

Systematic Review

Machine Learning, Neural Networks, and Computer Vision in Addressing Railroad Accidents, Railroad Tracks, and Railway Safety: An Artificial Intelligence Review

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Abstract

Ensuring robust railway safety is paramount for efficient and reliable transportation systems, a challenge increasingly addressed through advancements in artificial intelligence (AI). This review paper comprehensively explores the burgeoning role of AI in enhancing the safety of railway operations, focusing on key contributions from machine learning, neural networks, and computer vision. We synthesize current research that leverages these sophisticated AI methodologies to mitigate risks associated with railroad accidents and optimize railroad tracks management. The scope of this review encompasses diverse applications, including real-time monitoring of track conditions, predictive maintenance for infrastructure components, automated defect detection, and intelligent systems for obstacle and intrusion detection. Furthermore, it delves into the use of AI in assessing human factors, improving signaling systems, and analyzing accident/incident reports for proactive risk management. By examining the integration of advanced analytical techniques into various facets of railway operations, this paper highlights how AI is transforming traditional safety paradigms, paving the way for more resilient, efficient, and secure railway networks worldwide.

Keywords: machine learning; neural networks; computer vision; railroad accidents; railroad tracks; railway safety



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1. Introduction

Railway safety remains an infrastructural and social priority in Europe and worldwide. The latest analyses by the European Union Agency for Railways (ERA) indicate that EU railway systems are among the safest globally, although after a period of stability in 2018–2021, several serious incidents were recorded in 2022–2023, reminding us of persisting gaps in protection against human factors, infrastructure failures, and level-crossing events [1]. UIC (International Union of Railways) data for 2023 emphasize that despite a decline in the overall number of victims, accidents at road-rail crossings and track intrusions still account for a high share [2]. In the United States, the FRA (Federal Railroad Administration) database documents the ongoing need to reduce grade-crossing collisions, derailments, and pedestrian-related incidents, which reinforces the pressure for inspection automation, risk prediction, and faster operational response [3].

In this context, the role of artificial intelligence (AI), including machine learning (ML), neural networks (NN), and computer vision (CV), is growing, enabling automation of diagnostic tasks, hazard segmentation, and predictive maintenance. The latest literature reviews summarize the rapid progress of AI in rail transport, ranging from big data analytics and predictive models to visual perception systems and multimodal fusion both onboard and trackside [1–4]. These findings align with the paradigm shift from manual and periodic inspection toward continuous monitoring and condition-based maintenance (CBM), where algorithms learn from data streams generated by cameras, lidars, vibration sensors, and fiber-optic measurement systems.

Although rail systems are among the safest modes of transport in the European Union and in other regions of the world, they still have a significant risk of accidents and incidents, centered around several recurrent scenarios, such as violations at level crossings, intrusion of people on tracks, and failures of tracks and infrastructure elements. To emphasize the practical importance of the problem, quantitative data were cited. According to the latest reports of the European Railway Agency, the International Union of Railways, and the Federal Railroad Administration, in 2023, 1567 significant railway accidents were recorded in the European Union, as a result of which 841 people died and 569 were seriously injured. Incidents involving unauthorized persons on the tracks, referred to as trespassers, accounted for about 58.4 percent of all fatalities, while accidents at level crossings accounted for about 26.6 percent of deaths and a significant part of the total number of incidents [1–3]. From a cost perspective, infrastructure maintenance and safety disruptions generate an estimated cost of more than EUR 1 billion per year, including asset inspections, speed limits, and unplanned rail traffic stoppages.

Literature reviews to date on AI applications in the field of railway safety have typically focused on single tasks, such as detecting rail surface defects, or on single data modalities, such as video analytics alone, but rarely combine the three safety axes, i.e., railway accidents, track condition, and system safety, with the three families of methods including machine learning, neural networks, and computer vision within a coherent taxonomy and bibliometric basis. This review fills this research gap by creating links between tasks, data modalities, and operational requirements, and adding a quantitative layer on research field dynamics, while maintaining full repeatability by revealing the search query used, the inclusion rules, and the datasets used.

The relationship between the level of demand and safety in rail transport is essentially of an expository nature. As the number of passengers, train-kilometers traveled, timetable density, and platform traffic increases, the unit risk associated with a single operation may remain low, while the absolute number of incidents increases. The inverse relationship arises when safety indicators are standardized in relation to train-kilometers or passenger-kilometers, which often leads to a reversal of observed trends. Therefore, in this review, the applications of AI methods are analyzed, taking into account demand-side variables such as the frequency of the service, the level of filling and congestion, and the occurrence of time peaks. At the same time, it is recommended that future studies and evaluations of the effectiveness of solutions in this area take into account exposure-standardized safety indicators alongside strict numerical values.

Track infrastructure is the main area of CV/ML applications. For railhead and surface damage detection, object detection models and transfer learning have been effectively applied, from solutions based on YOLO/RetinaNet and knowledge transfer for limited image datasets [5], through Fast R-CNN for crack and spalling diagnostics [6], to lightweight YOLOv4/YOLOv5 variants adapted for real-time operation [7,8]. In parallel, methods for detecting defects in joints and fasteners have been developed, including enhanced YOLOX Nano and YOLOv5s architectures with attention mechanisms and optimization for edge

computing [9]. Beyond the railhead and joints, CV supports ballast and fouling assessment, where datasets and deep learning-based segmentation methods improve objectivity and repeatability [10]. For track geometry, interest is growing in learning models for estimating and predicting irregularities from vehicle and measurement data, which can shorten inspection intervals and support maintenance planning [4].

Obstacle collision prevention and level-crossing safety form the second pillar of applications. In metro systems and conventional lines, deep networks are deployed to detect obstacles (vehicles, pedestrians, animals) in the track area, often combining camera and LiDAR data to enhance robustness against lighting and weather conditions [11]. At level crossings, the use of violation and intrusion detection systems is increasing, automating video analysis and metadata generation for safety services [12,13]. These solutions complement rather than replace existing traffic control systems, providing an additional layer of environmental perception and data for risk analytics.

In electric traction, CV/ML support monitoring of overhead lines and pantographs. It has been shown that integrating domain knowledge into the ML pipeline significantly improves inspection effectiveness metrics (e.g., F1 score) while meeting time requirements for linear deployments [14], and YOLO algorithms enable reliable detection of pantographs and their features in complex backgrounds [15]. In parallel, surrogate methods based on deep learning are being developed to estimate pantograph–catenary interactions in near-real time, supporting diagnostics without costly finite element simulations.

At the accident prediction and risk analysis level, ML models have been compared with classical statistical approaches, achieving improved forecasting quality for crossing events and accident severity, particularly when applying class imbalance handling methods (resampling, boosting, ensemble) [16]. More recent studies combine supervised learning with descriptive narrative processing (NLP) from incident reports to better identify and prioritize risk factors using explainable AI (e.g., Shapley values) [17]. Such approaches align with the “system of systems” trend, where perception (CV), diagnostics (CBM), and prediction (ML) feed into safety management frameworks at enterprise and regulatory levels.

In parallel, distributed acoustic sensing (DAS) and other remote perception solutions are being developed, which, combined with ML/ensemble methods, enable detection of natural hazards (falling rocks, landslides, trees) along rail lines, enhancing early warning and continuous corridor surveillance [18]. DAS applications complement wayside and onboard monitoring, offering long-range, high-resolution “virtual” sensors without the need for field power supply.

Despite dynamic progress, limitations and challenges remain: dependence on data quality and labeling, class imbalance (rare defects/accidents), domain variability (weather, time of day, line), and costly real-world validation. Responses include few-shot and transfer learning techniques for rare defect inspection [19], model compression for edge implementations, normalization and standardization of datasets, and predictive uncertainty methods in safety-critical tasks. Additionally, for track geometry and degradation prediction, combining ML with physical/empirical models is recommended for improved generalizability and interpretability.

This work systematizes and critically evaluates the latest applications of ML/NN/CV for railway safety in three complementary areas:

- Accident prevention (risk prediction, obstacle perception, intrusion detection),
- Diagnostics and maintenance of track infrastructure (rail defects, fasteners, ballast condition, track geometry),
- Rolling stock and traction equipment (wheelset bearings, wheels, pantograph–catenary interaction, wayside systems including HBD/HABD).

The contributions of the article are as follows:

- A consistent taxonomy of learning tasks (detection, segmentation, classification, prediction) linked to data modalities (video, LiDAR, ultrasound, acoustics, DAS, operational data),
- A review of implementation requirements (edge vs. cloud, real-time operation, computational constraints) and evaluation practices (metrics, reference datasets, validation protocols, reproducibility),
- Synthesis of results in comparative tables and identification of research gaps.

We highlight key development directions: multimodal fusion for domain robustness, open benchmarks covering rare events, continuous/online learning on data streams, and explainability and uncertainty modeling in safety-critical applications.

The main aim of this article is to systematically organize and critically assess the applications of artificial intelligence methods in railway safety, with particular emphasis on machine learning, neural networks, and computer vision. The work seeks to identify dominant research directions, highlight thematic and methodological gaps, and analyze the dynamics of publication development between 2016 and 2025. The ultimate outcome is to provide a synthetic overview that will facilitate further research and practical deployment of AI tools in the field of rail transport safety.

The structure of the article reflects this aim. Section 2 (Materials and Methods) presents the research design, data sources, search strategy, and publication qualification criteria, as well as the selection procedure, classification scheme, and analytical and bibliometric tools used in the study. Section 3 (State of the Art) discusses the current body of work, organizing it according to AI method classes and railway safety categories, pointing out both achievements and shortcomings of existing solutions. Section 5 (Discussion) contains the interpretation of the results, reference to the research questions, as well as identification of future research directions and potential practical implications. Section 6 (Conclusions) summarizes the key findings, synthesizes the contribution of the study, and emphasizes the significance of artificial intelligence in transforming railway safety paradigms.

2. Materials and Methods

Section 2 structures the methodological framework of the review and guides the reader from the general research concept to the details of data acquisition, selection, and processing. The study design and data sources are presented first, including the rationale for choosing Scopus as the sole controlled repository, as well as the temporal, linguistic, and disciplinary scope of the corpus. Next, the search strategy is introduced, with the full query wording across title, abstract, and keyword fields, together with the applied restrictions and filters. Subsequent sections cover the inclusion and exclusion criteria and the two-stage selection procedure with the PRISMA scheme, which specifies the counts at the stages of identification, screening, eligibility assessment, and inclusion of publications, thus ensuring transparency and reproducibility of the process. A consistent classification framework is then introduced, encompassing AI method classes, main safety categories, document types, countries of authors' affiliation, and methodological approaches. This is followed by a description of the extraction of fields from records, the set of metrics used for comparisons, and the bibliometric and visualization tools applied, including term density maps and co-occurrence networks prepared in VOSviewer 1.6.20, with appropriate figure captions and reference to the tool's source.

2.1. Research Design and Data Sources

The study was designed as a systematic review with a bibliometric analysis component, aimed at identifying and synthesizing the applications of artificial intelligence methods in railway safety, with particular emphasis on machine learning, neural networks, and

computer vision. The article search procedure included a single source of record acquisition, precise eligibility criteria, and a fully replicable pathway. The only controlled data source was the Scopus database. The search was conducted in the fields of title, abstract, and keywords for a query constructed around railway safety, and was limited to the years 2016–2025, the English language, and the subject areas of computer science and engineering, with the document type “tb” excluded. In the first stage, 120 records were obtained; after narrowing the scope to three thematic safety axes, namely, railroad accidents, railroad tracks, and railway safety, 100 publications remained, and after manual verification of full texts, 5 items outside the scope were excluded, resulting in a corpus of 95 works for further analysis.

The selection was carried out in two stages: first, thematic consistency was assessed based on metadata and abstracts, then, in ambiguous cases, the full text was analyzed. In parallel, a consistent classification framework was prepared. Each publication was assigned across five interdependent dimensions: AI method class, including machine learning, neural networks, computer vision; safety category, including railroad accidents, railroad tracks, and railway safety; country of authors’ affiliation, including Australia, Canada, China, France, India, Singapore, Turkey, United Kingdom, United States, and the category other; document type, including conference paper, article, other; methodological class, determined manually based on content and authors’ declarations, including Experiment, Literature analysis, Case study, Conceptual. This multidimensional structure enables cross-sectional comparisons and mapping of the research landscape from the perspective of algorithmic approaches and safety areas.

To ensure replicability, the exact wording of the query (including filters) and the full list of 95 retrieved records with metadata (authors, affiliations, DOI identifiers, and keywords), together with the input files used for bibliometric mapping, were archived and are available from the corresponding author upon reasonable request. Term co-occurrence and keyword density maps were generated using VOSviewer 1.6.20. Each figure was accompanied by a caption indicating the origin of the visualization, and the reference list included the source publication of VOSviewer 1.6.20.

2.2. Search Strategy

The search strategy was based exclusively on the Scopus database in order to ensure high metadata quality and consistency of selection criteria, with results limited to English-language publications in the fields of computer science and engineering, covering the years 2016 to 2025. Searches were conducted in the fields of title, abstract, and keywords, which made it possible to capture both works explicitly framed in the terminology of railway safety and publications where artificial intelligence vocabulary appeared within the keyword structure. This procedure was consistent with the editorial assumptions and ensured the possibility of fully replicating the query.

The search was carried out using the following query, which included exclusions of subject areas not meeting the technical criterion, as well as language and temporal restrictions:

“TITLE-ABS-KEY (“Safety” AND (“Railway Safety” OR “Railroad Tracks” OR “Railroad Accidents”)) AND PUBYEAR > 2015 AND PUBYEAR < 2026 AND (XCLUDE (SUBJAREA,“AGRI”) OR EXCLUDE (SUBJAREA,“ECON”) OR EXCLUDE (SUBJAREA,“NEUR”) OR EXCLUDE (SUBJAREA,“PHAR”) OR EXCLUDE (SUBJAREA,“PSYC”) OR EXCLUDE (SUBJAREA,“MULT”) OR EXCLUDE (SUBJAREA,“EART”) OR EXCLUDE (SUBJAREA,“CENG”) OR EXCLUDE (SUBJAREA,“BIOC”) OR EXCLUDE (SUBJAREA,“BUSI”) OR EXCLUDE (SUBJAREA,“CHEM”) OR EXCLUDE (SUBJAREA,“ENVI”) OR EXCLUDE (SUBJAREA,“MEDI”) OR EXCLUDE (SUBJAREA,“ENER”) OR EXCLUDE (SUB-

JAREA,"MATE") OR EXCLUDE (SUBJAREA,"SOCI") OR EXCLUDE (SUBJAREA,"DECI") OR EXCLUDE (SUBJAREA,"PHYS") OR EXCLUDE (SUBJAREA,"MATH") OR EXCLUDE (SUBJAREA,"HEAL") OR EXCLUDE (SUBJAREA,"ARTS")) AND (EXCLUDE (DOCTYPE,"tb")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (EXACTKEYWORD,"Machine Learning") OR LIMIT-TO (EXACTKEYWORD,"Machine-learning") OR LIMIT-TO (EXACTKEYWORD,"Learning Systems") OR LIMIT-TO (EXACTKEYWORD,"Support Vector Machines") OR LIMIT-TO (EXACTKEYWORD,"Neural Networks") OR LIMIT-TO (EXACTKEYWORD,"Neural-networks") OR LIMIT-TO (EXACTKEYWORD,"Convolutional Neural Networks") OR LIMIT-TO (EXACTKEYWORD,"Convolutional Neural Network") OR LIMIT-TO (EXACTKEYWORD,"Convolution") OR LIMIT-TO (EXACTKEYWORD,"Deep Neural Networks") OR LIMIT-TO (EXACTKEYWORD,"Computer Vision"))".

One hundred and twenty-one records were obtained at this stage. An additional narrowing was then applied to the railway safety axis by refining the keywords.

