sensors

Systematic review

From Detection to Prediction: A Systematic Review of Intelligent Fault Detection in Industrial Conveyor Belt Systems

Mounia Achouch [1,] *, Rizck Dhouib[2], Romain Beaudouin [2], Solyvan Ear Kong[2], Christopher Mitride[2] and Eric Sénéchal[2]

[1] Centre de recherche et d'innovation en intelligence énergétique CR2ie, 175 rue de la Vérendrye, Sept-Îles, QC G4R 5B7, Canada
[2] Institut Technologique de Maintenance Industrielle ITMI, 175 rue de la Vérendrye, Sept-Îles, QC G4R 5B7, Canada
* Correspondence: Mounia.Achouch@cr2ie.com

Highlights

What are the main findings?

- Intelligent conveyor belt fault detection increasingly relies on deep learning, with CNN-based vision models becoming the dominant analytical approach.
- Effective fault detection depends on matching the sensing and analytical method to the specific fault mechanism and deployment conditions.
- Existing diagnostic approaches remain concentrated on fault detection rather than prediction.

What are the implications of the main findings?

- Development of prognosis-oriented and physics-informed modeling frameworks may improve the predictive value and transferability of future diagnostic systems.
- Integration of principled multi-sensor fusion with calibrated, explainable inference represents a promising direction toward genuinely predictive and trustworthy conveyor belt monitoring.

Abstract

Industrial conveyor belt systems are critical infrastructure where unexpected failures cause major downtime, safety hazards, and economic losses, motivating growing research on AI-based fault detection. However, previous reviews have generally focused on individual sensing technologies or considered conveyor systems within broader mining applications, with limited attention to the extent to which current approaches support predictive, industrial-scale deployment. Following PRISMA 2020 guidelines, this review examines intelligent fault detection in industrial conveyor belt systems, with particular attention to sensing technologies, AI-based analytical methods, and deployment feasibility. The analysis considers the main fault types reported in the literature and the sensors and algorithms used for their detection. Deep learning was the dominant analytical approach, with CNN-based architectures such as YOLO, ResNet, and U-Net widely used for vision-based applications, while LSTM and GRU models were more commonly applied to acoustic and vibration signals. Vision/camera sensing accounted for 42.7% of studies, and mining represented 76.0% of applications. Despite substantial progress in automated fault detection, most studies remain focused on identifying existing faults rather than

Academic Editor: Firstname Lastname

Received: date
Revised: date
Accepted: date
Published: date

Citation: To be added by editorial staff during production.

anticipating future degradation. Remaining-useful-life estimation was absent, while physics-informed modeling, multi-sensor fusion, domain adaptation, calibrated uncertainty, and explainability were each reported in no more than one study. Future advances should therefore place greater emphasis on prognosis, cross-site generalization, uncertainty-aware inference, explainable models, and principled sensor fusion to support more reliable and transferable predictive maintenance systems.

Keywords: Conveyor systems; Predictive maintenance; Anomaly detection; Multi-sensor fusion; Deep learning; Machine learning; Computer vision; Edge computing; Industrial IoT

1. Introduction

Conveyor systems are essential for many industries, such as mining, ports, and manufacturing, for transporting goods and products safely and effectively [1–3]. For instance, in mining, conveyor belts support continuous bulk material handling in harsh environments, motivating research on early damage/anomaly detection and safety-oriented inspection [4–6]. Moreover, for the improvement of productivity and minimization of interruption risks for ports and industries, the automated monitoring of conveyor belt and idler conditions has been proposed [7–10]. However, if a conveyor system fails, it has significant consequences, as a small failure may disturb the entire system, leading to unexpected downtime and financial losses [1,3,11,12]. This is especially critical in continuous-flow operations where even short interruptions can generate downstream issues across production and supply chains [1,13].

Traditional maintenance of conveyor systems has mainly focused on manual or periodic inspection to identify any signs of wear or failure in components such as belts and idlers [6,14–16]. Although these approaches are simple, they are prone to subjectivity and may miss early-stage defects, particularly under challenging field conditions [4,5,17,18]. Many industries use schedule-driven interventions for different operations to avoid failure in a conveyor system, which can reduce catastrophic events but may increase unnecessary maintenance actions and operational costs [3,11]. Conventional sensing has been widely used to improve fault detection: vibration monitoring has been applied to characterize belt/roller–idler dynamics and diagnose rotating components [19–21], while thermal/infrared approaches detect abnormal heating patterns associated with degradation, mis-rotation, or localized resistance [16,22,23]. Increasingly, these approaches are being augmented - or replaced - by intelligent, data-driven systems to improve diagnostic accuracy and automation[1,13,24].

Under Industry 4.0, the trend has been moving towards intelligent maintenance of the conveyor systems using data-driven approaches [1,24,25]. Anomaly and fault detection in conveyor systems is becoming earlier, faster, and increasingly automated by integrating artificial intelligence (AI), Industrial Internet of Things (IIoT) connectivity, and edge/cloud computing as modern solutions [24,26,27]. Also, by the emergence of smart sensing, the operational parameters of the conveyor systems are continuously being collected, thereby facilitating the acquisition of high-quality operational data (e.g., vibration/thermal/telemetry) [21,23,25]. These data can be processed locally (on-device/edge) or via connected architectures using machine learning and deep learning models for anomaly detection and predictive diagnostics [24,27,28]. In parallel, digital-twin approaches have been proposed to create a virtual replica of the conveyor system for testing, prediction, and maintenance strategy evaluation in a low-risk setting [3]. These intelligent systems aim to improve productivity, reduce downtime and costs, and support real-time decision-making and longer-term maintenance planning [1,3,11].

Although significant improvements have been made in the detection of anomalies that occur in conveyor systems, the maintenance process remains inadequate for most modern industrial needs. This is because manual inspection processes are time-consuming, irregular, and difficult to scale [17,22,29,30]. Additionally, the efficiency of intelligent inspection might be reduced under harsh conditions, such as those with poor lighting, noise, and clutter, which often corrupt the signal or affect the image quality [4,6,18]. Also, models developed in one setup may not be adapted to other sites or belt types, emphasizing the issue of transferability [24,25,31]. Real-time processing can also be constrained by edge hardware limits (e.g., compute, memory, energy/latency) [24,25]. Finally, limited labeled fault data and the need for standardized datasets remain persistent barriers for robust training and validation [5,30,32]. These challenges reinforce the need for intelligent, flexible maintenance systems that remain robust in dynamic industrial conditions.

