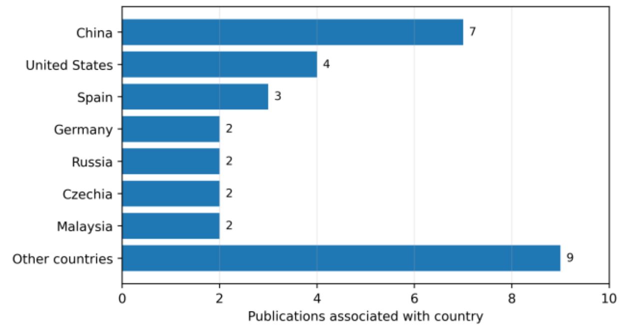

Fig. 4. Publication output by leading country; remaining countries are aggregated for legibility.

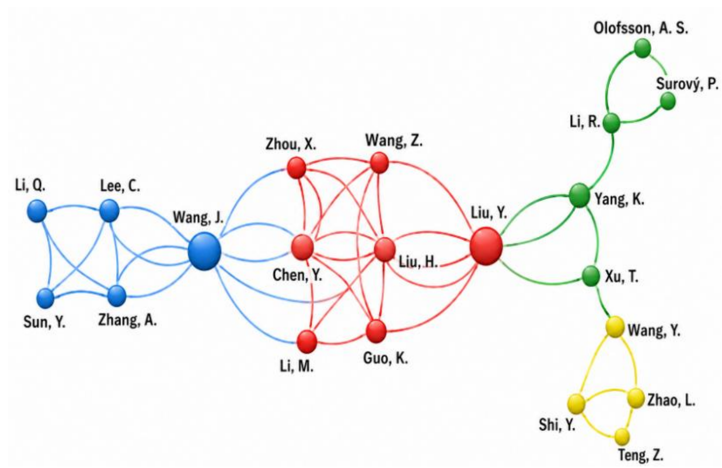

Fig. 5. Enlarged co-authorship network (VOSviewer; minimum two documents per author).