"AND (LIMIT-TO (EXACTKEYWORD,"Railroad Accidents") OR LIMIT-TO (EXACTKEYWORD,"Railroad Tracks") OR LIMIT-TO (EXACTKEYWORD,"Railway Safety"))",

This procedure yielded 100 publications. After manual verification of the full texts, five items outside the scope were removed, resulting in a final set of ninety-five works that were subjected to extraction and classification. The description of the query above corresponds to the adopted specification of the search field, namely, the combined search of titles, abstracts, and keywords using the terms Safety, Railroad Accidents, Railroad Tracks, and Railway Safety, with restrictions on years, language, and subject areas, as well as the inclusion of keywords describing artificial intelligence methods. This ensured that the resulting corpus was representative of the technical research stream in railway safety. In line with the adopted protocol, the full wording of the query and detailed counts for each stage are provided in the Zenodo database, thereby reinforcing the transparency and replicability of the research procedure.

The workflow for data collection and preparation is illustrated in Figure 1. The purple background indicates the phase of retrieving scientific publications from the Scopus database, while the green background denotes the phase of defining categories. In the upper part of the diagram, the parameters of the query controlling the search scope are shown. These include combined searches of the Title, Abstract, and Keywords fields, restriction of publication years to the 2016–2025 range, the English language filter, and limitation to the subject areas of computer science and engineering. In addition, a set of precise keywords describing artificial intelligence methods, such as machine learning, neural networks, and computer vision (together with their lexical variants), was applied. Furthermore, the presence of the terms Railroad Accidents, Railroad Tracks, and Railway Safety was required, which eliminated generalist works and maintained the technical profile of the corpus.

The lower layer of the diagram presents the classification framework applied in the subsequent analysis. Publications were assigned to three substantive axes of railway safety, namely, railroad accidents, railroad tracks, and railway safety, and to three classes of artificial intelligence methods, namely, machine learning, neural networks, and computer vision. Complementary dimensions included document types, namely, article, conference paper, and other; geographical classification by authors' affiliation, namely, Australia, Canada, China, France, India, Singapore, Turkey, United Kingdom, United States, and the category Other; as well as methodological classes, namely, experiment, literature analysis,

case study, and conceptual. This structure makes it possible to link specific algorithms with types of hazards and infrastructure elements, to compare detection, segmentation, classification, and prediction tasks, and to assess the maturity and methodological rigor of solutions depending on document type and geographical context.

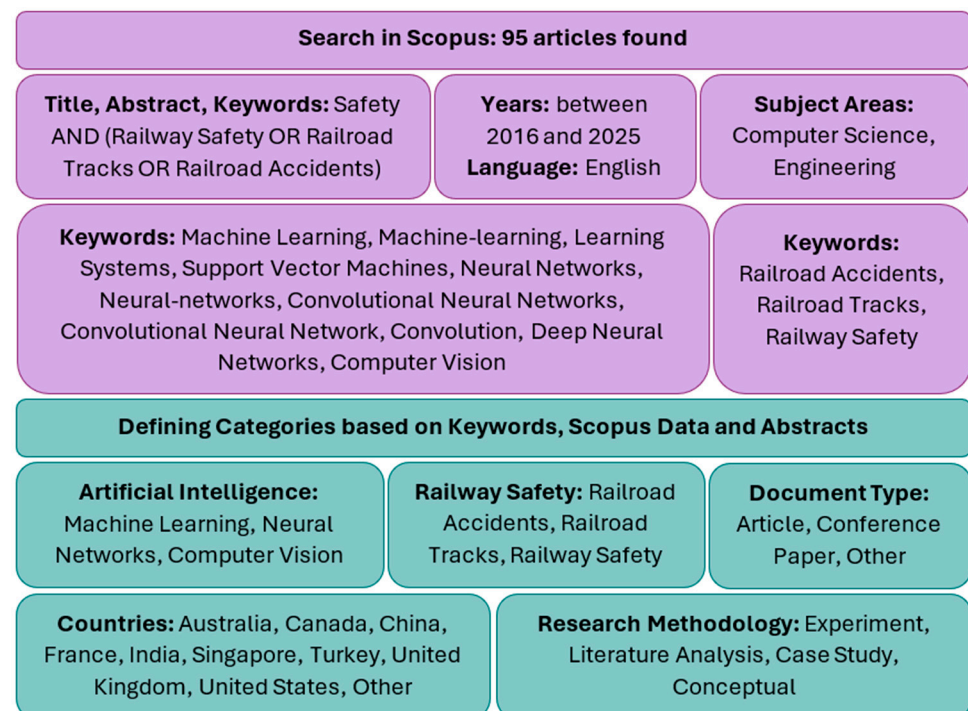


Figure 1. Workflow of data collection and preparation. The purple background indicates the phase of retrieving scientific publications from the Scopus database, while the green background indicates the phase of defining categories.

Methodologically, the framework confirms that the corpus was shaped by precise restrictions that minimized informational noise, namely, the exclusion of broad non-technical fields, the language filter, document type control, and the selection of keywords describing both AI methods and the domain of railway safety. It should be noted that the use of the EXACTKEYWORD formula may omit some publications employing alternative terminology; however, this risk was reduced through simultaneous searches of titles and abstracts, which made it possible to capture works addressing the same issues with different formulations. As a result, a consistent, technical set of ninety-five publications was obtained, prepared for further classification and synthesis of results within the adopted five-dimensional framework.

All extracted records and metadata supporting this review have been deposited in an open repository (Zenodo) under DOI: <https://doi.org/10.5281/zenodo.17113305>. The publications retrieved and analyzed in this study are numbered consecutively from 20 to 115.

The selection of publications included in the review was not accidental and resulted from clearly defined selection criteria. The source material was obtained from the Scopus database on the basis of a defined query and search parameters, and then filtered by thematic scope. Only articles presenting applications of AI methods directly related to railway safety are included. The inclusion criteria were as follows: (1) compliance with the three main areas analyzed in the work: railroad accidents, railroad tracks, and railway safety; (2) presentation of original applications of ML, NN, or CV methods; (3) availability of experimental data or results to compare approaches; and (4) geographical and methodolog-

ical representativeness of the literature. The selection process defined in this way ensures thematic consistency and allows for a reliable synthesis of the current state of research.

2.3. Rationale for the Review, Purpose of the Study and Problems of the Study

Existing studies on the applications of artificial intelligence in railway safety are fragmented, most often focusing on individual tasks and partial datasets, and rarely combining the three main safety axes, namely, railroad accidents, railway tracks, and systemic safety, with the three classes of methods, namely, machine learning, neural networks, and computer vision. There is a lack of a coherent taxonomy encompassing detection, segmentation, classification, and prediction tasks, as well as a lack of comparable metrics and transparent criteria for literature selection. This review addresses these gaps, is based on a clearly defined Scopus query, covers the years 2016–2025, the English language, and the fields of computer science and engineering, and the final corpus consists of ninety-five publications after manual scope verification. A five-dimensional classification framework was adopted, namely, method classes, safety categories, country of authors' affiliation, document type, and methodology, enabling cross-sectional comparisons and the identification of thematic and methodological gaps.

This review stands out from previous work in three key respects. First, it covers the full spectrum of safety, linking track infrastructure, events, and safety systems with specific classes of AI methods, which allows algorithmic solutions to be connected with real operational needs. Second, it introduces a bibliometric layer based on explicit metadata, enabling quantitative assessment of field dynamics, keyword evolution, geographic concentration of output, and methodological shifts. Third, it ensures full replicability, presenting the exact wording of the query, inclusion and exclusion criteria, the classification structure, and ready-to-use datasets and input files for visualization, thereby meeting editorial transparency requirements.

The main objective of the review is to systematically organize and critically assess the applications of AI methods in railway safety, mapping tasks against data sources and implementation requirements, and identifying thematic gaps and research priorities relevant to risk management and maintenance practice. The study addresses the following research questions:

1. Which classes of problems and tasks dominate the literature at the intersection of AI and railway safety, and which thematic gaps remain open?
2. Which data types and sensor configurations are most frequently used in the reviewed works, and which combinations demonstrate the highest effectiveness under operational conditions?
3. To what extent do the studies account for real-time requirements, uncertainty quantification, and integration with maintenance decision-making, and what conclusions follow for practice?
4. Is there a significant trend in the years 2016–2025 of increasing publication volume in the three thematic categories, namely, railroad accidents, railroad tracks, and railway safety, and what is the cumulative growth rate?
5. Does the structure of methods change over time, that is, is there an increasing share of works employing machine learning, neural networks, and computer vision, and are the observed changes statistically significant?
6. Is there a growing popularity of specific issues at the level of keywords and document types, namely, the share of thematic terms in titles and abstracts and the share of journal articles relative to conference papers, and are these trends statistically significant?

The first three questions are substantive, aimed at identifying dominant tasks and content gaps, as well as assessing the readiness of methods for real-time operation with

reliable uncertainty information and integration into maintenance processes. The next three questions are statistical in nature, measuring topic popularity and field dynamics, and include analyses of annual trends, cumulative growth rates, and significance testing of shifts in method shares and publication forms. Together, this set of questions structures both the practical and quantitative components of the review, enabling a coherent analysis and unambiguous interpretation of results in the subsequent sections of the paper.

2.4. Eligibility Criteria

The literature selection was designed to be transparent and replicable, with a two-stage screening process: titles, abstracts, and keywords were assessed first, followed by full-text analysis of borderline cases. The construction of the criteria follows good practices for reporting reviews in MDPI, including the way selection stages and decision justifications are presented in the PRISMA style, while strictly reflecting the parameters of the query applied in this study, namely, the years 2016–2025, English language, the fields of computer science and engineering, exclusion of the document type “tb”, filtering by AI method keywords, and filtering by the three axes of railway safety. After manual verification, the final corpus consisted of ninety-five publications, as listed in the working dataset.

Studies included in the analysis had to meet both substantive and formal requirements. A direct reference to railway safety in at least one of the three categories, railroad accidents, railroad tracks, or railway safety was required, together with the application of artificial intelligence methods, machine learning, neural networks, or computer vision, which had to be evident from the metadata or the full text. Publications in English published between 2016 and 2025, classified in Scopus under computer science and engineering, were accepted. Journal articles and conference papers were included, as well as items marked as Other, such as book chapters and review articles, provided they presented a consistent methodological contribution or synthesis of results, with sufficient description of data and evaluation procedures to allow unambiguous classification. Full text and complete basic metadata, including title, authors, affiliations, and DOI, were mandatory.

Works not meeting any of these conditions were excluded. Publications without an AI component or without a direct connection to railway safety, items outside the accepted years, language, and fields, incomplete records, and duplicates identified by DOI or title were eliminated, as was the document type “tb”. Non-technical works, such as social, legal, or economic studies, were rejected if they did not explicitly address railway safety using AI methods. Studies with inadequate reporting, i.e., lacking dataset and metric descriptions or missing information necessary to reproduce the evaluation, were also excluded.

The decision chain reflected the stages of the Scopus query. After applying the query and filters, 121 records were retrieved. Narrowing to the three safety axes yielded 100 publications, and manual scope verification resulted in the exclusion of five items outside the thematic scope, setting the final number at ninety-five. Justifications for inclusion and exclusion decisions were documented. Multiple classification assignments were allowed for the same publication, reflecting the multidimensional nature of the subject. Consistency of the procedure with MDPI good practices and examples from the literature ensures comparability and replicability of the selection for future updates of the review.

2.5. Selection Procedure and Screening

Screening was carried out in two stages: first, titles, abstracts, and keywords were assessed, followed by full-text analysis of included or ambiguous items. Before the main screening, a short calibration exercise was performed on a random sample of records, with the aim of harmonizing the interpretation of criteria and the vocabulary of terms related to artificial intelligence methods and the axes of railway safety. Two reviewers conducted

the assessment independently, recording decisions in a form with three possible outcomes: include, exclude, unclear. Discrepancies were resolved through consensus, and if necessary, with the involvement of a third reviewer. For transparency, each decision was assigned a reason code, such as lack of AI component, lack of railway safety relevance, inappropriate document type, incomplete metadata, or insufficient methodological information, which allowed later aggregation of exclusion categories in the results report.

In title and abstract screening, a minimal set of decision questions was applied to determine whether the work directly concerned railway safety in one of the three substantive categories, and whether it employed artificial intelligence methods, understood as machine learning, neural networks, or computer vision. If the answer was positive, the publication proceeded to full-text assessment, if negative, it was excluded, if unclear, it was marked as such and also forwarded for full-text assessment. At this stage, multiple assignments of topics and methods were permitted, reflecting the complexity of tasks, and terminological inconsistencies were reduced by normalizing keywords to a reference list; for example, merging variants of convolutional neural networks into a single class. Deduplication was confirmed technically based on DOI and titles, and borderline cases of sibling publications, that is conference and journal versions of the same study, were resolved in favor of the more methodologically complete version.

Full-text assessment verified whether a publication met all substantive and formal criteria, in particular, whether it contained an AI component applied in the context of railway safety, reported input data and task-relevant metrics, and provided a methodological description sufficient for unambiguous classification. In the case of review and conceptual articles, a consistent taxonomy or methodological conclusions referring to the defined axes was required. Lack of full-text access, incomplete metadata, or inconsistencies between title, keywords, and content resulted in exclusion and recording of an appropriate reason code. All decisions at this stage were logged, and disputed classifications were corrected by consensus.

The flow of records between stages, together with counts at each step, is shown in the PRISMA diagram (Figure 2). The diagram covers identification, screening, eligibility assessment, and final inclusion. With this organization of the process, calibration of reviewers, independent double screening, a register of exclusion codes, and explicit documentation of decisions, the selection is transparent, auditable, and replicable without repeating information presented in other subsections.

During screening, all 120 records were assessed, with 20 excluded solely on the basis of keyword refinement in Scopus, leaving 100 items for further evaluation. No publication was lost at the full-text retrieval stage. In the eligibility stage, the full texts of 100 publications were analyzed, with five excluded for substantive reasons, resulting in 95 works included in the final corpus.

Stage indicators confirm the effectiveness of the procedure: retention after screening was 83.3%, full-text exclusions accounted for 5.0% of analyzed reports, and the inclusion rate relative to identified records was 79.2%. The absence of duplicates and the absence of lost reports increased transparency and replicability of the process, while the dominant reason for exclusions at the screening stage, keyword refinement, confirms that thematic narrowing was conducted at the metadata level before content evaluation. This selection process ensured a technical, homogeneous corpus suitable for further classification and quantitative analyses.

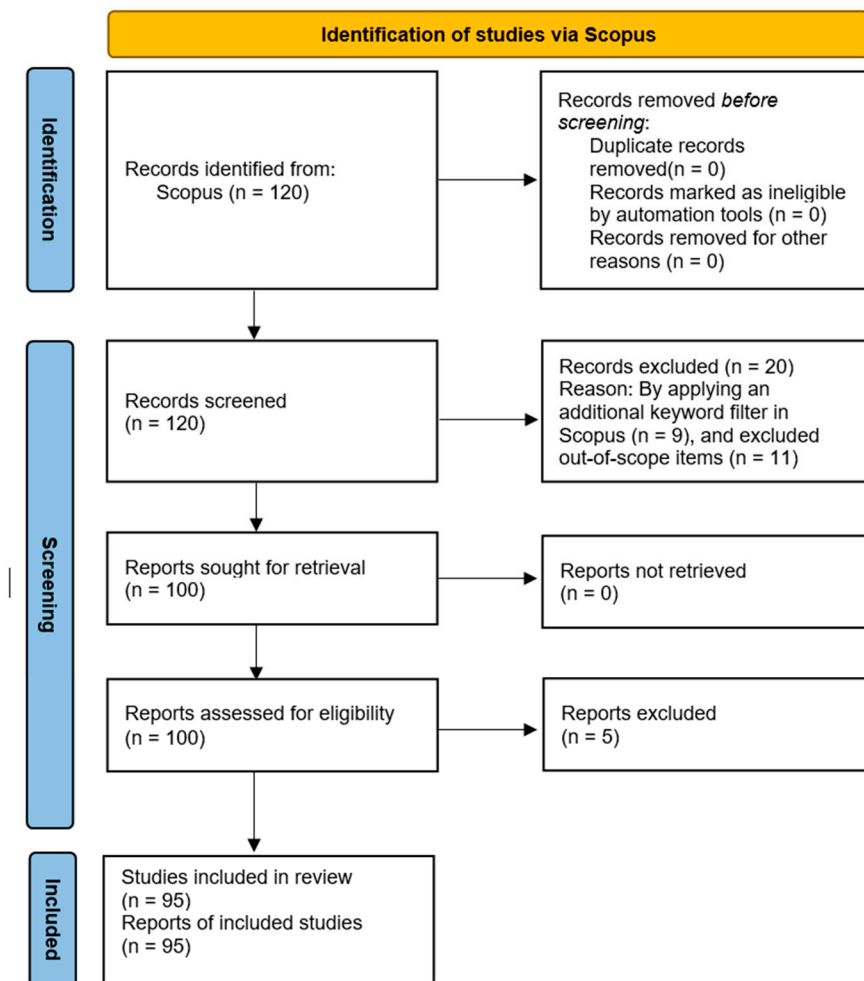


Figure 2. PRISMA flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies retrieved from Scopus.