Several reviews have examined intelligent conveyor monitoring, but their scope remains relatively narrow or addresses conveyor systems only as part of a broader asset class. For instance, Rzeszowska et al. [33] reviewed sensing and signal-based approaches for conveyor belt damage detection but did not include a formal assessment of methodological quality or deployment characteristics. Rios-Colque et al. [34] focused specifically on computer-vision-based techniques for conveyor belt monitoring, providing a detailed bibliometric and thematic analysis of vision methods but excluding acoustic, vibration, thermal, and magnetic modalities by design. Rojas et al. [35] examined AI-based predictive maintenance across several mining assets, with limited focus on conveyor systems. None of these reviews included a structured risk-of-bias assessment or considered performance, sensing, deployment, and economic feasibility together. The present review addresses these gaps by synthesizing evidence across sensing modalities specifically for conveyor systems and, to our knowledge, is the first in this field to combine a PRISMA 2020-guided review [36], with a structured assessment of methodological quality. Studies published between 2010 and 2025 are evaluated in terms of sensor technologies, machine-learning methods, IIoT connectivity, edge-cloud architectures, and deployment feasibility. This broader assessment also helps identify the methodological and technological developments required to move conveyor monitoring from fault detection toward reliable predictive maintenance within Industry 4.0 environments.

2. Materials and Methods

2.1 Review design and reporting framework

We conducted this review following the PRISMA 2020 guidelines [36], given that this methodology is widely recognized for its rigorous and structured transparent approach. It allows a depth comprehensive assessment of available literature, therefore, identifying the knowledge gaps and thematic areas that require further investigation. This review addresses three main research questions: Q1) What are the most studied components of the conveyor system and types of anomalies in smart maintenance re-search, and what types of sensors are used for this purpose? Q2) What are the most promising artificial intelligence or machine learning techniques for achieving good trade-offs between detection accuracy, speed, and deployment feasibility (edge vs cloud)? Q3) What are the main knowledge gaps to be addressed to improve smart maintenance of conveyor systems?

Regarding the eligibility criteria, only peer-reviewed articles published in English between 2010 and 2025 were included. Also, they must focus on research conducted on industrial conveyor systems (belt and other components such as idlers and rollers). Additionally, they had to investigate anomaly detection, fault diagnosis, condition monitoring, or predictive maintenance using sensor data analyzed with machine learning, deep learning, computer vision, signal processing, or a combination of these methods. We excluded review articles, conference papers, and other non-peer-reviewed publications, as well as studies unrelated to industrial conveyor systems. Conceptual studies without empirical evaluation and approaches based only on manual inspection or simple threshold rules were also excluded. Papers that did not provide enough methodological or quantitative information to address Q1–Q3 were not retained. Methodological quality was not used to determine eligibility, with all studies meeting the inclusion criteria being kept and the appraisal results being considered when interpreting the findings. The reasons for exclusion at the full-text stage were summarized in the PRISMA flow diagram (Figure 1).

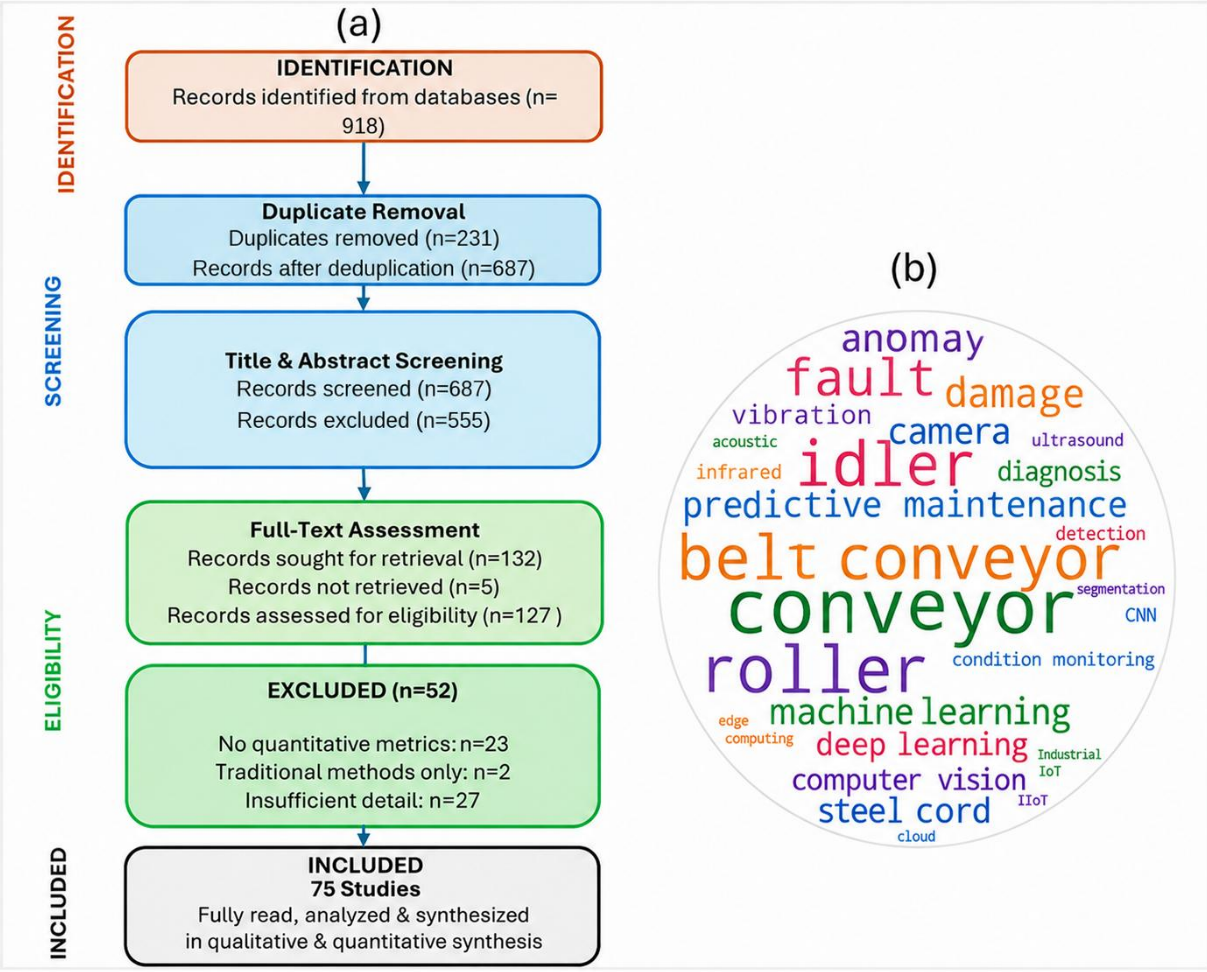

Figure 1. a) PRISMA 2020 flow diagram of the study selection process. The diagram illustrates systematic identification, screening, and eligibility assessment. A total of 75 peer-reviewed studies were included in the qualitative and quantitative synthesis. b) The keyword map of the review scope, the word size indicates the relative emphasis of each keyword in the review framework.

A comprehensive literature search was performed in applied-science bibliographic databases including IEEE Xplore, Scopus, ACM digital Library and MDPI (Table S1). The final search was completed in May 2026. The search strategy was based on combinations of keywords related to four main themes using Boolean operations (AND and OR) : (1) conveyor system: conveyor, belt conveyor, idler, roller, pulley, steel cord; (2) monitoring task: anomaly, fault, damage, condition monitoring, diagnosis, predictive maintenance; (3) sensing technology: vision/camera, thermal/infrared, acoustic/ultrasound, vibration, magnetic/inductive; and (4) computation and deployment: machine learning, deep learning, computer vision, CNN, detection, segmentation, edge computing, Industrial IoT, and cloud.