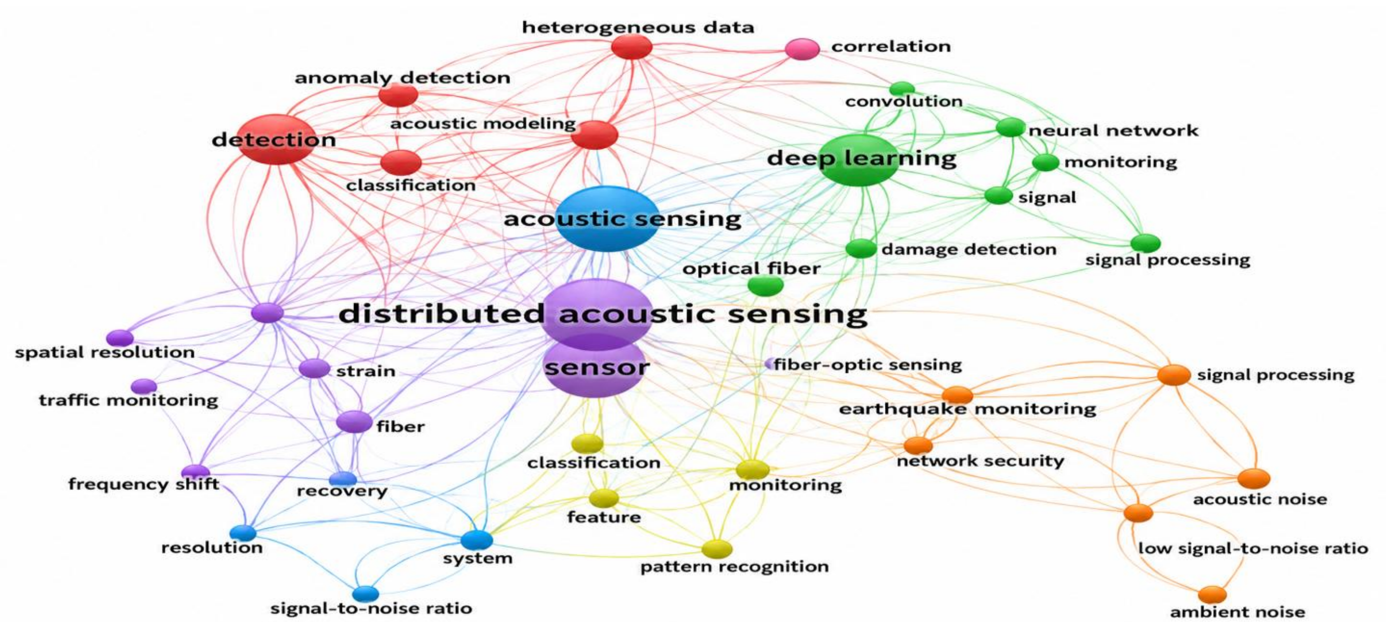

Fig. 6. Enlarged keyword co-occurrence network (VOSviewer; minimum three keyword occurrences).

C. Primary-Study Landscape and Quality

The 16 primary studies span laboratory, field, mixed, and synthetic settings. Seven are laboratory or controlled-bench studies [1], [2], [10], [12], [15], [16], [27]; six are field deployments [5], [6], [11], [13], [21], [28]; two report mixed validation [3], [22]; and one is synthetic [14]. Open-science practice remains limited: Tomasov et al. [5] release a public dataset, and Robles-Urquijo et al. [14] provide a validated synthetic-data pipeline, while no primary study in the reviewed set releases both model weights and complete training code. Methodologically, the set includes convolutional and recurrent models, classical ML, deep neural networks (DNNs), and autoencoder (AE)-based self-supervised learning (SSL), together with newer meta-learning and graph-diffusion approaches. Table IV summarises the 16 primary studies. Their methodological and application-domain distributions are shown in Fig. 7, and the temporal distribution of ML families is shown in Fig. 8.

TABLE IV. REPRESENTATIVE DAS-WITH-ML PRIMARY STUDIES

No.	Study	Application domain	ML method	Dataset	Open?
1	Lalam (2024) [1]	Pipeline monitoring	Deep neural network (DNN) multiparameter regression	Laboratory	N
2	Usenco (2022) [2]	Security/anomaly	LSTM neural network	Laboratory	N
3	Karapanagiotis (2023) [3]	Railway monitoring	ANN and CNN for denoising	Mixed	N
4	Tomasov (2025) [5]	Perimeter security	CNN (power-spectral-density features)	Field	Y
5	Ende (2023) [6]	Road traffic	Self-supervised deconvolution autoencoder (AE)	Field	N
6	Shi (2019) [10]	Perimeter security	2D CNN on spatiotemporal matrices	Laboratory	N
7	Luong (2024) [11]	Urban infrastructure	Meta-learning few-shot classifier	Field	N
8	Kozmin (2025) [12]	Perimeter security	Semi-supervised autoencoder	Laboratory	N
9	Corera (2023) [13]	Road/highway traffic	Support-vector machine (SVM) with Hough-like tracking	Field	N
10	Robles-Urquijo (2025) [14]	Road/highway traffic	U-Net CNN (super-resolution)	Simulation	P
11	Chen (2024) [15]	Structural SHM	Modified sliding-window principal component analysis (PCA)	Laboratory	N
12	Brusamarello (2024) [16]	Structural SHM	SVM with time/frequency features	Laboratory	N
13	Yurekli (2025) [21]	Railway safety	Hybrid voting classifier	Field	N
14	Rahman (2024) [22]	Railway track condition	Deep CNN-LSTM	Mixed	N
15	Gu (2025) [27]	Signal separation	Dual-path RNN	Laboratory	N
16	Jeong (2025) [28]	Perimeter security	GraphDiffusion (GNN + diffusion model)	Field	N

[b] Open: Y = public dataset; P = validated synthetic-data pipeline; N = not released.