2.6. Classification Scheme

The classification framework was based on five parallel axes, which ensure consistent coding of content and comparability of results in subsequent analyses. Each document could receive more than one label within a given axis if this followed from its substantive scope or metadata.

The first axis concerns classes of artificial intelligence methods. Three overarching categories were distinguished: machine learning, neural networks, and computer vision. Variant and synonymous terms were normalized to these categories; for example, machine-learning, learning systems, and support vector machines were assigned to machine learning, while convolutional neural network, convolutional neural networks, deep neural networks, and convolution were assigned to neural networks. Normalization eliminates indexing artifacts and enables comparisons across studies.

The second axis covers areas of railway safety, namely, railroad accidents, railroad tracks, and railway safety. At least one of these labels had to appear in the metadata or full text of a publication for it to be included in the review. This arrangement reflects three main application directions: accident prevention and analysis, diagnostics and maintenance of track infrastructure, and systemic safety.

The third axis reflects the geographical origin of the output based on authors' affiliations. The following set was applied: Australia, Canada, China, France, India, Singapore, Turkey, United Kingdom, United States, and other. In cases of multi-country co-authorship, all appropriate labels were assigned, enabling analysis of international collaboration.

The fourth axis organizes document types according to Scopus classification. The categories considered were article, conference paper, and other. The group other included, among others, book chapters and review articles, provided they met the substantive and formal criteria.

The fifth axis describes the methodological approach determined from the content. Four categories were used: experiment (original measurements or tests), literature analysis (reviews and literature syntheses), case study (implementations and case studies), and conceptual (models and method proposals without an experimental part). This distinction facilitates assessment of the maturity of solutions and methodological rigor.

The adopted framework allows construction of cross-tabulations, in particular, method $\times$ safety topic, analysis of distributions by document type and authors' countries of affiliation, and unambiguous interpretation of bibliometric results in subsequent parts of the study.

The term density map presented in Figure 3 reveals three areas of highest activity. The central focal points are the terms railroad accidents, railroad tracks, and machine learning, surrounded by medium-density fields, namely, railway safety and computer vision, as well as the family of concepts related to convolutional networks and classical learning methods. Yellow clusters are concentrated around two axes of safety, railway accidents, and railway tracks, confirming that the query effectively captured the thematic core. A smaller but noticeable intensity relates to the terms convolutional neural network, convolutional neural networks, and deep neural networks, indicating a strong embedding of deep methods in computer vision applications. The presence of lexical pairs with the same meaning, for example, machine learning and machine-learning, neural networks and neural-networks, reflects the indexing practices in Scopus. In the quantitative analysis, these were merged, while in the density visualization, they remain as separate clusters, which does not alter the overall picture of the dominance of three poles: accident safety, track condition, and learning methods.

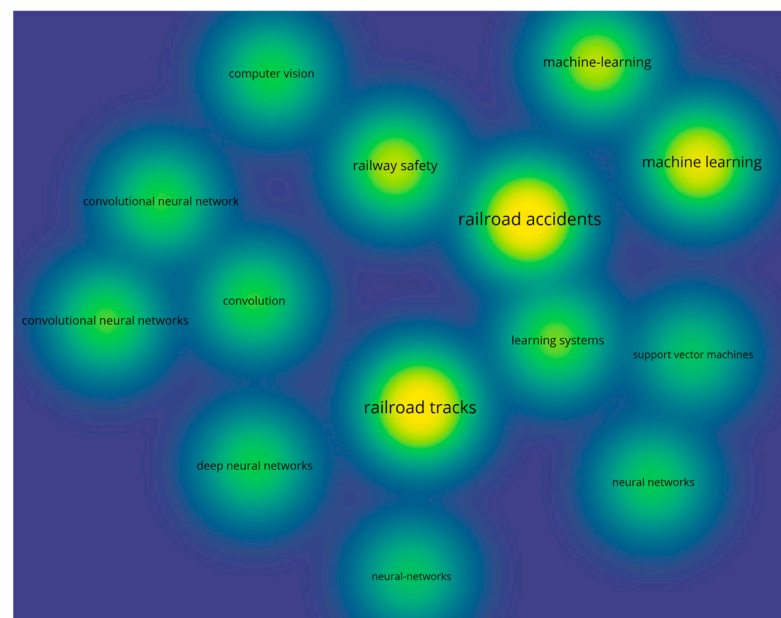


Figure 3. Term density map (color scale: yellow—highest term density; green—medium; blue—lowest). Yellow indicates the highest keyword density, indicating the most central and frequently co-occurring topics.

The co-occurrence network map of terms, shown in Figure 4, organizes the conceptual space into three clusters. The first cluster, predominantly red, centers on machine learning,

railroad accidents, railroad tracks, learning systems, and support vector machines, and points to a line of work dominated by classical learning techniques, often applied in risk analysis of events and classification tasks based on features extracted from tabular data. The second cluster, in shades of green, comprises computer vision, railway safety, convolutional neural network, convolutional neural networks, and convolution, representing the stream of machine vision linked to systemic safety, defect detection, and scene perception. The third cluster, in shades of blue, includes deep neural networks and neural networks, serving as a bridge to borderline tasks where deep networks are combined with operational data or measurement metadata.

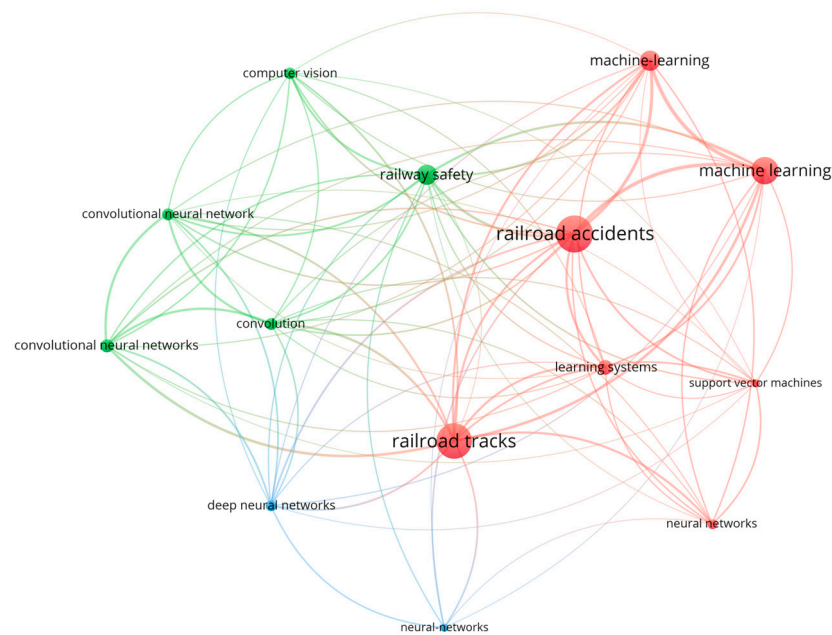


Figure 4. A map of the co-occurrence network of terms (colors indicate thematic clusters; node size reflects term occurrence; link thickness reflects co-occurrence strength). Visualizing the interconnections and thematic clusters identified in the analyzed publications.

The thickness of the edges between the nodes railroad tracks and computer vision, and between railroad accidents and machine learning, indicates strong content couplings, while railway safety functions as an intermediary node connecting vision components with classical learning methods. This structure suggests two dominant developmental pathways: first, applications of machine vision and convolutional networks in track and infrastructure inspection; second, the use of classical learning methods, including SVM, in event analysis and risk modeling. Both streams are connected by the growing role of deep networks in predictive tasks and by integrative topics that facilitate multimodal approaches toward tools ready for operational deployment.

In the analysis of the co-occurrence of keywords, a controlled process of selection and normalization of terms was used. First, a stop-word list was created that included general expressions that did not increase thematic resolution. Subsequently, synonyms and variants of writing were standardized (e.g., combining abbreviated and developed forms), and singular/plural harmonization was carried out. A threshold of minimum instances/co-occurrences was used to stabilize the network structure, and rare dates were left only when they acted as links between thematic groups. All steps were performed in a configuration consistent with the VOSviewer 1.6.20 parameters used to build the maps.

2.7. Data Extraction and Benchmarks

From each publication, a standardized set of fields was extracted, enabling comparable characterization of studies and their results. The recorded items included the learning task, that is, detection, segmentation, classification, or prediction; the modality and data sources, including video, LiDAR, ultrasound, acoustics, DAS systems, and operational data; as well as the description of the model or architecture with key parameters. In addition, information was noted on the deployment environment, namely, whether computation was performed in edge or cloud mode, the time requirements, and whether resource constraints were indicated. Supplementary notes concerned reproducibility, in particular, the presence of reference datasets, validation protocols, and open Zenodo database.

Comparative measures were selected to reflect the nature of the tasks. For detection and segmentation, metrics such as mAP and F1 were applied; for classification, AUC and F1; and for regression tasks, error measures such as RMSE. Results were normalized to the most frequently reported metrics within each task class and presented in comparative tables, which enabled direct comparison of effectiveness with consideration of data type, architecture, and experimental conditions. Where authors reported additional indicators, such as processing times or resource usage, these were included in the interpretative commentary to link algorithmic quality with operational feasibility.

The bibliometric layer was prepared using VOSviewer 1.6.20. Density maps of terms and co-occurrence networks of keywords were constructed to identify thematic clusters and central nodes. Each figure was provided with the recommended caption. Input files for VOSviewer 1.6.20 and the normalization dictionary of terms are provided in the Zenodo database.

The synthesis of results was conducted in two ways. First, a thematic synthesis within the three main axes of safety—railway accidents, railway tracks, and systemic safety—and the three AI method classes—machine learning, neural networks, and computer vision—was conducted, which allowed linking specific tasks with data types and implementation requirements. Second, a quantitative aggregation was carried out, covering geographical distribution, document types, and methodological approaches, with the possibility of constructing cross-tabulations, for example, method $\times$ safety topic, as well as analyzing trends of popularity within the corpus.

The description of the procedure complies with MDPI guidelines and transparency requirements. The Scopus query with filters, inclusion and exclusion criteria, definitions of classification categories, and the complete list of ninety-five publications with metadata are provided in the Zenodo database. In this way, the subsection integrates extraction, comparative measures, bibliometrics, and synthesis, which ensures reproducibility of conclusions and enables updating of the review in future editions.

2.8. Limitations

The scope of the review is defined by a single source, the Scopus database, the English language, the years 2016–2025, and restriction to the fields of computer science and engineering. This choice ensures metadata consistency and uniform selection criteria, but it also introduces the risk of omitting publications indexed only in other databases or published in other languages. Indexing delays must also be considered, as they may result in underestimation of the most recent works.

Another limitation arises from the construction of the search query. The use of EXACTKEYWORD descriptors for AI terminology increases precision but may exclude studies that use less common synonyms. This risk was reduced by combined searching of titles, abstracts, and keywords and by normalizing lexical variants, but isolated false negatives cannot be ruled out, nor can borderline inclusions.

The selection procedure included independent double screening and consensus-based decisions. Despite these safeguards, classification along the five axes, namely, method, safety topic, country of affiliation, document type, and methodology, contains an element of expert judgment. Subjectivity particularly concerns multi-thematic cases and publications in which the description of methods and data is limited. To reduce errors, a normalization dictionary and exclusion codes were applied, but some ambiguities may remain.

A strong barrier to comparisons is the heterogeneity of reported metrics and datasets. Authors apply different versions of measures, for example, mAP at varying IoU thresholds; F1 calculated with different decision thresholds; different train-test splits; as well as proprietary datasets without public access. Under these conditions, there is no basis for formal meta-analysis of effects, and comparative conclusions should be treated as descriptive. In addition, many studies do not report time requirements, such as latency and throughput, which hinders assessment of readiness for real-time operation.

The bibliometric layer relies on analysis of keyword co-occurrences and VOSviewer 1.6.20 maps. These maps are descriptive in nature, reflecting indexing structures and term frequencies, rather than method quality or strength of evidence. Results depend on the threshold for term inclusion, synonym merging rules, and the choice of clustering algorithms. Therefore, cluster and centrality interpretations should be related to the substantive content of the review rather than treated as causal indicators.

At the external level, publication and selection bias must be considered. Technical literature is dominated by positive results, while reports of failures are rare, which may inflate expected performance metrics. The review does not include grey literature, such as industry reports and internal documents, which often contain data on deployments and operational limitations.

The generalizability of conclusions is constrained by environmental and operational differences. AI applications in railway safety depend on sensor configurations, climate, lighting, infrastructure geometry, and regulatory requirements. Many studies are laboratory-based or prototype in nature, and real-world field results may differ from the claims made in the publications. Some works do not report predictive uncertainty, which complicates the assessment of risk from erroneous decisions in critical environments.

These limitations do not invalidate the conclusions of the review, but they do indicate the boundaries of their applicability. Future iterations are planned to extend the query to additional databases, including IEEE Xplore and Web of Science, to include selected non-English languages, to refine the synonym dictionary, and to report inter-rater agreement. It is also recommended to promote open benchmarks and standardized evaluation protocols, which would enable more rigorous comparisons in future studies.

3. State of the Art

This chapter establishes the substantive framework for the subsequent analysis. Its aim is to coordinate the perspective of artificial intelligence methods with the perspective of systemic railway safety, in order to ensure consistent operationalization of concepts, metrics, and evaluation requirements. The adopted structure organizes the existing body of work, identifies research gaps, and guides the synthesis of conclusions with regard to their operational and regulatory usefulness.

The structure of Section 3 is fourfold. In Section 3.1, Artificial Intelligence, the main streams of machine learning, neural networks, and computer vision in railway applications are presented, with particular attention to data sources, representations, validation metrics, time requirements, uncertainty quantification, and domain transfer of models. In Section 3.2, Railway Safety, technological results are translated into the framework of risk and reliability, covering accident analysis, track integrity, and operational and organiza-

tional conditions. In Section 3.3, Future Research Perspectives, directions of research and implementation are synthesized, including dataset standardization, multimodal information fusion, interpretability, compliance with certification requirements, and scalability of solutions in real-time environments. In Section 3.4, Summary, cross-cutting conclusions are consolidated and design implications for the following sections of the study are formulated.

3.1. Artificial Intelligence

The body of work based on classical ML demonstrates how railway safety can be supported by lightweight, transparent models and rapid prototyping. Early warning against the effects of natural phenomena in high-speed rail achieves high effectiveness with LSSVM, creating a practical chain “data–forecast–action” [20]. In another line, surrogate models accelerate reliability calculations, for ballastless track structures, computation time is reduced more than $1000\times$ while maintaining accuracy, turning vulnerability analysis into an engineering tool rather than an academic exercise [21]. Following maintenance practice, LightGBM accurately predicts rail fractures in suburban traffic (with adjustments for class imbalance), identifying key risk factors: terrain slope, speed, and defect history [22]. Importantly, ML adapts well to two extremes, standardization and personalization. In the first case, AutoML eliminates hundreds of design choices and can outperform competition-winning solutions in track defect classification [23]. In the second case, where data are scarce or costly to acquire, hybrids prove effective: ANFIS and ANN can rapidly estimate slope stability ($R^2\sim 0.9999$), directly relevant to embankments and cuts [24], while SVM on operational data distinguishes four classes of S&C switch faults without costly measurement campaigns [25]. Finally, graph-based explainers (e.g., SHAP) reveal which variables actually carry the structural load of steel components, so the engineer not only knows that the model works but also why it makes its predictions [26].