A representative search query was formulated by combining terms from the four thematic groups: ("conveyor" OR "conveyor belt" OR "idler" OR "roller" OR "steel cord") AND ("fault" OR "anomaly" OR "damage" OR "condition monitoring" OR "diagnosis" OR "predictive maintenance") AND ("vision" OR "camera" OR "thermal" OR "infrared" OR "acoustic" OR "ultrasound" OR "vibration" OR "magnetic" OR "inductive") AND ("machine learning" OR "deep learning" OR "computer vision" OR "segmentation" OR "edge computing" OR "Industrial IoT" OR "IIoT" OR "cloud"). The query was adapted to the syntax of each information source. The complete source-specific search strategies are provided in Supplementary Table. 1.

All records identified through the search were imported into Zotero, where du-plicate entries were removed. Study selection was then carried out in two stages. Titles and abstracts were first screened for relevance to industrial conveyor systems and intelligent maintenance. The remaining studies were assessed in full text against the eligibility criteria (Table 1, Figure 1). The screening process involved Two independent authors, and any differences were resolved out in discussions. Data from the included studies were extracted using a standardized form. The extracted information covered study characteristics, the conveyor component or fault investigated, sensing modality, analytical method, deployment characteristics, reported performance, external validation, reproducibility, and cost reporting (Table 1).

The researchers did not prospectively register this systematic review in a review registry, and they did not prepare a formal review protocol prior to conducting this study. The completed PRISMA 2020 checklist is provided in the supplementary materials (Table S2).

Table 1. Summary of the structured data extraction categories applied to all 75 included studies following PRISMA 2020 guidelines.

Category	Extracted Data
Study Descriptors	Year, venue, industrial sector, laboratory vs field context
Targets (Q1)	Conveyor component(s) and anomaly type(s) (e.g., idlers/rollers, belt surface damage, steel-cord defects, mistracking, foreign objects, thermal anomalies)
Sensing (Q2)	Modality (vision/camera, thermal/IR, acoustic/ultrasound, vibration, magnetic/inductive, pressure/force, and multi-sensor fusion)
Algorithms (Q2)	Approach family (traditional ML, deep learning, classical computer vision, hybrid), task formulation (classification/detection/segmentation/regression), and training (supervised/unsupervised)
Deployment (Q2)	Local, edge, cloud, hybrid, or not-reported processing; real-time constraints; and reported compute/hardware information
Performance and Feasibility (Q2)	Reported metrics (e.g., accuracy, precision, recall, F1, mAP, AUC, error rate), latency when available, and deployment constraints (lighting, dust, noise, occlusion, speed)
Advanced Modeling Techniques (Q3)	Presence or absence of remaining-useful-life/prognosis modeling, physics-informed modeling, principled multi-sensor fusion (versus feature-level concatenation), domain adaptation or transfer learning for cross-site generalization, calibrated uncertainty quantification, post-hoc explainability (e.g., class-activation mapping), and digital-twin integration
Evidence Gaps (Q3)	Dataset availability, labeling strategy, reproducibility artifacts (code/data), external validation, statistical reporting (variance, repeated runs, confidence intervals), and cost reporting.

2.2. Assessment of methodological quality

Quality assessment was performed using an adapted checklist based on Joanna Briggs Institute (JBI) criteria for appraisal of evidence [37]. To our knowledge, no JBI appraisal tool has been developed specifically for this type of engineering and AI validation study, and formal risk-of-bias assessment has not yet been applied to conveyor-monitoring research. We therefore developed a tailored checklist for this review. The following ten domains were assessed: purpose of the study, design of the study, description of the data set, truth of the ground, methodology clarity, protocol of evaluation, baseline assessment, statistical method, external validation, and reproducibility. Each domain was rated as YES, PARTLY, NO, UNCLEAR, or NOT APPLICABLE (Table S3). YES was assigned 2 points, PARTLY 1 point, and NO or UNCLEAR 0 points. Domains rated NOT APPLICABLE were excluded from the score calculation. Then, each study was categorized into low, moderate, and high methodological concern according to the normalized score and rating of these key domains. The two co-authors assessed each study independently and agreed by consensus.

3. Quantitative Overview of Included Studies

3.1. Study Selection and Characteristics

According to the PRISMA 2020 protocol, the systematic search and screening process resulted in the identification of 75 empirical studies published between 2010 and 2025 that fulfilled the inclusion criteria for the review (Figure 2). The publication trend over the years shows an increased rate of research activities in intelligent conveyor belt monitoring. Most of the studies included were published recently, 92% appeared between 2019 and 2025, compared with only six studies between 2013 and 2018, and zero included study during the period 2010-2013. This pattern suggests that research on intelligent conveyor belt monitoring has expanded mainly over the past few years and remains a relatively young field.

From the application perspective, mining accounted for most of the literature, with 57 studies (76.0%), followed by general industrial applications with 11 studies (14.7%). Ports and shipping and manufacturing each accounted for three studies (4.0%), while one study (1.3%) addressed another application area (Figure 2B). The predominance of mining reflects the importance of conveyor systems in continuous material handling operations and the operational consequences associated with belt failures.

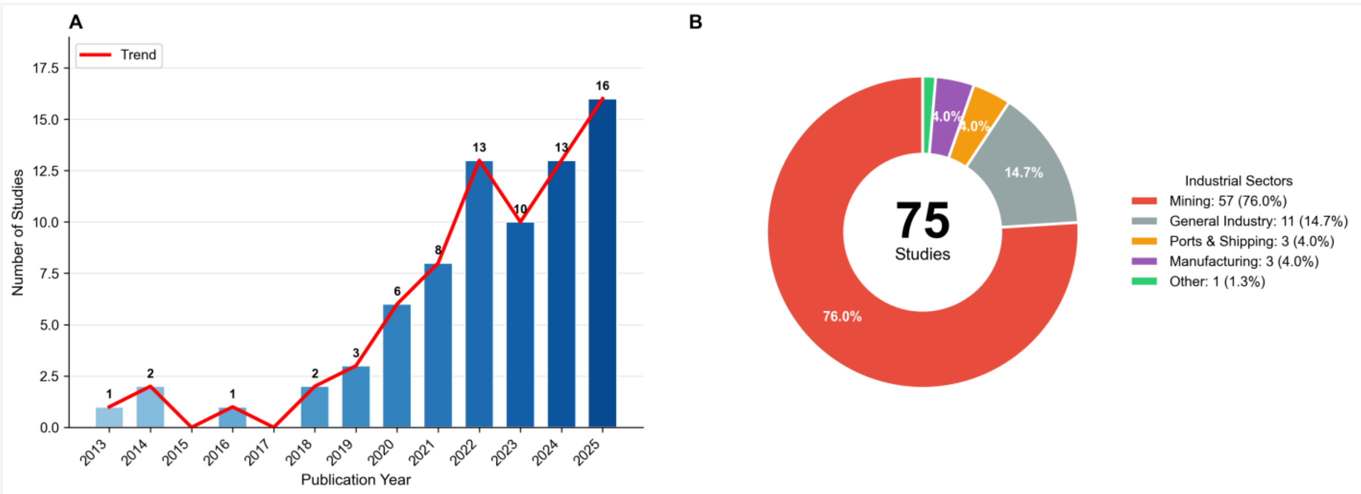

Figure 2. Study distribution by time and sector (n = 75). (A) Publications per year with fitted trend line. (B) Industrial application sector distribution (% of studies).