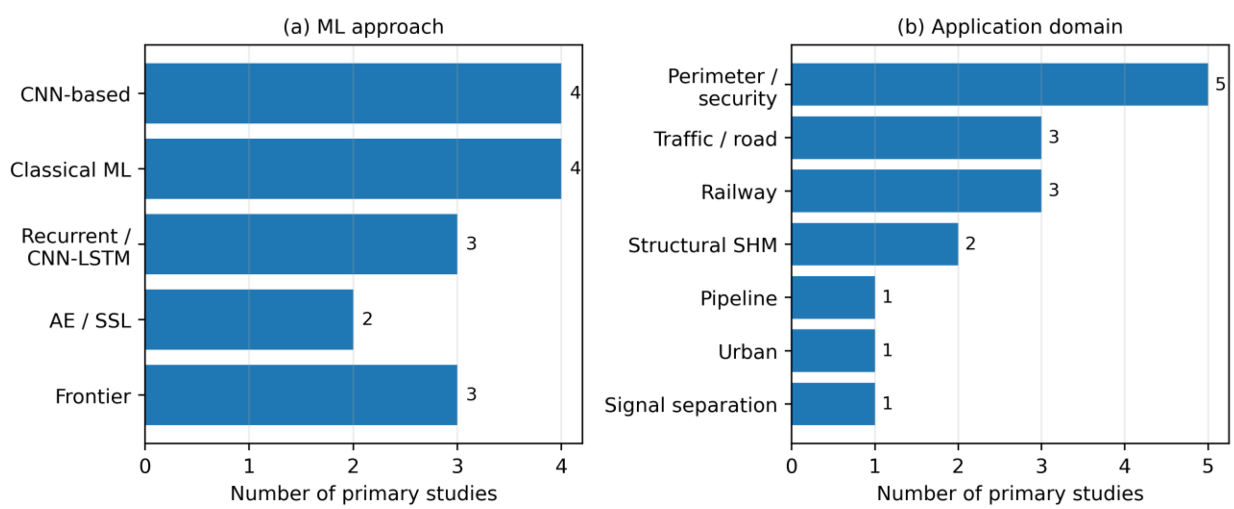

Fig. 7. Distribution of the 16 primary studies across (a) ML approach and (b) application domain.

Table V cross-tabulates ML method families against infrastructure application domains. The same relationships are visualised in Fig. 9; because the evidence base contains only 16 primary studies, empty or sparse cells are interpreted only as not observed in this screened corpus.

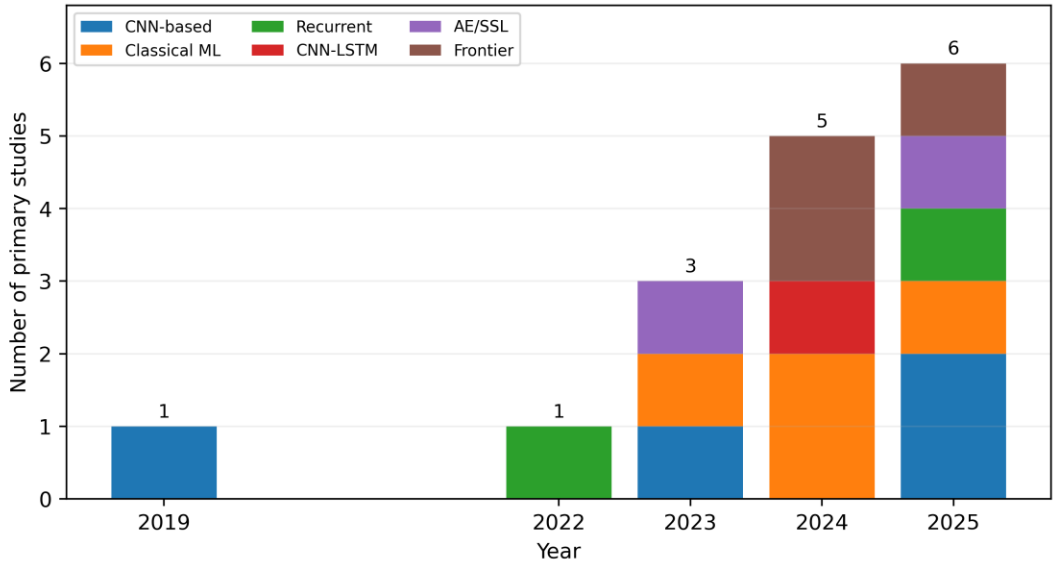

Fig. 8. Annual distribution of the 16 primary DAS-with-ML studies by ML family.