At the other end, neural networks learn representations without manual feature engineering and link vehicle–track dynamics with prediction algorithms. In driving safety models, N-BEATS processes sequences of train–track–bridge responses and predicts derailment factors in real time [27], while TCN + BiLSTM more accurately forecasts track irregularities than classical time-window models [28]. When fast yet reliable output is required, uncertainty-aware architectures provide support; Bayesian autoencoders improve estimation of track quality indices (TGI), delivering confidence intervals useful for maintenance decision-making [29]; and PDK-TransTCN reproduces the seismic response of HSRTBS structures at a fraction of simulation cost while retaining high R^2 even with limited samples [30]. LSTMs are also applied to track circuits, where reducing false alarms yields real operational gains [31], and hybrid algorithms combining CNN and regression connect geometry defects with sleeper layouts [32]. This “map” of methods is complemented by reviews of HSR developments, emphasizing that the shift from incidental measurements to continuous diagnostics is today primarily a challenge of data and organization rather than technology [33].

In parallel, modal fusion is advancing. The integration of fiber DAS signals with accelerometry, linked in a graph with attention (FusionHGAT), enables detection of loose fasteners with accuracy close to 100% [34], similarly in DSAD/DSAD-VAE (supervised/unsupervised), which in field tests reached near-perfect accuracy [35]. Algorithms applied to DAS signals can also track train movements, estimating position, speed, and direction with accuracy of 98.6% [36]. Perception chains can also include rail temperature forecasts with BLSTM (important for buckling risks and speed restrictions) [37] and estimation of adhesion coefficient with MC-DCNN from STFT spectra, enabling early detection of low adhesion without additional sensors [38].

NNs also perform well where data are scarce or atypical. One-shot models based on Siamese networks identify rare rail defect classes [39], and MemFormer combines memory with cross-channel multi-head attention to detect metro anomalies with high sensitivity at 47.6 FPS [40]. In turnout drive fault prediction, LSTM outperforms BP-NN [41], deep NNs detect bearing failure symptoms with one-day lead time [42], and CNN-MH-MLP (trained on FEM data and onboard signals) shows that three sensors represent a reasonable compromise between cost and TGI estimation quality [43]. From an operational perspective, A2C (DRL) suggests traction–braking strategies to reduce longitudinal forces in trainsets [44], while DNNs predict casualty numbers in weather-related events better than classical regressions, supporting preventive planning [45].

Neural networks have also entered the analysis of information and knowledge. A text classifier based on multilayer CNN structures classifies safety reports [46], while NER + RF build knowledge graphs for quantitative risk assessment [47]. In electromagnetic domains, where traditional models are too rigid, a toolbox combining GPR and NN supports prediction of induced voltages already at the planning stage of power line routes near tracks [48]. It has also been shown how ANN/SVM help predict accident events at the intersection of technical and organizational failures [49], while AE-LSTM brings rail crack detection to the cloud, enabling scalable solutions in near-real time [50]. Maintenance-related tasks are supplemented by rail gauge predictions in tram networks; interestingly, ANN dominates on straight sections while SVR prevails on curves [51], and by review syntheses that systematize the role of ANN and Bayesian models in geometry analytics, highlighting the growing importance of climatic factors [52].

What the train and its systems “see” determines not only comfort but above all safety, and here the greatest qualitative leap is visible. In obstacle and intrusion detection, YOLOv5 is used to warn about human presence near tracks [53], and in combination with microwave radar (and Kalman filtering) it improves reliability under challenging environmental conditions [54]. For detecting hazardous situations at level crossings, both video (lightweight CCTV models) and redundancy with active sensors are applied [55]. In practical deployments, such as the MTR system in Hong Kong, extremely low FAR 0.01% and MDR 0.94% were achieved [56]. Infrared detectors (RIO dataset) reach mAP 93% at 97 FPS, showing that “night and fog” are no longer excuses [57], while CenterNet already serves as a basis for robust front-train recognition with efficiency maintained [58]. Complementary approaches include background subtraction algorithms from moving cameras, capable of handling unknown obstacle classes [59], and comprehensive reviews mapping the full domain of intrusion detection, from ground platforms to onboard and UAV systems [60]. At the system architecture level, the concept of distributed monitoring along tracks (sensors + ML + communication) was designed for staged deployment in large networks [61].

The second trajectory of CV is scene understanding and segmentation. EDFNet demonstrates that dual-stream fusion can be both fast and accurate, useful for both automation and line monitoring [62], while ERTNet achieves mIoU 92.4% with only 0.5 M parameters, placing it among edge-ready models [63]. Classical SegNet still outperforms basic approaches in difficult scenes [64]. When combining tasks (detection + segmentation + tracking), multitask learning improves detection of rare faults [65], and DOE studies of CNN parameters show how to avoid “over-tuning” without performance loss [66]. In terms of efficiency, lightweight adaptive CNNs operate at speeds of about 81 FPS with mAP ~95% [67].

The third axis is component inspection. Literature reviews organize the CNN/YOLO/R-CNN family and identify two major gaps: lack of standardized datasets and the need for real-time operation [68]. In practice, 3D laser and DCNN generate objective indices of track component condition (TCHI) [69], and change detection (>98%) allows comparisons of

fastener and spike condition between inspections, capturing subtle differences missed by pass/fail evaluations [70]. For fasteners and joints, both lightweight CNNs [71] and enhanced YOLOv5-CGBD heads (CBAM, GSConv, BiFPN) with mAP50 0.971 are applied [72]; freight wagon bolt inspection has been automated to ACC 99.96% at 9 FPS [73]. For rail surfaces, both one-shot approaches [39,74] and anomaly-attention methods (RAG-PaDiM) [75] are applied, and when data domains shift, UIUDA uses uncertainty to improve generalization (mIoU 80.17% on FRSD) [76]. Inspections can also be supported with LiDAR (completeness 97.1%, correctness 99.7%) [77], eddy current signal classification with MobileViTv2 (~99% ACC) [78,79], or lightweight-hybrid YOLOv4 (mAP 94.4, 78.7 FPS) [80]; in data-scarce conditions, CTGAN and RF classifiers (ACC 0.99) provide support [81]. In rolling stock, combined SVM/CNN approaches accelerate detection of flat spots and wheel out-of-roundness from wayside signals [74], while DCNN-AFDM speeds up turnout diagnostics in HSR (ACC ~96.7%) [82]. Collectively, this forms a coherent picture: CV is no longer “laboratory-bound”; it operates on lines, platforms, and trains [83–87].

In Ref. [88], a toolbox based on GPR (Matérn 3/2 kernel) and a 3-layer neural network with Bayesian optimization was developed to predict EMI AC-induced voltages on tracks with limited design data. The solution supports early risk assessment and has implementation at Manitoba Hydro. In Ref. [89], a monitoring system for ballast-free turnouts on KDP bridges is presented, combining FBG technology and intelligent video identification. BP neural networks and multiple regression were used to predict indicators, and cluster analysis was applied for early warning of abnormal conditions. In Ref. [90], the MSRConvNet model was proposed, i.e., a multiscale residual CNN network for the classification of track defects. With parallel multiscale convolutions and data augmentation, very high efficiency (ACC 99.83%, F1 99.83%) was achieved, ensuring reliable recognition of four defect classes. In Ref. [91], a systematic review of methods for assessing the quality of railway tracks using acceleration measurements from inertial sensors and ML algorithms was carried out. The analysis indicates the growing importance of data-driven approaches, but also the challenges related to data quality, robustness of models, and their adaptation to different conditions. In Ref. [92], an unsupervised method for detecting anomalies in track inspection is presented, based on symmetry analysis of railway images. The metric model learns the similarities between symmetric areas, which allows you to efficiently identify unknown classes of anomalous objects without the need for anomaly labels. In Ref. [35], a system for monitoring loose track connectors based on DAS technology and ML/LV algorithms is proposed. The DSAD and DSAD-VAE models achieved very high success rates in field tests (F1 = 0.9917 and 100%, respectively), enabling precise and automatic detection of anomalies in real time.

To conclude the methodological part of Section 3.1, a summary table (Table 1) was prepared. It organizes the discussed threads under the subcategories of machine learning, neural networks, and computer vision, presenting for each group the main theme, data and sensor types, research task, applied models and techniques, and metrics and requirements, with references [n]. The table serves as a conceptual and methodological map, standardizes terminology across the chapter, enables comparison of data ranges and algorithms, and supports assessment of operational readiness, runtime, and treatment of uncertainty. This closes the methodological section and provides the basis for the synthetic conclusions in Section 3.3.

Table 1. Thematic overview of artificial intelligence methods in railway applications, machine learning, neural networks, and computer vision.

Subcategory	Thematic Focus	Data Types and Sensors	Research Task	Models and Techniques	Metrics and Requirements	Examples/Representative Items
Machine Learning	Early warning and climate risk in high-speed rail	Weather, hydrology, topography	Event risk prediction and speed restriction policy	LSSVM, regression DNNs	Forecast accuracy, operational readiness	[20,37,45]
	Predictive maintenance of rolling stock	Locomotive telemetry, operational logs	Failure prediction and downtime planning	MLT RPM, ensemble classifiers	Reduced downtime and energy use	[93]
	Safety assessment and knowledge acquisition	Incident reports, technical documentation	Concept extraction, risk models, certification support	NER, Random Forest, ACASYA, CHARADE, CBR	Scenario completeness, auditability	[47,94–98]
	Track geometry and condition indices from vehicle response	Onboard accelerations, telemetry	TGI estimation, change detection, degradation forecasting	Bayesian autoencoders, TAN TQI, Matrix Profile, AutoML	MAPE and uncertainty bounds, classification accuracy	[23,29,43,52,91,99,100]
	Reliability and surrogate modeling	Design parameters, simulation data	Fast reliability and resilience evaluation	SVM surrogate, PDEM, surrogate models	Computation speedup, accuracy agreement	[21,101,102]
Neural Networks	Forecasting track irregularities and dynamics	Inertial signals, onboard sensors	TG forecasting, derailment coefficient	TCN, BiLSTM, N-BEATS	Higher effectiveness than baselines	[27,28]
	Seismic response and HSRTBS analysis	Simulations, structural measurements	Prediction of structural response	PDK TransTCN, Transformer TCN	High R ² with small samples	[30]
	Safety critical subsystems diagnostics	Track circuits, APS signals	Fault detection and classification	LSTM, DCNN AFDM	High sensitivity, low false alarms	[31,41,82]
	Wheel rail contact and adhesion conditions	Axlebox accelerations, STFT spectra	Friction coefficient estimation	MC DCNN	Accurate estimates during normal service	[38]
	Multimodal fusion and distributed sensing	DAS, accelerometers	Loose fastener detection, train tracking	GNN FusionHGAT, CNN on DAS	Near 100 percent accuracy, correct localization	[34–36]
	Anomaly detection with memory	Metro video, event sequences	Real time anomaly detection	MemFormer, DOE for CNN configurations	High recall at 47.6 FPS	[40,85]
	Collision events and active safety	Video, simulation data	Crash detection and crash energy management	GJADet, surrogate models, CNN for braking	AP improvement and prediction agreement	[102–104]
	Subsystem maintenance	Bearing vibrations, operational telemetry	Early fault detection	Deep NN, LSTM	High accuracy with time advance	[41,42]
	Low data regimes and 1D signals	Defect images, eddy current signals	Defect identification	One shot, MobileViTv2	Effective classification with few samples	[39,78,79]
	Train handling and longitudinal force control	Train telemetry	Reduction of longitudinal forces	A2C DRL	Improved safety and comfort	[44]
	Text and report analytics	Safety reports	Document classification	Multi-layer CNN	Automated categorization	[46]

Table 1. Cont.

Subcategory	Thematic Focus	Data Types and Sensors	Research Task	Models and Techniques	Metrics and Requirements	Examples/Representative Items
Computer Vision	Scene understanding and track area segmentation	Onboard and fixed cameras	Semantic segmentation of rail scenes	EDFNet, ERTNet, SegNet	High mIoU with few parameters	[62–64]
	Obstacle and intrusion detection, including night and fog	RGB camera, IR, radar	Object detection and tracking	YOLOv5, IR with decoder, CenterNet	High mAP and FPS, low FAR	[53,54,57,58,67,105]
	Platform safety and operational deployments	Platform CCTV	Hazard detection on platforms	YOLOv8, ByteTrack, SAM	Field proven deployments	[56,83]
	Track component inspection	2D images, 3D laser, LiDAR	Detection of looseness, missing parts, change detection	DCNN, change detection, YOLOv5 CGBD, light CNN	Over 98 percent accuracy in many tasks	[35,69–73,77]
	Rail surface defects and material classification	RSDD images, ECT signals, defectograms	Segmentation and classification of defects	RAG PaDiM, DDRSNet, one stage YOLO, MobileViTv2, NN	High AUC and mAP, solid generalization	[39,68,75,76,79,85–87]
	Generalization and unknown object handling	Onboard video	Detection of unknown obstacle classes	Background subtraction, unsupervised methods, light CNN	Good effectiveness with limited labels	[59,67,92]
	Reviews and standardization	Multiple datasets and sensors	Critical assessment of methods and data gaps	Systematic reviews	Gaps and future directions	[60,68]

3.2. Railway Safety

When accidentality is viewed from a systemic perspective, three layers can be distinguished: perception (to prevent incidents), resilience (when incidents occur), and processes (to learn from them). The process layer is strengthened by methods of knowledge acquisition and verification: ACASYA tools help detect omitted scenarios in safety analysis [95]; the rule-based CHARADE generates complementary risk scenarios [94]; CBR + ML structures the safety assessment of critical software [95]; and ELBowTie integrates big data into the “bowtie” framework, which effectively maps barriers and consequences [96]. At the data level, ontologies with ML can extract knowledge from multilingual reports [98], while “human-in-the-loop” reduces false violations in formal verification [97]. Together, these approaches create a more auditable and learnable safety process.

The perception and operations layers relate to early warning and prevention. Beyond CV/IR systems (described above), alternative channels are important: audio analytics detects anomalies in crossing warning bells [106], while predictive maintenance systems for rolling stock (MLT-RPM) help reduce downtime and exposure to incidents [93]. At the level of safety measure assessment, models explicitly addressing uncertainty are applied, NB-LSTM improves the reliability of crash modification factors (CMF) for crossings [107]. Finally, the human factor: HRV/PPG + ML detects driver fatigue in near-real time [108], while ML + ZINEBS models estimate how increasing penetration of CAV will reduce the number of crossing incidents [109]. Overarching all of this is the influence of weather: DNNs predict the number of casualties in weather-related events better than classical methods, supporting resource and service planning [95], and reviews show that integration of sensors, ML, and communication is key to scalability in large networks [110].

Track safety begins with understanding degradation. In time series, both fully data-driven methods (e.g., Matrix Profiles for automatic change-point detection without synchronization of runs [99]) and classification-based approaches focused on degradation patterns

(TAN-TQI outperforming short-term TQI [100]) prove effective. When insights at the signal component level are required, decomposition methods dominate, with comparisons showing the superiority of VMD in distinguishing types of impact-induced damage in wheel–rail signals [111]. Where computational cost matters, DL + PDEM hybrids deliver 10–30× acceleration of reliability analyses for damping tracks without loss of quality [101]. A cross-cutting review of track quality estimation methods from accelerations, from hand-crafted features to representation learning, highlights where data are lacking and where better curation is sufficient [61].

The horizontal perspective connects perception, maintenance, and safety culture. In practice, this means a transition from incidental inspections to continuous monitoring (platform systems, scene understanding, component inspections), supported by data standardization as well as analytical and formal tools described above. It is worth emphasizing that in many projects it is not algorithmic limitations but rather processual and organizational barriers that determine how quickly real lines benefit from AI, a theme strongly echoed in studies on reliability and cultural transformation [84].