3.2. Methodological Quality and Appraisal Concerns

Most studies were classified as having a moderate risk of bias, accounting for 64.0% (n=48), followed by studies with a high risk of bias at 18.7% (n=14) and those with a low risk of bias at 17.3% (n=13) (Figure 3A). High concern classifications were associated with low normalized scores or failure in a critical domain, particularly ground-truth reliability or the evaluation protocol. These findings indicate that, although many studies reported clear objectives and methodological procedures, substantial weaknesses remain in validation, statistical robustness, and reproducibility.

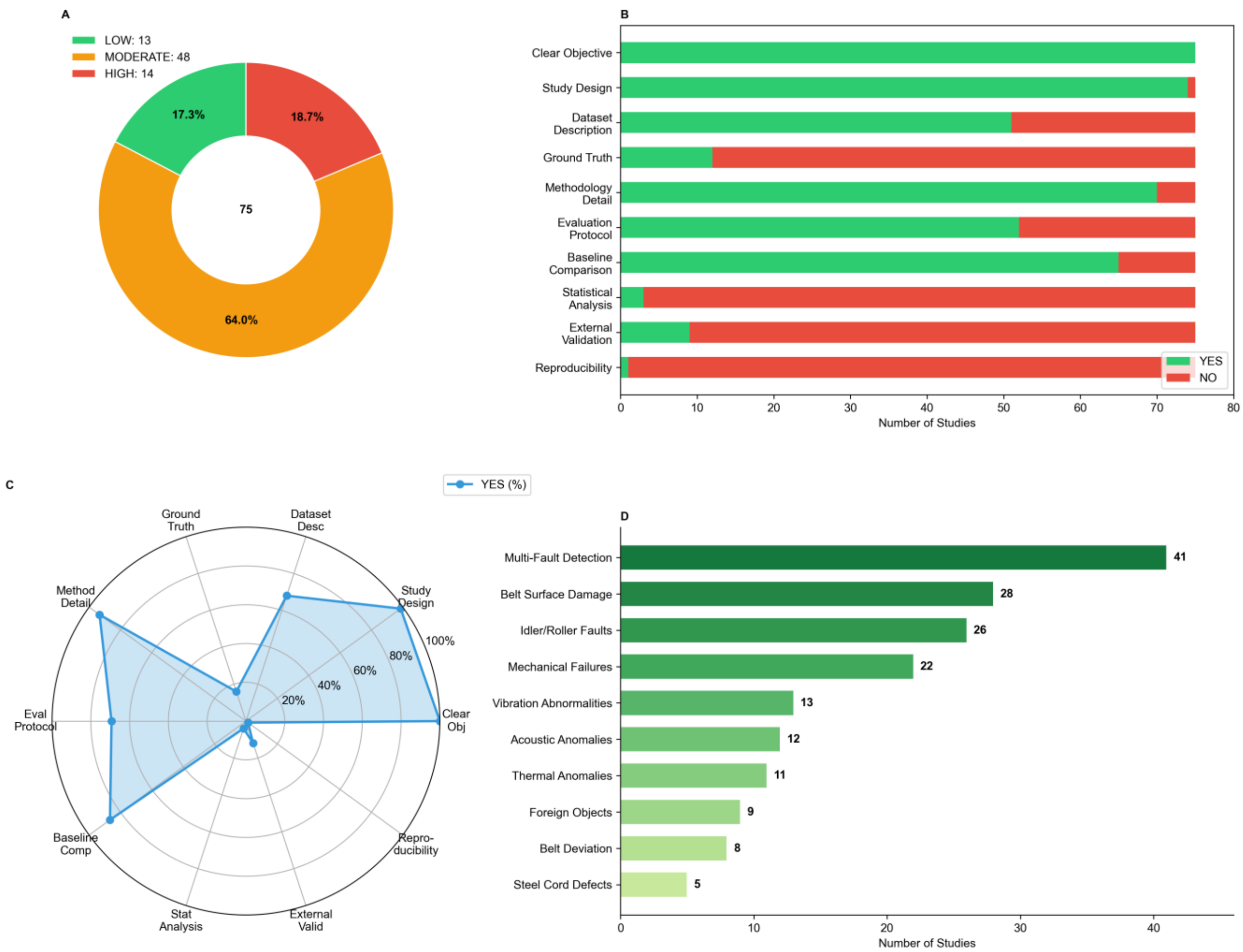

Figure 3. Methodological quality and anomaly coverage of included studies (n = 75). (A) Overall methodological appraisal concerns: low, 17.3% (n = 13); moderate, 64.0% (n = 48); and high, 18.7% (n = 14). (B) Criterion-level assessment showing studies that fully met each criterion (YES) versus criteria not fully met (PARTLY, NO, or UNCLEAR). (C) Radar-chart visualization of the percentage of studies fully meeting each criterion. (D) Frequency of anomaly types addressed in the reviewed literature; studies could report multiple anomaly categories. See Table S3 for definitions and typical causes.

Almost all 75 articles included in our analysis explicitly stated their research objective and presented an appropriate methodology (Figure 3B). In fact, an adequate methodology description was present in 70 articles (93.3%); 65 (86.7%) included comparisons with reference values; 52 (69.3%) described the evaluation protocol; and 51 (68.0%) correctly characterized the datasets. The main limitations in our included studies concerned the quality of the evidence and reproducibility. For instance, we found validation relative to the "ground truth" was demonstrated only in 12 articles (16.0%), while the statistical analysis was adequate in 3 studies (4.0%). Also, only Six articles (8.0%) used public datasets, and 3 (4.0%) provided source code (Figure 3C).

3.3. Validation and Deployment Characteristics

Distribution of validation environments

Most studies evaluate proposed methods under controlled conditions, with laboratory validation representing the most dominant category (n = 38, 50.7%; Figure 4A). Single-site validation is nearly as prevalent (n = 34, 45.3%), indicating that a significant portion of the evidence is based on actual facilities, but generally in a single operational context. In contrast, multi-site validation remains rare (n = 3, 4.0%). The limited frequency of multi-site validation is a major constraint for generalization, as conveyor systems vary considerably from one facility to another in terms of belt type, operating speeds, loading regimes, lighting, dust levels, and visual expression or defect signals. Therefore, performance reported from laboratory or single sites may not be reliably transferable to unknown conditions without recalibration, domain adaptation, or additional site-specific data collection.