TABLE V. CROSS-TABULATION OF ML FAMILIES AGAINST APPLICATION DOMAINS FOR THE 16 PRIMARY STUDIES

ML family	Pipeline	Railway	Struct. SHM	Traffic	Security	Urban	Signal	Total
CNN-based	-	[3]	-	[14]	[5], [10]	-	-	4
Recurrent	-	-	-	-	[2]	-	[27]	2
CNN-LSTM	-	[22]	-	-	-	-	-	1
Classical ML	-	[21]	[15], [16]	[13]	-	-	-	4
AE / SSL	-	-	-	[6]	[12]	-	-	2
Frontier	[1]	-	-	-	[28]	[11]	-	3
Total	1	3	2	3	5	1	1	16

[c.] AE = autoencoder; SSL = self-supervised learning; "-" means no study observed in this screened corpus. Because the matrix contains only 16 studies and most of its 42 family-domain cells are empty, an empty cell is interpreted only as "not observed in the present corpus"; it is not evidence that the combination is absent from the wider research field.

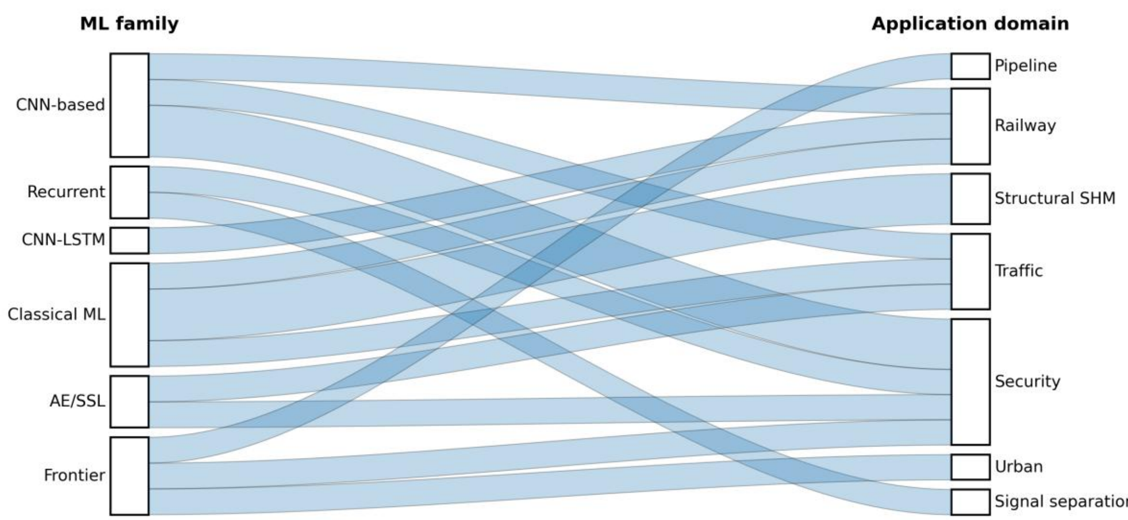

Fig. 9. Alluvial mapping of ML families to application domains. Ribbon width is proportional to study count; sparse flows should be interpreted as corpus-level coverage only.

Study quality is reported in Table VI and visualised in Fig. 10. The combined assessment shows that reproducibility is the weakest criterion across the primary-study corpus.

Cross-study comparability, dataset-reporting limitations, and operational-computing requirements are synthesised in Table VII.