In Ref. [111], a lightweight dual-stream CNN model (LDSC) for recognizing railway worker activity from portable cards was proposed; it combines temporal and spatial analysis of signals. The model outperforms SOTA methods on UCI-HAR, UniMiB-SHAR, and WISDM harvests, supporting the reduction of accident risk on construction sites. In Ref. [103], a GJADet network with adaptive neck and gradient-led representation loss was developed for train crash detection, using the new Crash2024 dataset (75 scenes). The model increases accuracy by 3.5 AP and reduces the problem of class imbalance in the detection of rare crash events. In Ref. [102], a variable fidelity surrogate model (VFMS) was developed to optimize energy absorption parameters in train collisions. The approach combines LSTM-MC and transfer learning between 1D and 3D models, achieving high accuracy in crash dynamics prediction and reducing peak accelerations.

In Ref. [98], an ontology-based ML approach to extracting safety information from multilingual accident reports (German, French, Italian) is presented. The method has achieved 98.5% accuracy and stores data in a graphical NoSQL database, allowing integration with other railway data sources. In Ref. [104], a CNN-based active safety system was proposed that recognizes objects on the track and predicts braking dynamics to prevent collisions. The experiments confirmed the effectiveness of the algorithm in correctly detecting obstacles and supporting the decision to reduce speed. In Ref. [112], a hybrid SNN-STLSTM method was proposed for the dynamic assessment of human error in high-speed railways, taking into account the influence of performance factors (PSFs). The model combines the SNN autoencoder with STLSTM, outperforms other AI approaches, and enables real-time prediction of train driver errors, supporting preventive actions. In Ref. [113], a system for detecting foreign objects on railway tracks based on YOLOv5 was developed, trained on a dedicated set of intrusion images. The model has achieved high efficiency, meeting traffic safety requirements and providing the basis for practical applications in accident prevention systems. In Ref. [114], a hybrid NB-LSTM model was proposed to evaluate the effectiveness of safety measures at level crossings, taking into account aleatoric uncertainty. The method significantly improves the accuracy of CMF calculations (reduction of RMSE by 62.5%, MAE by 61%) and indicates optimal actions such as barriers, bells, or flashing lights.

In the same way, the summary presented in Table 2 integrates findings within the perspective of railway safety and organizes them into the subcategories railroad accidents, railroad tracks, and railway safety, while maintaining the same column layout and reference convention as in Table 1. This makes it possible to translate technological results into the language of risk and reliability, to indicate areas with the strongest empirical evidence, and

to identify thematic and measurement gaps. This closes Section 3.2 and provides a direct starting point for the developmental discussion in Section 3.3.

Table 2. Thematic overview of research in the area of railway safety, railroad accidents, railroad tracks, and railway safety.

Subcategory	Thematic Focus	Data Types and Sensors	Research Task	Models and Techniques	Metrics and Requirements	Examples/Representative Items [n]
Railroad Accidents	Early warning and weather impact	Weather, rail temperature monitoring	Risk and consequence prediction, speed policy	LSSVM, BLSTM, DNN	Better accuracy than classical methods	[20,45,75]
	Level crossings, perception and treatment effects	CCTV, radar, incident databases	Object detection, CMF estimation with uncertainty	YOLO, redundant radar channel, NB LSTM	High mAP and low FAR, credible CMFs	[55,56,83,114]
	Collision events and crashworthiness	Video, simulation models	Crash detection and CEM optimization	GJADet, surrogate models, CNN controllers	AP gains, agreement with simulations	[102–104]
	Human factors and impact of CAV	PPG HRV, level crossing crash data	Fatigue detection, CAV penetration impact	RF, SNN STLSTM, Bayesian models	High detection, risk reduction with CAV	[108,109,113]
	Safety processes and auditability	Reports, documentation, event databases	Knowledge acquisition and formal verification	ACASYA, CHARADE, CBR, knowledge graphs, formal verification	Completeness, consistency, fewer false violations	[47,94–98]
Railroad Tracks	Track geometry and condition indices	Onboard accelerations, telemetry	TGI estimation and degradation forecasting	Bayesian AE, TAN TQI, CNN MLP, Matrix Profile	MAPE and confidence bounds, change localization	[29,43,52,99,100]
	Rail surface defects	RSDD images, ECT, defectograms	Defect detection and segmentation	RAG PaDiM, DDRSNet, YOLO one stage, MobileViTv2	High AUC and mAP, domain transfer	[39,45,75,79,85,87]
	Fasteners, bolts and change detection	2D images, 3D laser, DAS, accelerometers	Loose or missing fasteners, visual change detection	Light CNN, YOLOv5 CGBD, DCNN, DSAD and DSAD VAE	Near 100 percent in field tests	[35,70–73]
	Safety critical systems and turnouts	Track circuit signals, HPSS data	Fault classification	LSTM, SVM	High sensitivity and precision	[31,82,108]
	Wheel rail contact conditions	Axlebox accelerations, STFT	Friction coefficient estimation	MC DCNN	Estimates during normal service	[38]
	Inventory and spatial perception	Low density LiDAR	Track extraction from point clouds	Sensor agnostic algorithms	97.1 percent completeness, 99.7 percent correctness	[77]
	Line side objects and intrusions	Camera, IR, radar	Object detection and tracking	YOLOv4, YOLOv5, CenterNet, light CNN	High mAP and FPS, low FAR	[53,57–59,67,80,105]
	Rolling stock, wheels and bearings	Wayside and vibration signals	Detection of wheel and bearing defects	SVM, custom CNN, deep NN	Early warning and accurate classification	[42,74]
	Trackbed reliability	Design parameters, simulation data	Reliability and risk assessment	SVM surrogate, PDEM	Ten to thousand times speedup	[21,101]
	Impact analysis and signal decompositions	Impact signals	Damage type identification	VMD plus classifiers	Effective separation of damage types	[111]
	Track gauge and geometric dependencies	Geometry measurements, operation history	Gauge forecasting and sleeper dependencies	ANN, SVR, CNN plus regressions	Different models on tangents and curves	[32,51]
	Unsupervised anomaly detection	Video, signals	Rare event detection	Symmetry based methods, memory-based anomaly models	Competitive with SOTA	[40,92]

Table 2. *Cont.*

Subcategory	Thematic Focus	Data Types and Sensors	Research Task	Models and Techniques	Metrics and Requirements	Examples/Representative Items [n]
Railway Safety	Scene understanding, platforms and maintenance transformation	CCTV, onboard video	Scene segmentation and event detection	EDFNet, ERTNet, operational systems	Deployment evidence and culture shift	[56,62–64,73,83,84]
	Methodological frameworks and assessment	Reports, event databases, documentation	Standardization and audit	ACASYA, CHARADE, ELBowTie, formal verification	Consistency and traceability	[94,96,97]
	AutoML and data augmentation	Image and tabular datasets	Robust and stable model building	AutoML, CTGAN plus RF	High accuracy with limited data	[23,81]

In the context of implementation, it is worth emphasizing that some of the analyzed solutions achieve parameters that coincide with operational requirements: detection of “near real-time” hazards in tracks and their surroundings has been demonstrated on stream data using lightweight models and sets of methods [17], and scenarios with increased criticality, such as rail-road crossings or platform zones, are increasingly addressed with specialized detectors and video surveillance systems [54,82]. Resistance to night conditions and underexposure are improved by approaches with infrared imaging and the integration of additional modalities (e.g., radar), which reduces fluctuations in the quality of recognition in difficult situations [53,56]. At the same time, progress in the segmentation of infrastructure defects and anomalies (“efficient” models with a smaller computational footprint) makes it easier to place inference at the edge of the system, without a significant deterioration in quality indicators [62]. This direction is consistent both with the latest reviews of the state of knowledge in the field of computer vision for railways, as well as with the literature on recognizing track surface defects [2,7], which together indicates the real possibility of transferring results from laboratories to operational applications while maintaining the budget of delays and stability of system operation.

3.3. Prospects for Further Development

The collected corpus shows that further progress requires parallel work on data quality, model maturity, and the pathway to operationalization. First, standardization of datasets, metadata descriptions, and validation protocols is necessary, both for track quality estimation from inertial measurements and for image-based inspections of track components. Reviews explicitly point to the absence of unified benchmarks and to metric discrepancies, which hinder comparability of results and the transfer of findings into practice [52,68,91]. A natural complement is the development of domain adaptation techniques, especially in defect segmentation, where uncertainty-based adaptation improves generalization without costly annotations, and where one-shot methods and judiciously applied generative augmentation perform promisingly with limited examples [39,76,81].

Second, multimodal perception is becoming a prerequisite for reliability under extreme conditions. Fusion of vision with radar and infrared improves effectiveness at night and in fog, while the integration of LiDAR and distributed photonics with accelerometry brings benefits in inspection and in tracking linear events [54–56,67,69,77,83,106,113]. Real-time and energy-budget requirements enforce edge implementations, which favor lightweight segmentation and detection architectures as well as memory-based anomaly detection models that maintain high quality under constrained computational resources. At the same time, deployment evidence in operational environments confirms that such a compromise is achievable [40,41,56,63,67,80].

Third, hybridization of models with physical knowledge and digital twins is gaining importance. Coupling train–track–bridge dynamics with safety indicator prediction, surrogate models of seismic response, and crash energy management reduces computational costs and enables exploration of design spaces previously unattainable. Accelerated reliability analyses of track structures play a similar role, and in operational diagnostics the estimation of wheel–rail friction directly from onboard data is of increasing significance [30,51,56,92,102,114].

Fourth, the pathway from prediction to decision requires embedded uncertainty quantification, explicit interpretation rules, and compliance with safety assessment processes. In practice, this means combining estimators with confidence intervals with safety measure assessment frameworks and knowledge acquisition tools, as well as applying formal expert-in-the-loop verification loops that reduce false violations and facilitate auditing. The human dimension is not marginal, as models of operator fatigue and error must enter the same decision processes as technical predictions [26,47,94,96,97,108,114].

Fifth, resilience planning for climatic factors requires integrating environmental hazard forecasts with predictions of infrastructure and rolling stock parameters. Tools based on weather data and rail temperature monitoring provide a foundation for dynamic speed restriction policies and prioritization of actions, directly impacting risk and network continuity [20,37,45]. Finally, the scale and diversity of railway networks favor iterative deployments, starting at critical points and in test corridors, followed by scope extensions. Experience from lines with proven detection systems shows that such a trajectory is both organizationally and technically effective [56,83,93].

3.4. Summary

The collected results form a coherent picture of progress, in which three main streams come to the forefront: representation learning and hybrids with physical knowledge, multi-modal perception with emphasis on edge computing, and procedures ensuring auditability and integration with safety processes. Summaries 3.1 and 3.2 organize this body of work in a uniform column layout, making it easy to link task types with data classes and model families, and then to assess operational maturity and approaches to uncertainty. In particular, it is clear that computer vision results are confirmed in field conditions and achieve high quality at high processing speeds; for example, mIoU 92.4 percent with very few parameters [63], mAP about 94.4 percent at 78.7 FPS [80], mAP 94.75 percent at 81 FPS [67], infrared accuracy around 93 percent at 97 FPS [57], and in line-deployed systems extremely low false alarm and missed detection rates were achieved [56]. In track and component diagnostics, near 100 percent results recur for loose and missing fasteners using DAS and unsupervised methods [35], high AUC in surface defect segmentation [75], completeness and correctness of track extraction from LiDAR at 97.1 and 99.7 percent respectively [77]. In regression models, the inclusion of uncertainty is advantageous, as shown by Bayesian autoencoders with MAPE in the range of 2.7 to 3.8 percent for geometry indicators [29]. In reliability studies, surrogate models and accelerated methods dominate, with speed gains ranging from an order of magnitude to over a thousandfold while preserving result consistency [21,101]. These observations are consistent with the findings in Section 3.1 and the safety framework presented in Section 3.2.

With respect to Research Question 1, the thematic corpus clusters around three families of tasks: scene perception and component inspection using computer vision, estimation and forecasting of geometry and condition indicators based on vehicle and distributed sensor data, and safety process analytics and knowledge acquisition tools [29,30,33,52,54,56,58,62,67–70,77,83,91,94,96]. The strongest empirical evidence comes from edge implementations validated in operations, while gaps remain in dataset and met-

ric standardization, systematic evaluation of domain transferability, and formal linkage of results with certification practices. With respect to Research Question 2, the most frequently used streams are video and its combinations with radar and infrared, complemented by LiDAR for inventory, while in infrastructure diagnostics inertial and vibration signals from vehicles and distributed photonics dominate. The highest effectiveness in operational conditions is confirmed by configurations combining complementary modalities with lightweight segmentation and detection architectures plus tracking; particularly promising is the integration of DAS and accelerometers with graph modeling [5,34,54,56,63,69,83,101,105]. With respect to Research Question 3, a significant share of studies report near-real-time operation with low false alarm rates and increasing presence of uncertainty measures, which facilitates decision-making with explicit safety margins. In practice, the greatest value arises from combining uncertainty mechanisms with safety measure assessment frameworks, with knowledge structuring tools, and with domain models, which completes the pathway from data to decisions and increases the likelihood of regulatory acceptance [29,40,52,56,94,96,97,102,114].

From the perspective of the summaries in Tables 1 and 2, the most important conclusion is that critical technical trade-offs have in many cases been resolved in favor of practice. Lightweight models do not necessarily mean loss of quality, multimodal fusion genuinely improves reliability at night and in fog, and the inclusion of physical knowledge and uncertainty enables the transfer of forecasts into maintenance decision-making. The authors recommend a further research program focused on standardization and transferability, on multimodal perception in edge implementations, and on auditable integration of models with safety and maintenance processes, which in the following sections is translated into design requirements and an evaluation plan based on the referenced benchmarks and metrics.

It should be noted that AI applications in areas of increased security importance require not only high quality metrics, but also predictability of operation and the ability to audit decisions. Examples of “near real-time” implementation in track inspection and supervision of critical zones (m.in. platforms, crossings) presented in the paper indicate that achieving a low percentage of omissions and false alarms is possible under conditions similar to operational conditions [53,54,56,62,82]. In practice, three elements are crucial: (i) clearly defined limits of the solution’s applicability (lighting, weather, congestion conditions), (ii) human oversight with escalation thresholds and alarm acknowledgment mechanisms, (iii) explainability artifacts supporting event-based reviews and quality control (attention visualizations, trust reports). The “legibility” of the model’s operation, combined with maintaining a stable budget for delays and consistency in the registration of decisions, is a condition for integration with existing maintenance and supervisory procedures, and consequently, a condition for further implementation [53,54,56,62].

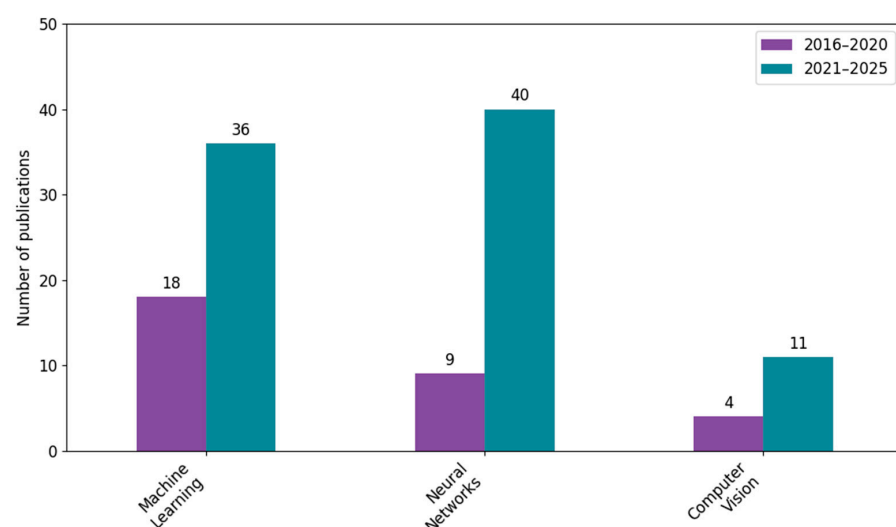
4. Statistical Overview

The growing interest in the applications of artificial intelligence in railway safety is confirmed by the entire analyzed corpus. In the years 2016–2020, 24 publications were identified, while in the years 2021–2025, as many as 71 were identified, which together gives 95 items and corresponds to 25.26% and 74.74% of the entire corpus, respectively. The numbers and shares are presented in Table 3.