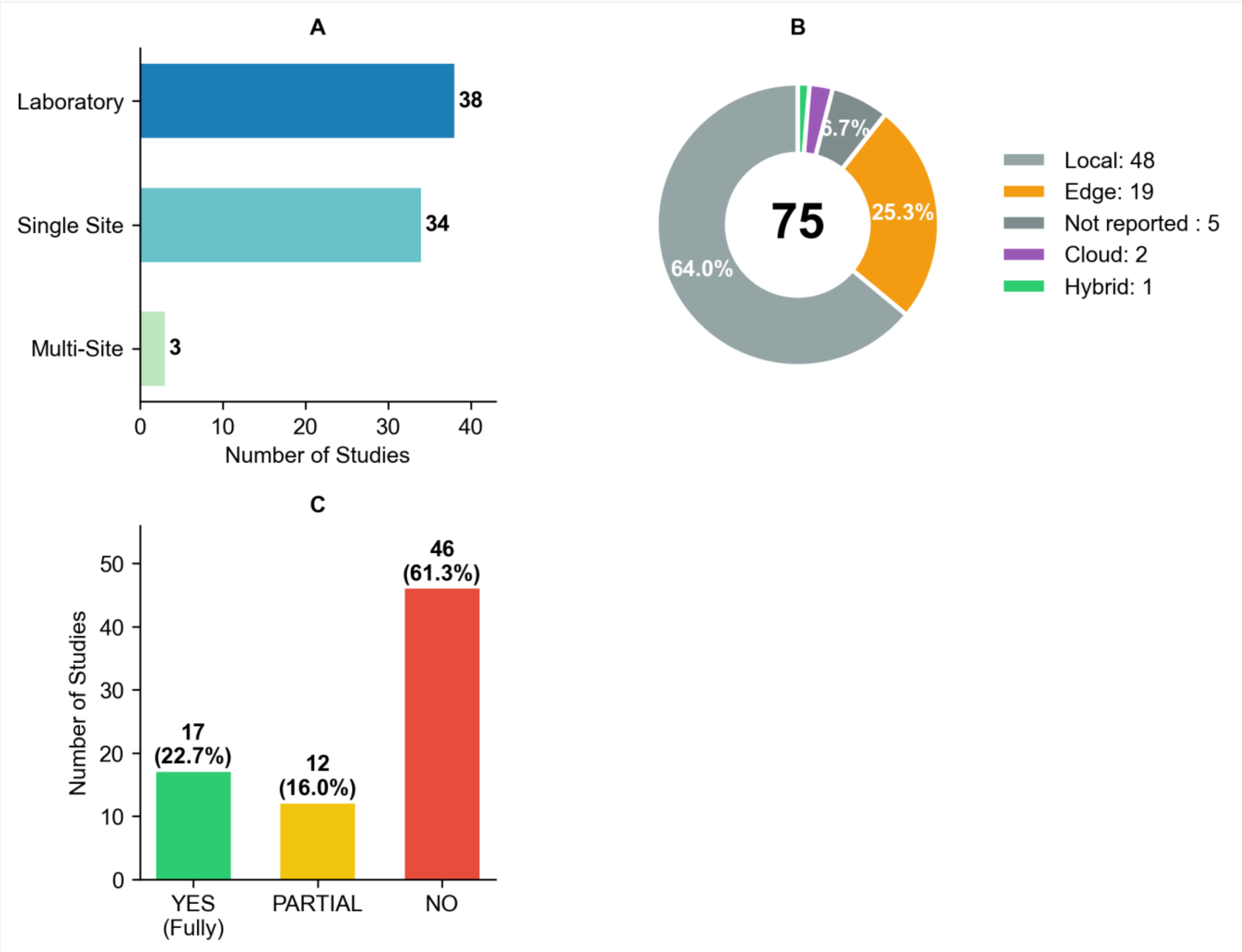

Figure 4. Validation setting, deployment architecture, and cost reporting across included studies (n = 75). (A) Validation environment used in empirical evaluation (laboratory, single site, multiple sites, or mixed laboratory + site). (B) Deployment type of the monitoring/analytics system (local/edge/cloud/hybrid, or not reported). (C) Reporting of implementation cost information, categorized as fully reported (YES), partially reported (PARTIAL), or not reported (NO).

Deployment architecture

Reported deployment targets show a strong preference for on-premises processing, with local deployment accounting for 64.0% of studies (n = 48; Figure 4B). Edge deployment is the second most common configuration (n = 19, 25.3%), reflecting growing emphasis on low-latency inference and reduced bandwidth requirements in industrial environments. Cloud-exclusive deployment is relatively rare (n = 2, 2.7%), and hybrid edge-cloud systems are rarely documented (n = 1, 1.3%), while deployment is not reported in 6.7% of the studies (n = 5). This pattern suggests that the field is already oriented toward on-site execution (local or edge), but the documentation of architectural details, particularly end-to-end data flow and integration with maintenance systems, remains inconsistent.

Implementation cost reporting

Economic feasibility is not sufficiently defined in the literature (Figure 4C). Only 38.7% of the studies include any form of cost discussion, of which 22.7% (n = 17) include comprehensive cost information and 16.0% (n = 12) include partial cost details. The majority of the studies (61.3%, n = 46) do not include any form of cost discussion. The decision to implement condition monitoring in an industrial setting relies on factors such as the cost of sensors, installation, hardware, and maintenance. When the cost or operational impact is discussed, the studies indicate that condition-based and predictive maintenance offer significant operational benefits, such as reduced unplanned downtime and improved scheduling efficiency, and thus advocate for the inclusion of economic reporting in future studies (e.g.,[1,38]).

4. Sensing Modalities, Fault Types, and Modeling Approaches

4.1. Common Anomalies in Conveyor Systems

The 75 studies included in the review covered a wide range of conveyor anomalies (Table 2), with multi-fault detection being the most common category (41 out of 75, or 54.7%) (Figure 3D). Belt-surface damage, including tears, cracks, scratches and wear, was examined in 28 studies (37.3%), followed by idler/roller faults in 26 (34.7%) and mechanical failures in 22 (29.3%). Vibration abnormalities were reported in 13 studies (17.3%), thermal anomalies in 11 studies (14.7%), and belt deviation or misalignment in eight studies (10.7%) (see Figure 3D). Literature on the subject indicates that sensor selection is typically based on the type of fault being monitored and the intended deployment conditions. This suggests that sensing strategies have evolved primarily through application-specific experience rather than from a common design framework.