TABLE VI. STUDY QUALITY ASSESSMENT OF THE 16 PRIMARY DAS-WITH-ML STUDIES

No.	Study	D	V	R	W	M
1	Lalam (2024)	✓	✓	-	-	✓
2	Usenco (2022)	~	~	-	-	✓
3	Karapanagiotis (2023)	✓	~	-	~	✓
4	Tomasov (2025)	✓	~	✓	✓	~
5	Ende (2023)	✓	✓	-	✓	✓
6	Shi (2019)	~	~	-	-	✓
7	Luong (2024)	✓	✓	-	✓	✓
8	Kozmin (2025)	~	~	-	-	✓
9	Corera (2023)	✓	✓	-	✓	✓
10	Robles-Urquijo (2025)	✓	✓	~	~	✓
11	Chen (2024)	✓	~	-	-	✓
12	Brusamarello (2024)	~	~	-	-	✓
13	Yurekli (2025)	✓	✓	-	✓	✓
14	Rahman (2024)	~	✓	-	~	✓
15	Gu (2025)	✓	✓	-	-	✓
16	Jeong (2025)	✓	✓	-	✓	✓
Met (✓)		11	9	1	6	15
Partial (~)		5	7	1	3	1
Not met (-)		0	0	14	7	0

[d] D = dataset transparency; V = validation rigour; R = reproducibility; W = real-world context; M = performance metrics.