Table 3. Publications by year in all categories.

Name	2016–2020	2021–2025	All Years	Share [%]
Total	24	71	95	100.0
Document Type				
Conference Paper	11	24	35	36.84
Article	13	44	57	60.0
Other	0	3	3	3.16
Artificial Intelligence				
Machine Learning	18	36	54	56.84
Neural Networks	9	40	49	51.58
Computer Vision	4	11	15	15.79
Railway Safety				
Railroad Accidents	14	29	43	45.26
Railroad Tracks	9	37	46	48.42
Railway Safety	6	20	26	27.37
Research Methodology				
Experiment	14	60	74	77.89
Literature Analysis	10	14	24	25.26
Case Study	6	10	16	16.84
Conceptual	15	43	58	61.05

Within the classes of artificial intelligence methods, solutions based on machine learning remain dominant. Across the entire period, machine learning appears in 54 publications, that is, 56.84%; neural networks in 49 publications, that is, 51.58%; and computer vision in 15 publications, that is, 15.79%. The temporal distribution shows a shift in emphasis: in 2016–2020, machine learning is present in 18 of 24 publications, 75.00%, and neural networks in 9 of 24, 37.50%; in 2021–2025, machine learning covers 36 of 71 works, 50.70%; while neural networks appears in 40 of 71, 56.34%. Computer vision remains stable: 4 of 24, 16.67%, and 11 of 71, 15.49%. These data indicate a gradual shift from classical techniques toward neural networks, while maintaining a steady, though smaller, presence of computer vision. As shown in Figure 5, the distribution of AI methods in the corpus (machine learning, neural networks, and computer vision) is presented for the periods 2016–2020 and 2021–2025.

**Figure 5.** Distribution of AI methods in the corpus: machine learning, neural networks, computer vision, 2016–2020 and 2021–2025.

In terms of document types, journal articles dominate, with 57 out of 95 items, 60.00%; conference publications account for 35 out of 95, 36.84%; and the other category accounts for 3 out of 95, 3.16%. The dynamics between the sub-periods confirm the maturation of the publication stream: in the years 2016–2020, articles accounted for 13 out of 24, 54.17%, and conferences 11 out of 24, 45.83%; in 2021–2025, articles are already 44 out of 71, 61.97%, and conferences accounted for 24 out of 71, 33.80%. The share of other categories appears only in the second subperiod and amounts to 3 out of 71, 4.23%. The figure suggests the transition of results from early stages to full forms, published in journals. As shown in Figure 6, the structure of document types in the corpus (article, conference paper, and other) is presented for the periods 2016–2020 and 2021–2025.

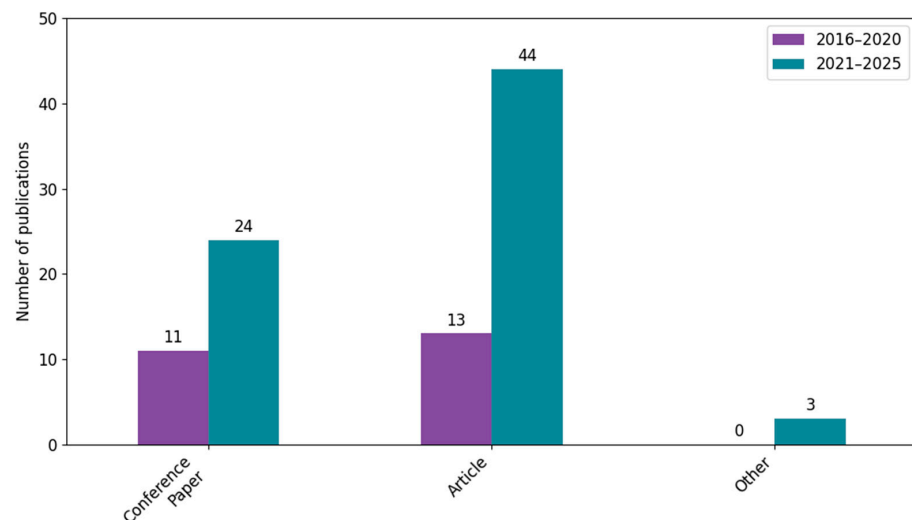


Figure 6. Structure of document types in the corpus: article, conference paper, other, 2016–2020 and 2021–2025.

In the safety axes, a couple of topics related to infrastructure and events dominate: In the entire collection, railroad tracks includes 46 out of 95 publications, 48.42%; railroad accidents includes 43 out of 95, 45.26%; while railway safety of a cross-sectional nature occurs in 26 out of 95, 27.37%. Over time, there is a clear shift towards track themes: in 2016–2020, railroad accidents appears in 14 out of 24, 58.33% and railroad tracks in 9 out of 24, 37.50%. In 2021–2025, railroad accidents drops to 29 from 71, 40.85%, and railroad tracks rises to 37 from 71, 52.11%. Railway safety increases the share from 6 out of 24, 25.00%, to 20 out of 71, 28.17%. This system demonstrates the growing emphasis on track diagnostics and maintenance, while maintaining significant attention to event analysis.

Methodological approaches are dominated by empirical research: In the entire period, experimental works includes 74 out of 95, 77.89%; conceptual approaches 58 out of 95, 61.05%; literature analyses 24 out of 95, 25.26%; and case studies 16 out of 95, 16.84%. Over time, the dominance of experiments is consolidated: In 2016–2020, 14 out of 24, 58.33%; in 2021–2025, 60 out of 71, 84.51%; with a simultaneous decrease in literature analyses from 10 out of 24, 41.67%, to 14 out of 71, 19.72%; case studies from 6 out of 24, 25.00%, to 10 out of 71, 14.08%; and conceptual approaches remain at a similar percentage of 62.50% and 60.56%. This figure confirms the transition from field diagnosis to data-driven testing and validation.

Structural changes were verified by tests of the independence of the chi-square in the cross-sections of document type, classes of artificial intelligence methods, security categories, and methodology. For none of the cross-sections was significance at the alpha level of 0.05 obtained, which means that in the studied period the volume of publications is primarily increasing, while the proportions in the main axes remain stable. Visible shifts

in emphasis towards track topics and neural networks are supported by numerical and percentage distributions. As shown in Figure 7, the safety categories in the corpus (railroad accidents, railroad tracks, and railway safety) are presented for the periods 2016–2020 and 2021–2025. As shown in Figure 8, the methodological approaches in the corpus (experiment, literature analysis, case study, and conceptual) are presented for the periods 2016–2020 and 2021–2025.

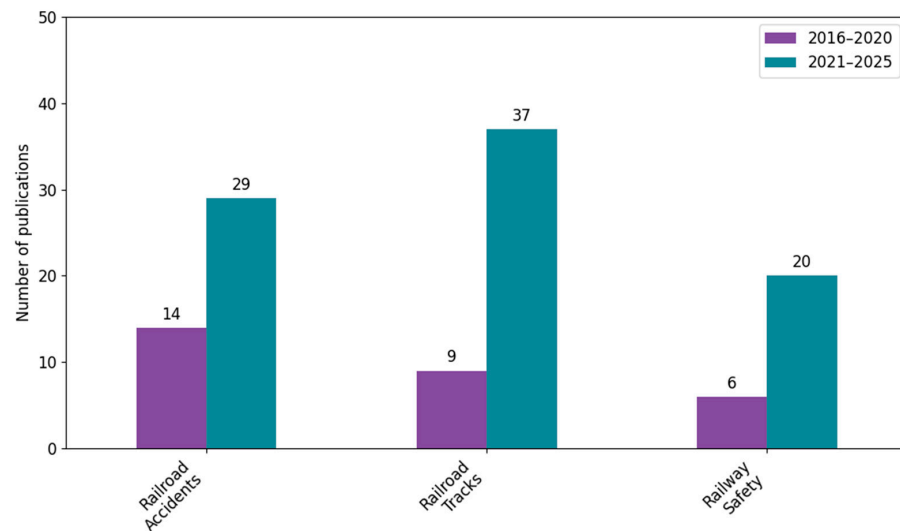


Figure 7. Safety categories in the corpus: railroad accidents, railroad tracks, railway safety, 2016–2020 and 2021–2025.

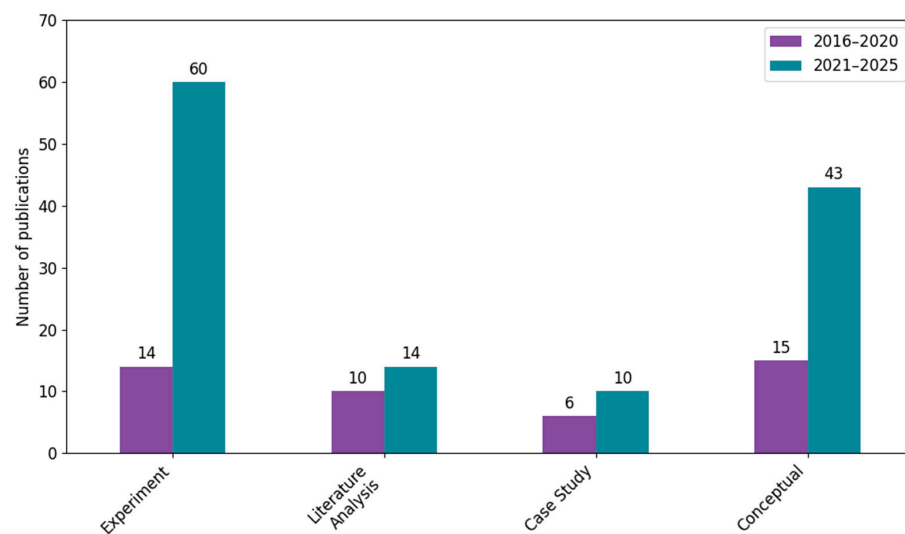


Figure 8. Methodological approaches in the corpus: experiment, literature analysis, case study, conceptual, 2016–2020 and 2021–2025.

The ranking shows that the dynamics of research development are highly concentrated and have clearly accelerated after 2020. Table 4 includes 95 publications, of which 24 are for the years 2016–2020 and 71 for the years 2021–2025. China dominates the entire horizon with 41 publications, which corresponds to 43.16% of all works. The second group consists of the United Kingdom with 11 publications (11.58%) and the United States with 8 publications (8.42%). Canada, France, and Singapore each had five publications (5.26% each), followed by Australia, India, and Turkey, with four publications each (4.21% each). The other category brings together 17 works, which constitute 17.89% of the analyzed works.

Table 4. Publications by year for countries.

Country	2016–2020	2021–2025	All Years	Share [%]
All countries	24	71	95	100.0
China	4	37	41	43.16
United Kingdom	3	8	11	11.58
United States	0	8	8	8.42
Canada	1	4	5	5.26
France	4	1	5	5.26
Singapore	0	5	5	5.26
Australia	4	0	4	4.21
India	0	4	4	4.21
Turkey	1	3	4	4.21
Other	7	10	17	17.89

A comparison of the two sub-periods reveals a strong shift in the center of gravity towards China. Between 2016 and 2020, 4 publications were identified there, which is 16.67% of the stream at that time, while in 2021–2025, this number increased to 37, which corresponds to 52.11% of all papers from that period. The United Kingdom maintains a stable share, with 3 publications in the first sub-period (12.50%) and 8 in the second (11.27%). The United States appears only after 2020 with 8 publications, which translates to an 11.27% share between 2021 and 2025. Canada increases the number of publications from 1 to 4, which means an increase in the share from 4.17% to 5.63%. Singapore also enters the ranking in the second subperiod with 5 publications, which is 7.04%. Two centers lose importance: France drops from 4 publications (16.67%) to 1 (1.41%) and Australia from 4 publications (16.67%) to zero. India and Turkey appear only after 2020, with 4 publications (5.63%) and 3 publications (4.23%), respectively. The share of the other category decreases from 29.17% (7 out of 24) in 2016–2020 to 14.08% (10 out of 71) in 2021–2025, indicating a growing concentration of results in several key countries.

The variability of the geographical distribution is confirmed in statistical terms: The χ^2 independence test for the two subperiods gave the result $\chi^2 = 34.94$ with $df = 9$ and $p < 0.001$, which means that the differences between the country distributions are statistically significant. In other words, after 2020, there was a significant shift in publishing activity towards China, with a simultaneous moderate increase in the share of several new centers and a decrease in the share of some European countries and Australia.

A cross-sectional analysis of the co-occurrence of AI methods classes with safety axes and methodological approaches organizes the corpus thematically and in terms of technique. Publications by artificial intelligence in other categories juxtapose three classes of methods with three safety categories and four ways of conducting research, and the corresponding heat maps make it easier to read differences and concentrations—see Table 3. It is worth noting that labels are not separable, so the totals in rows and columns can exceed one hundred percent, which reflects the co-occurrence of methods and topics in individual publications. As shown in Figure 9, the distribution of publications by the country of authors' affiliation is presented for 2016–2020 and 2021–2025.

The association of method classes with safety axes indicates different application preferences. In the railroad accidents group, there were 31 works using machine learning, which corresponds to 72.09% of this category, 14 works based on neural networks, or 32.56%, and 5 works with computer vision, which is 11.63%. Railroad tracks is dominated by neural networks with 29 works, accounting for 63.04% of the category, with 24 works for machine learning (52.17%) and 6 works for computer vision (13.04%). In the railway safety category, the distribution is more balanced, with 14 works in machine learning (53.85%), 12 in neural networks (46.15%), and 8 in computer vision (30.77%). The column approach confirms these accents: Out of 54 publications from machine learning, as many as 57.41% are about accidents, 44.44% about tracks, and 25.93% about the cross-sectional category;

among the 49 publications from neural networks, the largest share is on tracks, 59.18%, followed by accidents, 28.57%, and system security, 24.49%; in computer vision, system safety prevails, 53.33%, with 40.00% for tracks and 33.33% for accidents. The differentiation of these profiles is confirmed by statistical analysis. The distribution of the use of methods differs between the safety axes significantly, $\chi^2 = 9.8$, $df = 4$, $p = 0.04$, which means that the choice of methodological class depends on the type of safety problem.

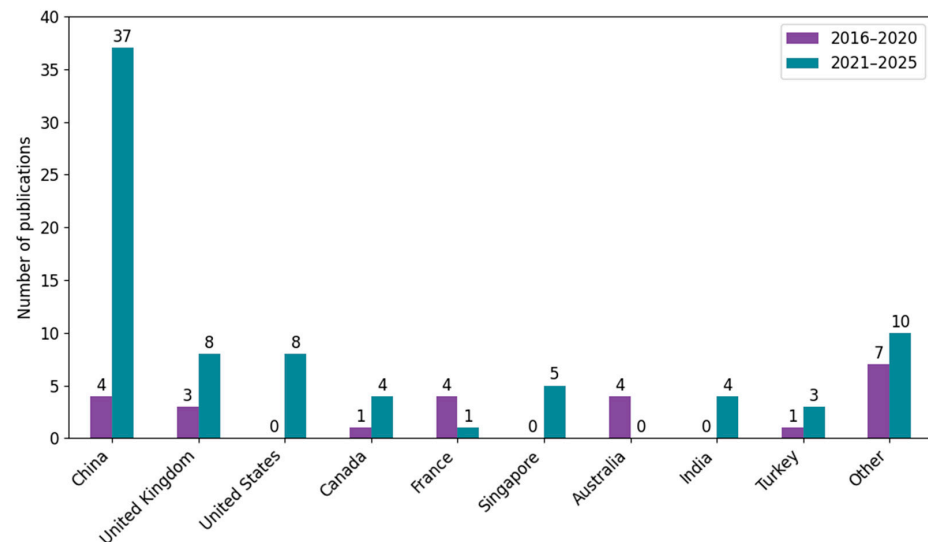


Figure 9. Distribution of publications by country of affiliation of authors in 2016–2020 and 2021–2025.