Table 2.Conveyor-system anomalies, principal mechanisms, and representative included studies

Component	Anomaly / target	Typical mechanisms or causes	References
	Longitudinal tears / rips	Foreign-object penetration, sharp impacts, progressive fatigue, and local stress concentration.	[15,18,45,46]
Belt	Surface damage (cracks, scratches, wear, breakage)	Abrasive loading, repeated friction, impact by conveyed material, aging, and environmental exposure.	[5,7,31,39]
	Deviation / misalignment	Off-center loading, uneven belt tension, skewed or damaged rollers, and geometric misalignment.	[55-57,59]

Component	Anomaly / target	Typical mechanisms or causes	References
	Steel-cord defects (breakage, corrosion, internal damage)	Cyclic fatigue, corrosion, manufacturing defects, local stress concentration, and progressive internal damage.	[38,60,62,63]
	Splice degradation / failure	Poor splice condition, local material degradation, repeated tensile loading, fatigue, and damage propagation.	[11,12]
Idler / Roller	Bearing and rotation faults	Lubrication loss, contamination, fatigue, wear, misalignment, and progressive rotational resistance.	[2,13,20,21]
	Overheating / thermal anomalies	Friction, blocked or slow-rotating idlers, bearing degradation, and localized mechanical resistance.	[16,17,53,54]
	Abnormal vibration	Imbalance, misalignment, bearing wear, looseness, contamination, and load-dependent dynamic changes.	[19,20,21,48]
	Acoustic anomalies	Internal friction, impact, loosened components, bearing degradation, and abnormal rotational dynamics.	[2,4,13,64]
System	Chute blockage / transfer-point obstruction	Oversized material, accumulated debris, foreign objects, irregular material flow, and transfer-point congestion.	[26,41]
	Foreign-object intrusion	Mining debris, anchor rods, steel pieces, gangue, wood, and operational spillage entering the belt path.	[41,73]
	Motor / drive-system anomalies	Mechanical or electrical degradation, imbalance, misalignment, load variation, looseness, and abnormal operating states.	[1,3,9,27]
	Load and operational-performance anomalies	Overloading, speed variation, unstable operating regimes, sensor drift, and inefficient system operation.	[3,24,25,27]

Belt surface damage and cracks

Surface damage is the most investigated anomaly category, mainly tears, cracks, scratches, wear marks, and breakage [28,31,39,40]. Image-based inspection dominates here because of its information density and low instrumentation burden relative to the inspection area covered. Chen et al. [5] reported 95.4% accuracy using a YOLOv8-based deep learning model adapted for real-time mining applications, and Wang et al. [41] developed a lightweight Single Shot MultiBox Detector (SSD)-based method to detect foreign objects, including bolts, waste steel, wood, and gangue, that can initiate longitudinal belt tearing, reporting 94.6% average detection accuracy at a processing speed exceeding 20 frames per second without GPU acceleration. Beyond visible surface defects, structural degradation at belt splices deserves more attention, since reduced splice strength can precede belt failure and is not always visible to surface-only inspection [12]. YOLO-based object detectors are common for surface-damage detection, while segmentation networks are used when defect boundaries are needed for maintenance planning [42]. Detection accuracy is reported to depend heavily on defect diversity and environmental variability, and limited datasets remain a persistent constraint [30,32]. For small defects specifically, accuracy tends to fall, which is why several studies now favor multiscale architectures [43].

Longitudinal tear detection

Longitudinal tear detection and early warning. Longitudinal tears, which can lead to catastrophic belt failure, have been studied using computer vision[15,43,44], thermal infrared imaging [45], and acoustic detection [46,47]. Laser-based methods are the most common choice for this fault type [44], though they require careful threshold calibration and may not generalize well without larger datasets or broader operating analysis [15]. Deep learning is increasingly used here too, improving reliability and enabling real-time localization [8], but several studies still call for validation beyond controlled setups and under harsher environmental conditions [28,29].

Idlers, rollers, and bearing dynamics

Idler and roller faults, particularly bearing failures, represent the second major anomaly category. This fault family relies heavily on thermal, acoustic, and vibration sensing because early degradation manifests as a temperature anomaly or a temporal signature well before it becomes visible [2,13,20,21,48–52]. The danger extends beyond mechanical failure, since overheated idlers generate friction that can create fire hazards in continuous operation: Siami et al. [42] reported 99.9% accuracy for semantic segmentation of thermal defects in belt conveyor idlers, and Dąbek et al. [53] and Xiuyu et al. [54] highlighted the value of thermal monitoring for early fire-risk detection in mining environments, where overheating in gearboxes, motors, and braking systems was effectively identified. Vision-based methods targeting rotation speed or visible end-surface cues are promising but often require visible or trackable features, which limits generalized deployment [22]. Recurrent models and hybrid architectures are repeatedly positioned as effective for time-series data because they learn the temporal structure linked to incipient fault states [1,49], though datasets in this area are still collected mostly in laboratory simulations or single contexts, leaving open how well they hold up under field-level noise and operating variability.

Belt deviation, misalignment and internal steel-cord

Belt deviation and misalignment were addressed using computer-vision techniques capable of detecting even slight changes in belt alignment before operational failures occur [55–58]. Zhang et al. [59] quantified conveyor-belt deviation using image-derived lateral-offset and deflection-angle measurements, with a laser-assisted computer-vision implementation operating at approximately 26 frames per second in a laboratory conveyor setup. Internal steel-cord integrity and NDT-constrained anomalies. Magnetic flux leakage and similar NDT techniques (e.g., X-Ray) are still important when internal defects cannot be easily determined based on surface features [60,61]. Studies highlight practical constraints such as lift-off effects and sensor placement sensitivity, and limitations tied to dataset size and class coverage [60,62]. Machine-learning enhancement of NDT signals can improve classification, but the evidence reinforces that these tasks remain strongly constrained by sensing physics and experimental coverage [60,63].

Taken together, method dominance within any one fault family should not be read as universal superiority. The strongest systems treat sensing and modeling as a coupled design choice, selecting the simplest approach that is reliable for the specific fault physics and deployment context, rather than defaulting to whichever architecture is most reported.

4.2. Sensing Modalities and Analytical Approaches: Distribution and Trends

The distribution of detection approaches shows deep learning as the dominant technique (n = 40, 53.3%), followed by machine learning (n = 15, 20.0%) and computer vision (n = 11, 14.7%) (Figure 5A). Smaller but operationally important streams include IoT/edge-oriented contributions (n = 5, 6.7%), signal processing/NDT (n = 3, 4.0%), and combined computer vision and IoT/edge studies (n = 1, 1.3%). This distribution traces a methodological trajectory from engineered, interpretable vision pipelines, to feature-based machine learning, and, more recently, to deep learning; each transition tracks a specific limitation of the stage before it rather than simply following a trend. Early studies relied on explicit computer-vision workflows, preprocessing, edge/morphological operations, belt-boundary tracking, and rule-based decisions that perform well when fault signatures are strongly geometric (e.g., deviation, rips/tears) and when labeled datasets are limited [6]. These methods remain attractive for safety-critical applications precisely because each processing stage is auditable and tunable, a property that end-to-end learned models trade away. Non-destructive testing and signal processing remain in use for the same reason, where interpretability, reliability, or sensing constraints dominate.