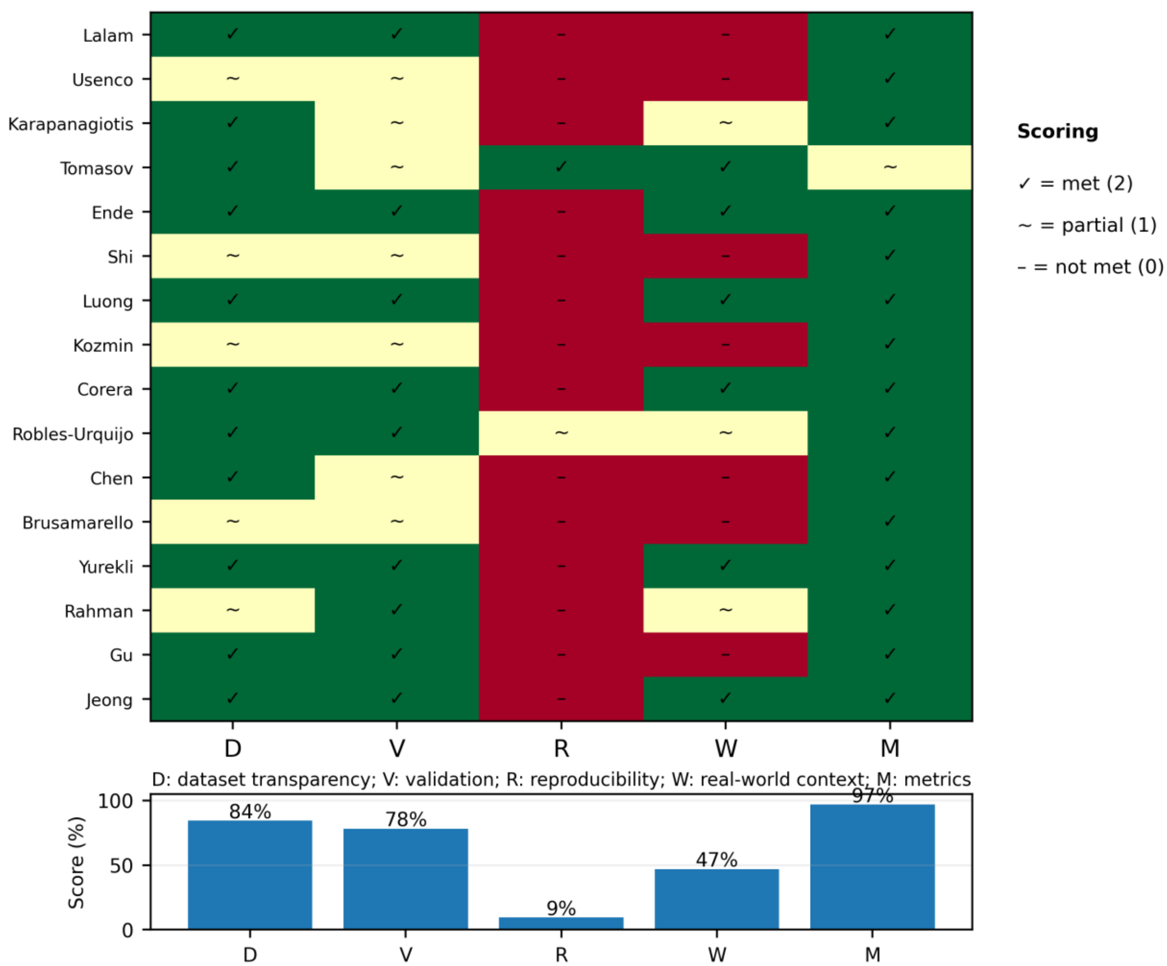

Fig. 10. Visual summary of the five-criterion quality assessment. Reproducibility remains the weakest criterion.

TABLE VII. CROSS-STUDY COMPARABILITY AND OPERATIONAL REPORTING IN THE 16 PRIMARY STUDIES

Dimension	Corpus-level observation	Why it matters	Minimum future reporting
Sensing environment	7 laboratory, 6 field, 2 mixed, 1 synthetic; most studies are site- or task-specific	Performance can reflect controlled conditions or site characteristics rather than transferable model skill	Site, cable installation, sensing environment, domain-shift conditions
Acquisition parameters	Sampling frequency, gauge/spatial resolution, channel spacing, preprocessing, and calibration are not reported with a uniform schema	Different acquisition bandwidths and spatial resolutions change the learning problem and can confound model comparison	Sampling rate, pulse repetition rate, gauge length/spatial resolution, channel count, calibration and preprocessing
Labels and class balance	Label-generation procedures and class-wise sample distributions are inconsistently documented; controlled experiments often have cleaner labels than field data	Unknown annotation uncertainty or imbalance can make aggregate accuracy optimistic and weaken reproducibility	Class counts, imbalance ratio, annotation source, annotator agreement/verification, ambiguous-event policy
Metrics and validation	Classification, regression, reconstruction, denoising, and anomaly-detection tasks use different metrics and split protocols; no common benchmark split exists	Reported headline scores are not directly comparable across task types or studies	Task-appropriate core metrics, confusion matrix or per-class scores, split definition, repeated-seed or cross-site validation where feasible
Computation and edge readiness	A few studies discuss real-time operation or training speed [10], [21], but parameter count, FLOPs, latency, memory, and energy are rarely reported systematically	Accuracy alone does not establish deployability on interrogator-adjacent or edge hardware	Parameters, FLOPs/MACs, device, batch size, latency, throughput, peak memory, energy/power
Long-term robustness	No longitudinal evaluation of concept drift, fibre ageing, model maintenance, or online adaptation was identified in the primary set	Operational sensing conditions evolve; static offline validation may overestimate lifetime reliability	Monitoring duration, drift tests, recalibration policy, missing/corrupted-data tests, update/rollback strategy

V. DISCUSSION

The corpus supports three broad conclusions. First, publication activity is rising rapidly, but the evidence base remains small: only 16 of 31 records are primary DAS-with-ML infrastructure studies. Second, methodological diversity is increasing, yet application coverage is thin. Third, quality assessment shows strong performance reporting but weak reproducibility and uneven real-world validation. These observations justify a cautious interpretation of apparent “gaps”: the cross-tabulation is useful for identifying under-represented combinations within this review, but its empty cells may result from corpus size, search boundaries, or publication practices rather than genuine absence across the entire field.