There are 43 papers from neural networks, which accounts for 58.11% of this category, 37 works from machine learning (50.00%), and 12 from computer vision (16.22%). In literature analysis, machine learning prevails with 20 papers (83.33%), while neural networks and computer vision appear much less frequently, with 5 (20.83%) and 4 (16.67%) respectively. The case study shows 11 machine learning papers (68.75%) and 8 neural networks papers (50.00%), with no computer vision publications. In conceptual, the values are similar for the two main classes: 33 neural networks works (56.90%) and 31 machine learning works (53.45%), with 9 computer vision works (15.52%). The columnar perspective highlights the strength of the experimental component in neural networks: 87.76% of all papers in this class contain an experimental part, 67.35% have a conceptual component, 16.33% have a case study, and 10.20% have a review character. In machine learning, 68.52% are experiments, 57.41% are conceptual works, 37.04% are literature analysis, and 20.37% are case studies. In computer vision, 80.00% are experiments, 60.00% are conceptual components, 26.67% are literature analysis, and no case studies are reported. The relationship between method classes and methodological approaches is at the limit of significance, $\chi^2 = 12.13$, $df = 6$, $p = 0.06$, which suggests real, though still ambiguous, differences in the way research is conducted for individual classes of methods. As shown in Figure 10, the links between AI method classes and safety axes are presented as a heat map (with numerical values in the cells). As shown in Figure 11, the links between AI method classes and methodological approaches are presented as a heat map (with numerical values in the cells).

The compiled results show that neural networks are clearly gaining importance in track diagnostics and maintenance, machine learning remains the most ubiquitous category in accident analysis, and computer vision more often accompanies cross-sectional approaches to safety and is strongly rooted in experimental research. This picture corresponds well with the earlier temporal dynamics and indicates that the field is maturing toward solutions with a high share of empirical validation.

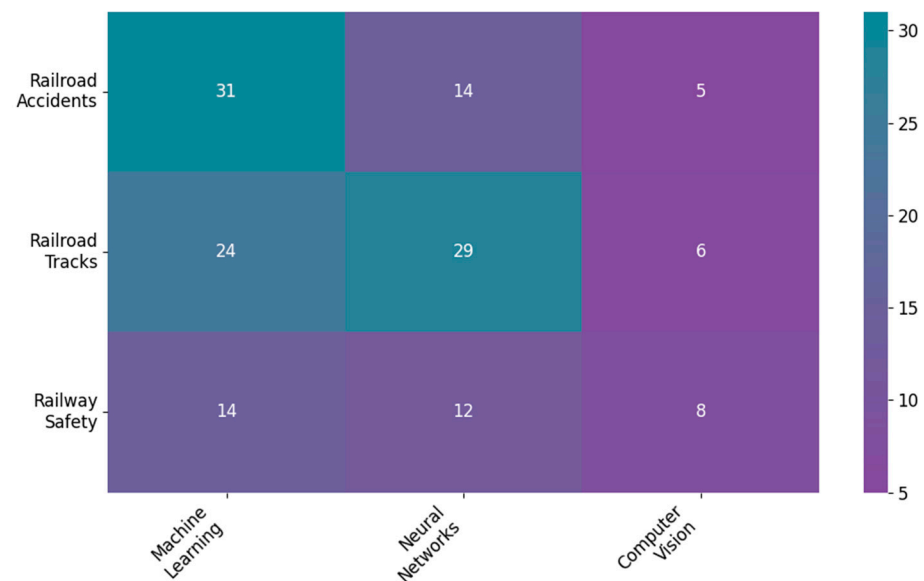


Figure 10. Links of AI method classes to safety axes (heat map, numerical values in cells).

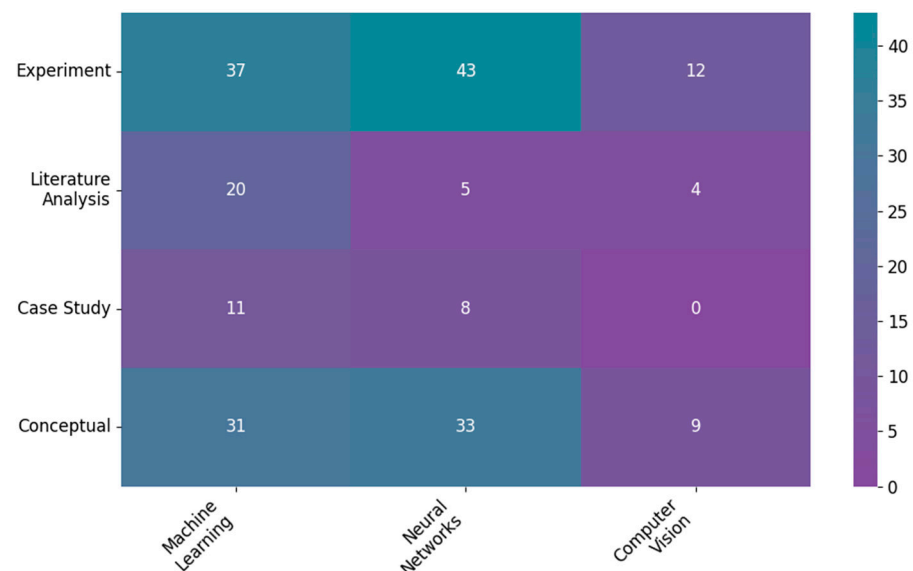


Figure 11. Linking AI method classes with methodological approaches (heat map, numerical values in cells).

The structure of the network confirms the presence of three dominant thematic clusters. In the infrastructure cluster, the density of connections around terms related to track inspection and visual perception is increasing, reflecting a shift in research towards solutions operating at the edge and in a near-real-world mode. The Generic Methods Cluster integrates terms related to learning algorithms and data representation and acts as a back-end that connects various tasks. Finally, the bridging cluster brings together concepts that organize the entire field and facilitate the flow of ideas between applications and the method layer. Nodes with the highest local cohesion are the core where the work with the highest thematic repetition is concentrated, while nodes with an increased intermediary role in the network correspond to the areas where the most solution transfers between tasks are observed. The change in timing in the overlay after 2020 indicates an intensification of terms related to track diagnostics and multimodal acquisition, which is consistent with the quantitative results in this section and the observed maturity of operational solutions.

In summary, after 2020, the research field has accelerated significantly. In 2016–2020, 24 publications were identified, while in 2021–2025 there were already 71, giving a total of 95 works, which corresponds to 25.26% and 74.74% of the entire corpus, respectively. This change is visible across all dimensions: the number of journal articles is increasing, the methodological profile is shifting, and the focus of topics is moving toward issues related to track infrastructure.

In the structure of document types, journal articles dominate: 57 of 95 items, 60.00%; conference publications account for 35 of 95, 36.84%; and other forms 3 of 95, 3.16%. Before 2021, journal articles made up 13 of 24 publications, 54.17%, and after 2020, already 44 of 71, 61.97%, while the share of conferences fell from 45.83% to 33.80%. This pattern indicates the maturation of the topic and more frequent placement of results in journals with full peer-review rigor.

In AI method classes, machine learning retains dominance: 54 works across the entire period, 56.84%; with a strong increase in neural networks: 49 works, 51.58%. Before 2021, machine learning appeared in 18 of 24 publications, 75.00%, and neural networks in 9 of 24, 37.50%. After 2020, the proportions are reversed: machine learning 36 of 71, 50.70%, neural networks 40 of 71, 56.34%. Computer vision maintains a smaller, stable share, at 15 of 95, 15.79%, with values of 16.67% and 15.49% in the two sub-periods. The relationship between method class and safety problem type is statistically significant. Chi-square test for the method $\times$ safety topic matrix yields $\chi^2 = 9.8$, $df = 4$, $p = 0.04$, meaning that different tasks tend to prefer different tools, with machine learning more frequent in accident studies and neural networks more frequent in track-related studies.

In safety topics across the whole set, railway tracks are most frequent: 46 of 95 publications, 48.42%; followed by railway accidents: 43 of 95, 45.26%; while the cross-sectional category railway safety covers 26 of 95, 27.37%. Before 2021, accidents dominated: 14 of 24, 58.33%; while after 2020, tracks prevail with 37 of 71, 52.11%; accident-related works decline to 29 of 71, 40.85%; and railway safety rises moderately from 25.00% to 28.17%. In methodological approaches, experiments dominate: 74 of 95, 77.89%. Conceptual contributions also remain strong: 58 of 95, 61.05%. Literature analyses account for 24 of 95, 25.26%, and case studies 16 of 95, 16.84%. After 2020, the share of experiments rises to 60 of 71, 84.51%, while literature analyses fall to 19.72% and case studies to 14.08%. The relationship between method classes and research approaches is at the margin of significance, $\chi^2 = 12.13$, $df = 6$, $p = 0.06$, suggesting real but not conclusive differences, with neural networks most often linked to experimental validation and machine learning more common in review-based studies.

The geographical distribution is highly concentrated. Across the whole period, China holds the largest share with 41 publications, 43.16%, followed by the United Kingdom with 11, 11.58%, and the United States with 8, 8.42%. Canada, France, and Singapore each have 5, 5.26%; Australia, India, and Turkey have 4 each, 4.21%; and the category other 17, 17.89%. After 2020, China's share rises to 37 of 71, 52.11%, while other falls from 29.17% to 14.08%. The chi-square test for country distribution confirms a significant shift between sub-periods, $\chi^2 = 34.94$, $df = 9$, $p < 0.001$.

The overall conclusion is clear: After 2020, the volume of work increased, the share of journal articles rose, methods shifted toward neural networks, topics moved toward track diagnostics, most studies took an experimental character, and publication activity became geographically concentrated with a strong dominance of Chinese institutions.

With respect to the first statistical question, concerning the trend in publication numbers across the three thematic categories, clear and differentiated growth rates are visible. For Railroad Tracks, the number of works increased from 9 to 37, more than a fourfold increase, with an average annual growth rate in the 2021–2025 period of about 32.7%, and

the category's share of publications grew by 14.61 percentage points, from 37.50% to 52.11%. For Railroad Accidents, the number of works grew from 14 to 29, a doubling, with an average annual rate of about 15.7%, while the share declined by 17.48 percentage points, from 58.33% to 40.85%. The cross-sectional category Railway Safety grew from 6 to 20, more than a threefold increase, with an average annual rate of about 27.2%, and its share rose by 3.17 percentage points, from 25.00% to 28.17%. Across the corpus as a whole, the average annual number of publications rose from 4.8 to 14.2, corresponding to an average annual growth rate of about 24.2%, confirming systematic acceleration after 2020.

With respect to the second statistical question, concerning changes in method structure, there is a clear shift in emphasis while overall proportions remain statistically stable. The share of works categorized as machine learning falls from 75.00% to 50.70%, a decrease of 24.30 percentage points, while neural networks rise from 37.50% to 56.34%, an increase of 18.84 points. Computer vision remains at a stable level, 16.67% earlier and 15.49% later, a decrease of 1.18 points. The chi-square test of independence does not confirm significance of the overall change in method class distribution between sub-periods, $\chi^2 = 2.97$, $df = 2$, $p = 0.23$, but the direction of the shift is clear and aligns with implementation practice, with network-based solutions increasingly applied in detection and segmentation tasks, while classical ML loses its percentage dominance despite maintaining a high absolute number.

With respect to the third statistical question, concerning the popularity of topics measured by publication type and geographical distribution, parallel processes of channel consolidation and geographical concentration are evident. The share of journal articles rises from 54.17% to 61.97%, an increase of 7.80 points; the share of conference papers falls from 45.83% to 33.80%, a decline of 12.03 points; and the category other appears only after 2020, with a share of 4.23%. Changes in document types do not reach statistical significance, $\chi^2 = 1.90$, $df = 2$, $p = 0.39$, but the proportions indicate a shift toward fully reviewed journal publications. In geography, the differences are strong and significant: China increases its share from 16.67% to 52.11%, a rise of 35.44 points; the United States from 0.00% to 11.27%; Singapore from 0.00% to 7.04%, while France declines from 16.67% to 1.41% and Australia from 16.67% to 0.00%; and the category other falls from 29.17% to 14.08%. The chi-square test of independence for country distribution yields $\chi^2 = 34.94$, $df = 9$, $p < 0.001$, confirming that after 2020 the center of gravity shifted toward a few key hubs.

Additionally, cross-sectional breakdowns linking method classes with safety axes and methodological approaches reinforce the answers to the statistical questions. In the method $\times$ safety topic matrix, machine learning dominates accident-related works, 31 of 43, 72.09%, while neural networks dominate track-related works, 29 of 46, 63.04%. Computer vision has its highest relative share in cross-sectional railway safety studies, 8 of 26, 30.77%. The relationship between method class and safety problem type is statistically significant, $\chi^2 = 9.8$, $df = 4$, $p = 0.04$, confirming that tool selection is correlated with task nature. In the relation of methods to research approach, the dominance of experiments is shared across all classes, but strongest for neural networks, where 87.76% of publications contain an experimental component. Differences in this dimension are at the margin of significance, $\chi^2 = 12.13$, $df = 6$, $p = 0.06$, suggesting that further growth in volume may soon tip the balance toward significance and firmly consolidate the empirical profile of the field.

The analyzed corpus of publications indicates a clear acceleration of interest in the applications of artificial intelligence in railway safety. In 2016–2020, a total of 24 works were identified, while in 2021–2025 there were 71, which is 95 items in the entire period. Cross-sectional lists (document types, method classes, safety axes, and research approaches) are presented in Table 3. The average number of publications per year increased from 4.8 in the first sub-period to 14.2 in the second, which corresponds to an approximate average annual growth rate of 24%. The increase in the volume of research is accompanied by

a thematic and methodological shift, which is confirmed by both statistical summaries and bibliometrics.

In the thematic dimension, we are observing a shift from the dominance of works focused on railway accidents to the growing burden of research on infrastructure, in particular, on track diagnostics (railroad tracks). In 2016–2020, publications in the area of events dominated, while after 2020 it was track-centric works that began to constitute the largest percentage of new items. The co-occurrence maps of keywords (Figures 3 and 4) reflect this evolution: The core concepts related to computer vision and track inspection are densifying, and the categories “railway safety” and “deep neural networks” act as links between the image engineering stream and the event modeling stream. Coinciding with these observations, the methodological layer shows an increase in the share of network solutions (NN), which take over detection and segmentation tasks, while maintaining the role of classic ML techniques where transparency and computational efficiency are a priority.

A geographical perspective indicates a significant diversity in the contribution of countries to the development of the studied area. To synthetically describe the degree of concentration without repeating the distribution of numbers, we introduce an additional derivative measure, the Herfindahl–Hirschman index (HHI), and several scale indicators. These values are summarized in Table 5. HHI was calculated as the sum of the squares of the shares of individual countries in the entire corpus (shares in parts of unity), based on the data from Table 4. To facilitate comparisons, we also provide a value scaled to the range of 0–10,000, commonly used in merger analyses. In addition, we report the total share of the three largest centers and the sample size, which allows us to interpret the level of concentration in the context of the scale of the phenomenon.

Table 5. Concentration and scale indicators.

Indicator	Value	Explanation
HHI (0–1)	0.2524	Sum of squares of countries' shares in the corpus; a measure of geographical concentration.
HHI (0–10,000)	2524	Conversion of HHI to a scale of 0–10,000 used in cross-disciplinary analyses.
Share of the three largest countries (%)	63.16	Cumulative participation of three major research centers.
Number of publications (n)	95	The total sample size during the analyzed period.

An HHI value of approx. 0.25 indicates a high degree of concentration of research activity: a significant part of scientific production comes from a relatively narrow group of countries. At the same time, the share of the three largest centers exceeding 63% indicates that it is these centers that shape the profile of methods and topics to the greatest extent, and, importantly, have the resources necessary for tests in conditions similar to operational conditions (access to data, sensory and computing infrastructure). From the point of view of interpreting thematic trends, such a distribution may be conducive to a rapid transition from experiments to implementations in dominant jurisdictions, but at the same time raises the risk of insufficient representation of different operating conditions (different signaling standards, climate, demand profile). In practice, this means that further reducing model uncertainty requires systematic expansion of the database to include cases from previously underrepresented regions and multi-center comparisons conducted according to unified protocols.