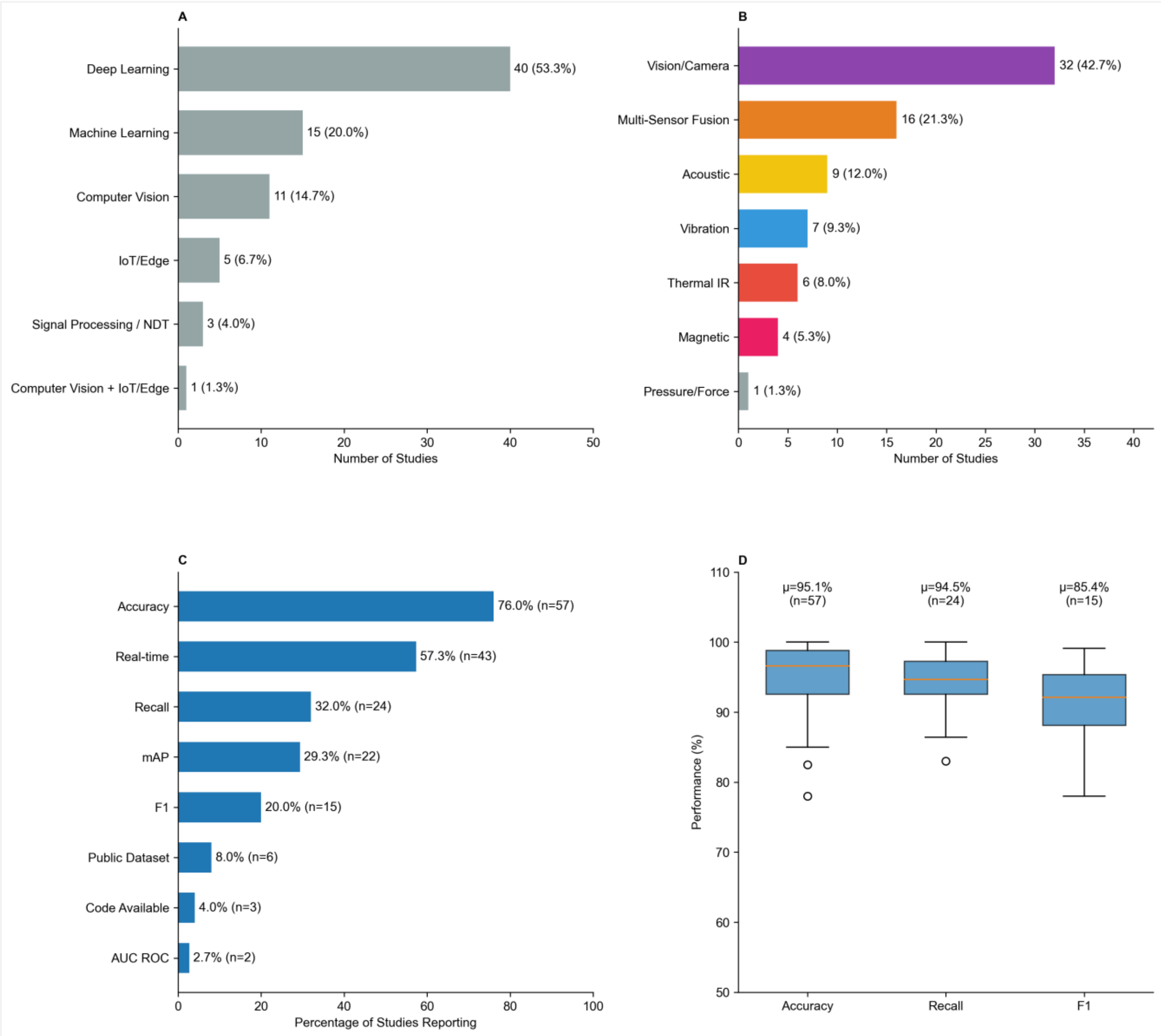

Figure 5. Methods, sensing modalities, and performance reporting in the included studies (n = 75). (A) Distribution of primary detection/analysis approaches. (B) Distribution of sensor modalities used for conveyor monitoring. (C) Reporting frequency of performance and implementation indicators (percentage of studies reporting each item). (D) Distribution of reported performance values (Accuracy, Recall, F1) shown as boxplots with sample sizes and mean values annotated.

From a hardware perspective, vision/camera systems are the most widely deployed modality (n = 32, 42.7%), reflecting the flexibility of optical inspection for belt-surface defects, alignment monitoring, foreign-object detection, and operational state recognition (Figure 5B, Table S4). Multi-sensor fusion is also prominent (n = 16, 21.3%), indicating that a substantial share of studies integrate complementary signals (e.g., RGB + thermal, vibration + acoustic) to improve stability under industrial noise, dust, occlusion, and illumination variability (Table S4). Thermal/infrared (n = 6, 8.0%) and acoustic sensing (n = 9, 12.0%) also show notable adoption (Figure 5B), but for different purposes: thermal imaging captures friction-related temperature increases and early bearing or idler degradation [17,46], , while acoustic sensing provides non-contact measurement of internal mechanical irregularities [2,64]. Vibration sensing (n = 7, 9.3%) is used mainly for diagnosing rotating components such as idlers and bearings [21,48], and magnetic sensing (n = 4, 5.3%) is associated with steel-cord integrity and internal-defect assessment [60,61]. Pressure/force sensing was the least frequent modality (n = 1, 1.3%).

4.3. Machine Learning Methods

Traditional machine learning (ML) approaches remain relevant, particularly when feature engineering is feasible and interpretability is prioritized, and when data are limited and informative feature sets can be extracted from vibrational or acoustic signals [3,20,63,65]. SVM-based models are the most frequently reported classical ML family [65], followed by decision trees and random forests (Figure S1). Empirical performance reported in the extracted studies indicates that ML pipelines can achieve high accuracy in targeted settings (Figure S1, Figure 5C). Hao & Liang [66] reported 97.63% accuracy using a multi-class SVM for vision-based surface damage detection. Wang et al. [29] reported 98.40% accuracy for a machine-vision tear-detection pipeline built on classical learning components. In vibration-driven monitoringRoos & Heyns [21] reported 100% accuracy in an in-belt vibration framework using wavelet packet decomposition-based feature representations. Li et al. [67] combined principal component analysis with a hybrid grey-wolf-optimized SVM to classify seven conveyor operating states from 19 IoT monitoring variables, reporting 97.22% test accuracy; however, this result was obtained from a test set of only 36 samples. The main limitation of these methods is generalization: performance shifts with sensor configuration, belt speed/load, and environmental conditions [20], because the hand-designed features that make these models interpretable are also what tie them to the conditions under which they were engineered. These findings show that classical ML can remain competitive for well-defined fault classes with informative engineered features, without establishing cross-study superiority over deep learning (Figure 5A).