CNN prevalence requires analytical rather than purely descriptive interpretation. DAS data are naturally arranged as dense channel-by-time matrices and are frequently transformed into spectrogram-like or image-like representations, making 2D convolution a convenient way to learn local spatial and temporal patterns [10]. CNNs also benefit from mature implementations, reusable architectures, and comparatively straightforward training. Their prevalence therefore reflects a strong representation-method fit and methodological accessibility; it does not prove that CNNs are intrinsically superior for all DAS tasks. Recent few-shot, graph, diffusion, and self-supervised approaches [11], [12], [28] are especially relevant where labels are scarce, spatial topology matters, or anomalies differ from training events.

Dataset heterogeneity is a central barrier to generalisation. The 16 primary studies mix controlled laboratory events, field deployments, mixed settings, and simulation, and they do not use a common acquisition schema. Sampling frequency, spatial resolution or gauge length, channel spacing, preprocessing, sensing geometry, and calibration are reported with different levels of detail. Annotation conditions also vary: controlled studies can assign event labels from designed experiments, whereas field studies may rely on operational logs, manual interpretation, or task-specific reference systems. Class-wise distributions and annotation uncertainty are not consistently exposed. Consequently, a model trained on one installation may learn site-specific coupling, noise, or event signatures rather than infrastructure-invariant features. Future benchmarks should therefore publish acquisition metadata, class counts, annotation procedures, environmental conditions, and standardised train/validation/test partitions in addition to raw signals.

Performance values are likewise not directly interchangeable across the corpus. Classification studies emphasise accuracy, precision, recall, F1-score, or confusion matrices; regression studies use continuous-error measures; signal-enhancement and reconstruction work uses signal-quality or reconstruction criteria; and anomaly-detection studies use threshold- or area-under-curve-based measures. Validation also ranges from laboratory hold-out testing and cross-validation to field evaluation, simulation, and mixed protocols. A high classification accuracy in a balanced controlled dataset therefore cannot be ranked directly against an F1- or AUC-based field result, nor against a denoising or regression metric. Future DAS-ML studies should report task-specific core metrics together with per-class results, split definitions, repeated runs where stochastic training is used, and cross-site or cross-condition tests whenever the claimed contribution concerns generalisation.

Computational evidence is substantially thinner than predictive-performance evidence. Shi et al. [10], for example, report a compact event-recognition network and retraining time, while the railway study by Yurekli et al. [21] explicitly targets real-time hazard detection. However, systematic reporting of parameter count, floating-point or multiply-accumulate operations, inference latency on named hardware, peak memory, throughput, and energy/power is uncommon. This limits claims about scalability and edge readiness. For long DAS arrays that can generate high-throughput streams, computational cost is part of model validity: a highly accurate model that cannot process the required channel rate or operate within edge memory and power constraints may be unsuitable for deployment.

Data quality and long-term maintenance deserve equal emphasis. Sensor configuration, thermal-mechanical cross-sensitivity, installation conditions, low-SNR noise, and multi-sensor fusion have already been recognised in adjacent distributed-sensing work [7]-[9], [17], [18], [20], [26]. In practice, calibration drift, environmental noise, fibre ageing, missing or corrupted channels, changing coupling conditions, and signal degradation can shift the input distribution after deployment. Yet the primary corpus contains little evidence on concept drift, online learning, continuous adaptation, recalibration schedules, or rollback/model-maintenance strategies. Robust deployment should therefore include explicit quality-control gates, missing-data stress tests, drift detection, periodic recalibration, and controlled model updates rather than treating the trained model as static.

These findings refine the five research gaps (Table VIII). Cross-infrastructure generalisation should explicitly include domain shift and concept drift; benchmark development should standardise acquisition and annotation metadata as well as splits; physics-data-driven integration should incorporate sensing physics and calibration constraints; interpretability should include uncertainty and confidence estimation for safety-relevant decisions; and operational deployment should combine model compression with latency, memory, energy, robustness, and maintenance evaluation. Cloud and storage architectures [25] may support multi-site analytics, but long-term DAS systems will require co-design across sensing hardware, signal quality, ML models, and deployment infrastructure.