The significance of Table 5 is not limited to the mere measurement of concentration. In combination with the dynamics of the volume of publications (Table 3), these indicators allow us to distinguish two complementary phases of the development of the field after 2020. The first phase is dominated by organic growth in the leading countries, which leads to the rapid maturation of technological components: lightweight near-real-time event and

defect recognition architectures and multimodal fusion (RGB/IR/radar/LiDAR). In the second phase, it becomes crucial to disperse competencies, create common benchmarks, and increase the share of research conducted in conditions different from those that determined early implementation successes. A high level of HHI with an increasing number of publications means that right now a relatively small increase in peripheral center activity may bring disproportionately large cognitive benefits: better calibration of uncertainty, greater diversity of scenarios, and consequently greater transferability of models.

Understood in this way, the structure of the field also helps to explain the tightening of the bonds between the “railroad tracks” and “computer vision” nodes observed in bibliometric maps. The countries with the largest share have a dense layer of IoT on the lines and rolling stock, which makes it possible to build image and signal bodies with a high variety of early and difficult cases (night, fog, obstruction). The increase in the availability of this data is conducive to the transition from event analytics to prevention and early detection of degradation, which directly explains the shift in the distribution of topics after 2020. At the same time, the continued importance of classical ML techniques in event analysis, clearly visible in the structure of the methods, indicates the need to combine approaches: perceptual components based on deep networks should be embedded in broader decision-making chains that use risk models or prediction of the frequency of exposure-scaled events.

From the point of view of practice, the results of the statistical section lead to two operational conclusions. Firstly, the rapid increase in the volume of publications, coinciding with technological maturation, creates the conditions for the standardization of evaluation protocols: the same appeal files, common definitions of quality and response time indicators, reporting uncertainty, and stability of operations under extreme conditions. Second, the level of concentration measured by HHI suggests that the greatest economies of scale in model improvement can be achieved by deliberately expanding cross-border collaboration to include data from outside the dominant centers in training and validation corpus. In practice, this means a better representation of the diversity of operating environments and a more reliable assessment of the portability of solutions.

In summary, the growth rate, thematic evolution, and geographical structure observed after 2020 form a coherent picture of a mature, rapidly scaling area of research. Additional indicators from Table 5 complete this picture by assessing the extent to which development is driven by resource concentration and by competence diffusion. The high but not maximal level of HHI and the clear advantage of the three most active centers indicate that the potential for further improvements, both cognitive and implementation, today lies primarily in the expansion of the assessment database and practices to new operational contexts, while leveraging mature AI components and IoT infrastructure.

5. Discussion

The safety of rail transport remains one of the key challenges of modern transport systems. According to data from the European Railway Agency (ERA), 1567 serious incidents were recorded in 2023, in which 841 people died and 569 were seriously injured. The largest share of casualties was made by intrusions of people on the tracks (58.4%) and incidents at rail-road crossings (26.6%). The annual costs of operational disruptions and safety-related maintenance activities exceed €1 billion. These indicators highlight the growing need for advanced analytical and detection tools to improve rail safety. Technologies based on machine learning, neural networks, and computer vision play an increasingly important role in infrastructure monitoring, hazard identification, and decision support in railway safety systems.

The presented results should be interpreted within the limits of a clearly defined scope of work. The article is a systematic review with bibliometrics and concerns the applications of AI in three safety axes, with an emphasis on track diagnostics and perceptual and operational decision support solutions. We do not knowingly conduct an analysis of events or accidents; it is a separate research area, although closely related to the discussed topic. The corpus and classifications used are described in Section 2, and the quantitative conclusions are based on the aggregates reported in the statistics chapter (cf. Tables 3 and 4, Figures 3 and 4). The limitations are mainly due to the heterogeneity of reported quality metrics and differences in experimental settings (datasets, environmental conditions, hardware configurations), which makes direct comparisons between works difficult. In addition, the geographical concentration shown in the analysis (HHI) means that the conclusions predominantly reflect practices and data from a few dominant centers, and the generalization of results to other operational contexts requires caution.

The practical and research implications follow the same logic. In the application layer, it is crucial to further organize the evaluation protocols (consistent metric definitions, reporting stability and latency across cross-sections of conditions), as well as to extend comparisons to multicenter and multimodal scenarios, compatible with the infrastructure of available sensors. In the development layer, the priority remains the stable operation of methods in the “near real-time” mode and integration with maintenance practices and human supervision, which is consistent with the shift towards track-centric solutions observed after 2020 and the increase in the importance of deep networks. Despite the lack of analysis of events in this paper, the presented results indirectly show that shortening the time of anomaly detection and reducing omissions may limit the window of exposure to operational risk; this is facilitated by both the maturity of the computing components at the edge and the densification of the sensor layer. Further progress therefore depends primarily on the quality of common benchmarks, transparency of reporting, and controlled diffusion of solutions outside the dominant centers, which will increase the transferability of results and the pace of their adoption in practice.

In summary, the quantitative and qualitative analysis indicates clear maturation of the field after 2020. The number of publications increased from 24 to 71, while overall proportions across the main thematic axes and method classes remained broadly stable, with a distinct shift toward neural networks and track infrastructure diagnostics. Journal publications dominate the corpus, suggesting stronger methodological rigor and more mature field studies. On the methods side, representation-based approaches are gaining ground, particularly CNN and LSTM, and the maintenance and track-inspection stream is strengthening, with confirmed platform and wayside deployments. These vectors of change align with the safety pressures reported by ERA, UIC, and FRA, and with the availability of onboard, wayside, and fiber-optic data streams that enable continuous monitoring and condition-based decisions [20,48,49,62,68,112].

In methods, computer vision and neural networks play a key role, having taken over detection, segmentation, and tracking tasks, especially in the inspection of track components, in recognizing hazards in the track zone and at level crossings, and in platform monitoring. YOLO and R-CNN families and their lightweight variants achieve high mAP at tens to hundreds of frames per second, including in infrared and night conditions, as confirmed by deployments with very low false alarm rates in operational systems [54,55,67,69,80,105]. In track geometry diagnostics and irregularity forecasting, sequential architectures such as TCN and LSTM, together with uncertainty-aware models, deliver confidence intervals useful for maintenance decisions [29,49,80]. RGB data are increasingly combined with IR and radar, and along rail corridors DAS fused with accelerometry and graph modeling raises detection effectiveness for loose fasteners and linear events to near-complete levels

in field tests [34,36,77]. In domains with limited labels, transfer learning, one-shot methods, and judicious generative augmentation yield sensible results, reducing annotation cost while maintaining high AUC and mAP for rare phenomena and defects [39,75,76,79,81].

Cross-cutting results also show a real coupling between method class and safety problem type. Railway accidents are more often addressed with classical ML and supervised learning supported by resampling, boosting, and ensembles, particularly in risk prediction at crossings and in consequence analysis using narrative reports and explainable methods [89,102]. Track infrastructure more frequently draws on neural networks and multimodal fusion, including detection of fastener faults, missing elements, and ballast degradation, as well as estimation of track quality indices from onboard signals and LiDAR [43,69–72,77]. Cross-sectional applications, covering safety culture, auditable processes, and standardization, benefit from both CV and ML, including knowledge-acquisition tools that organize hazard scenarios and facilitate formal verification, improving transparency and reproducibility of decisions [94,95].

First, three task families dominate, scene perception and component inspection in CV, estimation and forecasting of geometry and condition indices from vehicle and distributed sensor data, and risk and safety process analytics using narrative sources and incident databases. The strongest evidence concerns inspection and perception, where high mAP and mIoU at high processing speeds are reported, and track quality forecasting with uncertainty bounds. Gaps include the absence of standardized benchmarks for rare events, limited transferability across lines and operators, and inconsistent reporting of metrics and evaluation protocols [43,52,68,69,91]. Second, in data and sensors, video is most frequently used, the role of IR and radar is growing, LiDAR supports inventory and spatial perception, onboard accelerometry and DAS reinforce diagnostics and corridor-level monitoring, and the best field performance comes from combining complementary modalities with lightweight segmentation and detection architectures, consistent with operational examples from platform and crossing systems [54–56,69,83]. Third, real-time requirements are increasingly met, with many applications reporting 80–100 FPS while maintaining high quality. Maturity is further supported by uncertainty-aware regression for track geometry and condition indices. Integration with maintenance practice is best documented in vision-based inspection and degradation forecasting, and weaker for extremely rare events, where class imbalance compensation and ensemble solutions dominate [26,43,102,114].

Fourth, thematically, volumes are increasing across all axes, but after 2020 the emphasis shifts from accidents toward track infrastructure, consistent with the feasibility of automated perception and inspection at the edge and with the growing availability of LiDAR and DAS data. Proportions among the main axes remain relatively stable in the χ^2 sense; the change concerns volume and emphasis, as confirmed by counts and shares, while statistical significance is observed in the geographical distribution, where Chinese institutions dominate post-2020 [56,83]. Fifth, the method structure shifts toward neural networks, especially in detection and segmentation tasks, with a stable, though smaller, share of computer vision as a standalone category. Cross-analysis indicates a significant association between method class and safety problem type, reinforcing the thesis that tool choice is sensitive to task nature and available modalities [34,54,55,57,63,67,69,79,80,93,103,105]. Sixth, in publication forms, the share of journal articles is rising, typically accompanying a transition from prototypes and pilot studies to fully evaluated work, while in geography the field is concentrating, enabling rapid deployments and large-scale datasets in a few leading countries [56,83,93].

The results confirm that lightweight detection and segmentation architectures can operate in near real time while maintaining high quality, paving the way for broad wayside and onboard deployments. RGB-IR-radar fusion improves robustness under extreme

conditions, DAS plus accelerometry extends monitoring reach without additional field power, and predictive uncertainty enables forecasts to be coupled with safety margins in maintenance planning [34,41,55,69,79]. For geometry prediction models, combining learning with physical knowledge is advisable, since hybrids facilitate generalization and dialogue with certification practice [26,30,49]. In safety processes, knowledge-acquisition tools are useful to close the loop between observation, decision, and audit [79,94,110].

This review is based on Scopus records and English-language literature, which may omit part of the output indexed elsewhere and in other languages. The EXACTKEYWORD choice increases precision but risks missing publications using alternative terminology. Metric and dataset heterogeneity limits the feasibility of formal meta-analysis; some classifications required expert judgment, and reporting of uncertainty and computational budgets is sometimes inconsistent [43,52,68,76,91]. The most important tasks ahead are standardization of benchmarks, adoption of common evaluation protocols, further development of domain-robust multimodal fusion, and regular reporting of uncertainty and processing latency, so as to facilitate transfer of results into maintenance practice and regulatory processes.

Development prospects, demand, artificial intelligence, and the Internet of Things act as enablers of progress. In addition to the technical aspects, structural factors are important for further improving safety performance. Firstly, there is a rapid development of this research area, which is reflected in the increase in the number of scientific publications from 24 in 2016–2020 to 71 in 2021–2025, reflecting increasing research and implementation activity and an increasingly broad evidence base for practice. Second, the gradual maturation of AI methods, in particular, high-frequency and lightweight detection and segmentation algorithms, as well as uncertainty-sensitive forecasting methods validated in real-world operational applications, leads to reduced latency and improved decision quality in safety-critical loops. Third, the increasing saturation of transport infrastructure and rolling stock with IoT elements, including CCTV systems with infrared and radar sensors, LiDAR inventories, distributed acoustic sensors and on-board accelerometers, increases the spatial coverage and diversity of data sources, enabling reliable multimodal fusion and continuous monitoring at the edge level.

Together, these trends, including literature and deployment scale, algorithmic maturity, and sensor availability, contribute to increasing detection reliability, reduced response times, and stabilizing uncertainty calibration, which in turn can lead to a measurable reduction in incidents and a more resilient operation of rail systems.

Although we do not conduct a direct analysis of accidents in this paper, the presented quantitative results and a review of the literature suggest that the continuation of current trends may contribute to their reduction. After 2020, we can simultaneously observe a strong increase in research activity (from 24 to 71 publications in the second sub-period; 95 in total), a clear thematic shift towards track diagnostics (the share of track-centric work increased from 37.50% to 52.11%), and a change in the profile of methods in favor of neural networks (from 37.50% to 56.34%). The literature cited in the article demonstrated the operation of models with “tens of FPS”, with low false alarm and omission rates under near-operational conditions, as well as the benefits of modal fusion (CCTV/IR/radar/DAS), increasing detection stability in night and severe weather conditions [53,54,56,62,82]. A combination of these facts indicates that the reduction in the time of detection and localization of defects and the reduction in the percentage of omissions actually narrow the “window of exposure” for operational risk; as a consequence, we can expect a decrease in the frequency of events preceded by early warning signals and stabilization of risk indicators in areas dependent on the quality of recognition and the speed of response of the system.

6. Conclusions

The synthetic picture of the literature highlights three complementary axes of development: applications of artificial intelligence in event prevention and environmental perception, diagnostics and maintenance of track infrastructure, and systemic safety with emphasis on auditability and integration of domain knowledge into models. Within this triad, computer vision and sensor fusion solutions are the most established, providing effective perception of objects and intrusions under night-time and low-visibility conditions, surface inspections with accuracies exceeding 98 percent, and geometry inventories from point clouds with completeness of 97.1 percent and correctness of 99.7 percent. Machine learning and neural networks reinforce predictive tasks, from track quality index estimation with confidence intervals to surrogate models reducing computational cost in reliability, while in the process layer knowledge acquisition and formal verification tools strengthen traceability of decisions and integration with safety assessment practices. These emphases are consistent with the task–data mapping in Tables 1 and 2, where the uniform column structure links problem class to data type and model family, and then relates algorithmic quality to operational feasibility and risk management.

The quantitative layer confirms that after 2020 the field accelerated markedly. Between 2016 and 2020, 24 publications were identified, while between 2021 and 2025 there were 71, giving a total of 95 works. Journal articles dominate, with 60.00 percent, while conference papers remain stable at 36.84 percent. In method classes, machine learning leads with 56.84 percent of the corpus, alongside a rising share of neural networks, 51.58 percent, while computer vision maintains a smaller but steady share, 15.79 percent. Thematically, track infrastructure is increasingly emphasized, 48.42 percent, with railway accidents still substantial at 45.26 percent, and the cross-sectional category railway safety covering 27.37 percent. Publication activity is geographically concentrated, with China accounting for 43.16 percent of all works, and the chi-square test for country distribution between sub-periods confirms a significant shift, $p < 0.001$. The relationship between method class and safety problem type is statistically significant, $\chi^2 = 9.8$, $df = 4$, $p = 0.04$, meaning that different tasks favor different tools: neural models are more often linked with diagnostics and track maintenance, while classical ML approaches are more often applied in accident analysis.

Qualitative interpretation of these results reinforces methodological conclusions. Lightweight segmentation and detection architectures can combine high mAP and mIoU with near-real-time performance, enabling closure of the loop from prediction to decision, particularly when models provide outputs together with information on uncertainty and error costs. In regression tasks, inclusion of uncertainty improves the reliability of maintenance schedules, while in reliability analyses surrogate models of track surfaces and structures enable exploration of design variants without costly full-scale simulations. Tables 1 and 2 strengthen these observations by uniformly showing which data modalities are most productive in given tasks: video with radar and infrared for platform and crossing safety, DAS with accelerometry for fastener diagnostics and linear event tracking, LiDAR for geometry inventory, and inertial signals from vehicles for track geometry estimation. This facilitates sensor chain design and edge deployment.

Future research directions follow directly from the gaps and limitations noted in the material: standardization of datasets and metrics and open benchmarks covering rare events, domain-robust and annotation-efficient techniques including few-shot learning, transfer, and continuous learning on streams, multimodal fusion designed for edge implementations, integration of models with physical knowledge and digital twins for improved interpretability and transferability, and embedded uncertainty quantification with expert-in-the-loop verification for compliance with audit requirements. Methodologically, it is important to expand queries to additional databases and languages, report inter-rater

agreement, and replicate classification practices, which will strengthen the statistical layer and facilitate comparability in future review editions. From an implementation perspective, the most promising trajectories are iterative, starting with pilots at critical points and test corridors, balancing technical complexity, cost, and regulatory acceptance, and gradually expanding the scope of applications across the network.

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