TABLE VIII. RESEARCH GAPS, EVIDENCE, AND PROPOSED DIRECTIONS

Gap	Evidence from the corpus	Proposed research direction
Cross-infrastructure generalisation and drift	All 16 primary studies are tied to a specific infrastructure/site/task; no systematic cross-infrastructure or longitudinal drift study was identified	Cross-site/domain adaptation, transfer and multi-task learning, drift detection, online or periodic adaptation with rollback controls
Standardised benchmarks and open datasets	Only one public event dataset [5] and one validated synthetic-data pipeline [14] are represented; acquisition and annotation reporting are heterogeneous	Open multi-site DAS repositories, standard splits, acquisition metadata, class-balance and label-quality documentation, agreed core metrics
Physics-data-driven integration	Primary ML models rarely integrate Rayleigh-backscatter, phase-demodulation, wave-propagation, calibration, or coupling constraints directly	Physics-informed neural networks (PINNs), hybrid model-based/data-driven learning, calibration-aware loss functions and constraints
Interpretability and uncertainty	No primary study systematically reports explainable artificial intelligence (XAI) analyses together with calibrated prediction uncertainty	XAI adapted to spatiotemporal DAS inputs and graph models; calibrated confidence, uncertainty quantification, failure-case analysis
Operational robustness and edge deployment	Seven studies are laboratory-only; computational reporting is sparse; long-term drift, fibre ageing, missing-data robustness, maintenance, and edge energy are minimally evaluated	Model compression and hardware-aware design; latency/memory/energy benchmarks; robustness stress tests; data-quality monitoring; drift-aware maintenance and controlled updating

VI. CONCLUSION

This review maps the convergence of distributed acoustic sensing, broader distributed fibre-optic sensing, and machine learning for infrastructure monitoring over 2015–2025. From 291 records identified through Web of Science, Scopus, and IEEE Xplore, PRISMA-guided screening yielded 31 publications, including 16 primary DAS-with-ML studies. Publication output accelerates sharply from 2023 onward, while the primary evidence remains concentrated in perimeter security, traffic, railway, and structural-health applications.

CNNs remain prominent, but their dominance is best explained by the image-like spatiotemporal structure of DAS data, mature implementation ecosystems, and convenience rather than proven universal superiority. The more important field-level limitation is comparability: datasets differ in sensing environment and acquisition settings; labels, class balance, metrics, and validation protocols are inconsistently reported; computational cost is rarely quantified in deployment-relevant terms; and long-term robustness to drift, calibration changes, fibre ageing, missing data, and evolving operating conditions is largely untested.

The resulting research agenda therefore emphasises cross-site and cross-infrastructure generalisation, standardised open benchmarks with richer metadata, physics-informed learning, interpretable and uncertainty-aware predictions, and hardware-aware deployment with explicit latency, memory, energy, data-quality, and maintenance evaluation. These priorities shift the field from isolated high-accuracy demonstrations toward reproducible, comparable, and operationally trustworthy DAS-ML systems.

VII. LIMITATIONS

Several limitations should be noted. The analysis covers three databases and English-language records only, which may under-represent regional or non-indexed work. The corpus is small (31 records) and heterogeneous in document type and topic; consequently, bibliometric patterns and empty cells in the ML-application matrix should be interpreted descriptively rather than as definitive evidence of field-wide absence. Some acquisition, annotation, computational, and deployment attributes are inconsistently reported in the source studies, limiting quantitative normalisation across the corpus. Metadata normalisation may also introduce minor uncertainty. Finally, most primary studies were published in 2024–2025 and have had limited time to accumulate citations or long-term deployment evidence.

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DECLARATION ON GENERATIVE AI

During preparation of this manuscript, the authors used OpenAI ChatGPT for language refinement, consistency checking, and formatting assistance. The authors reviewed and edited all AI-assisted content and take full responsibility for the accuracy, originality, and integrity of the final manuscript.

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