4.4. Deep Learning Approaches and Architecture

Deep learning (DL) was the most common analytical method in our evidence base (Figure 5A; 53.3% of studies) because it can handle noisy and varying operating conditions, such as illumination changes, background clutter, and subtle or low-contrast defects, by learning features directly from raw industrial data rather than relying on hand-designed descriptors [5,8,68]. It has become dominant mainly because it reduces dependence on manual feature engineering and tolerates image variability that would otherwise require re-engineering features for every new site. End-to-end representation learning matters especially in conveyor systems, where signals are noisy and defect presentation shifts with operating conditions, including early mechanical degradation that first manifests as subtle temporal patterns in acoustic and vibration signals [13,49,64]. DL offers a framework that can handle diverse modalities (RGB/thermal imaging, vibration, acoustic, and multi-sensor data) and supports real-time decision-making pipelines for safety-critical monitoring and downtime prevention (Figure 6) [29,42,69].

Model selection in the reviewed studies is strongly dictated by data structure. For vision-based inspection (Figure 6), convolutional architectures dominate. YOLO-family detectors, particularly, are now used routinely for real-time anomaly detection on conveyor images because they balance accuracy and latency, enabling real-time localization of surface damage, tear cues, and foreign objects [70–74]. Zhang et al. [74] for example, combined EfficientNet with YOLOv3 to detect four types of mining conveyor-belt damage, achieving an mAP of 97.26%. ResNet/VGG backbones are commonly applied to defect classification, and encoder-decoder designs such as U-Net support segmentation when pixel-level localization is required to guide maintenance actions, such as mapping defect extent or hotspots. These choices are consistent with the prominence of camera-based monitoring in the literature (Figure 5B), where imaging offers dense, cost-effective coverage of belt surfaces and operating states. The same studies that report this performance, however, also report the conditions under which it was obtained: Chen et al. [5] note a limited range of belt types and damage diversity in their evaluation, Wu et al. [28] flag the need to test performance under harsher operating conditions. Also Yuan et al. [32] and Zhao et al. [30] identify computational complexity as a constraint on integrated deployment. The accuracy gains attributed to deep learning are therefore real within the tested conditions, but the tested conditions are narrower than the operating envelope of an actual mine or port, a gap this review returns to in Section 5.

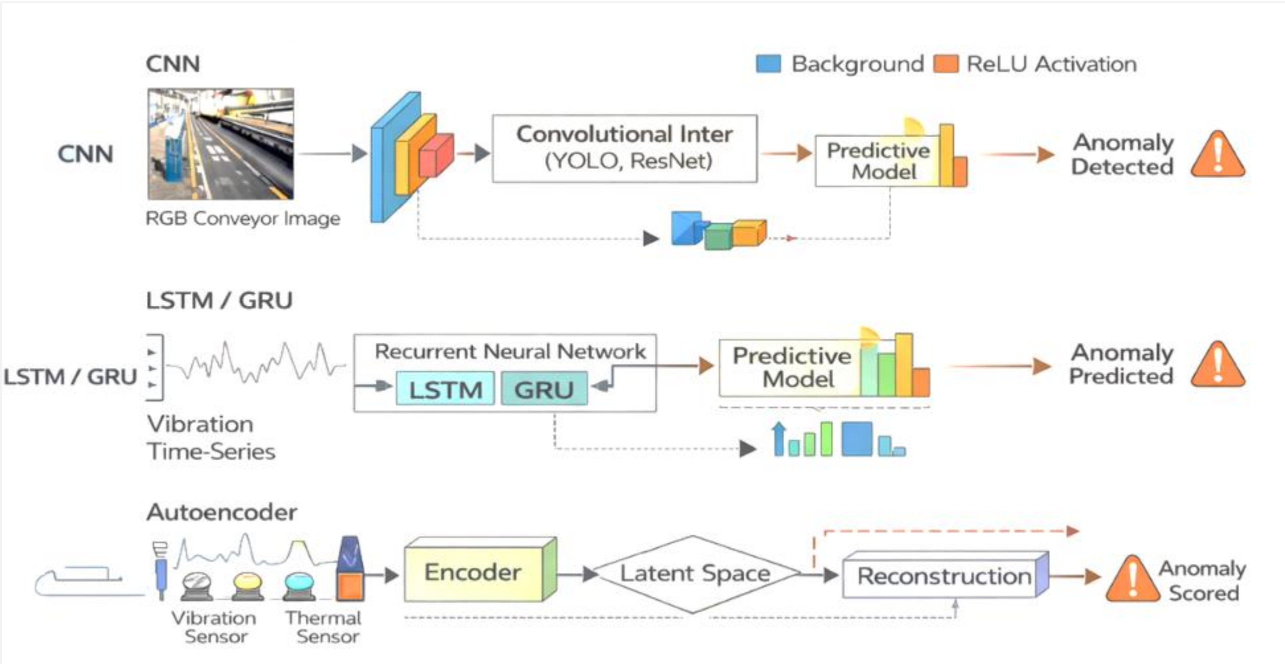

Figure 6. Deep-learning architectures for conveyor anomaly detection. CNN-based models process RGB images for visual anomaly detection; LSTM/GRU networks analyze acoustic and vibration time series; and autoencoders identify deviations through reconstruction error. The framework links model architecture to data modality and monitoring objective. Created by the authors based on the synthesis of included studies.

For time-series-dominated monitoring (Figure 6), especially idler/bearing and rotating-component diagnostics, recurrent networks (LSTM/GRU) and hybrid CNN-RNN pipelines are frequent because diagnostic information is often embedded in temporal evolution rather than static appearance (Figure S1). These architectures suit early warning, where subtle temporal deviations can precede visible damage [49,71,75].

When labeled fault examples are inadequate, autoencoder-based approaches provide a practical alternative (Figure 6). By learning "normal" behavior and flagging deviations via reconstruction error, these models enable data-efficient anomaly scoring and can generalize to unknown or emerging failure modes [26,76]. DL also extends beyond binary detection toward actionable localization, for example through thermal semantic segmentation of overheated idlers [42], and emerging dataset contributions aim to improve benchmarking comparability across studies [30,32].

4.5. Computer Vision-Based Monitoring

Computer vision (CV) remains a major methodological stream in conveyor condition monitoring (Figure 5A; 14.7% of studies), offering interpretable, engineering-driven pipelines that extract diagnostic cues from images through photometric and geometric processing rather than fully end-to-end learned representations. Across our evidence base, CV is most frequently associated with vision/camera acquisition and is increasingly extended to thermal infrared and laser/structured-light systems to capture failure signatures that may be weak in RGB alone or that require higher geometric precision [14,17,44].

A typical computer-vision workflow maps to four operational stages (Figure 7). (1) Image acquisition uses fixed RGB cameras, thermal infrared systems, or laser-based scanning for surface geometry [6,44]. (2) Image enhancement applies denoising, illumination compensation, and contrast normalization to improve stability under dust, fog, and variable lighting [17,29]. (3) Feature extraction and geometric reasoning identify belt edges, centerlines, and defect regions through edge detection, morphology, segmentation, region-of-interest definition, and tracking [15,56]. (4) Decision rules or trained classifiers convert these features into alarms using shape, threshold, and temporal-consistency criteria.

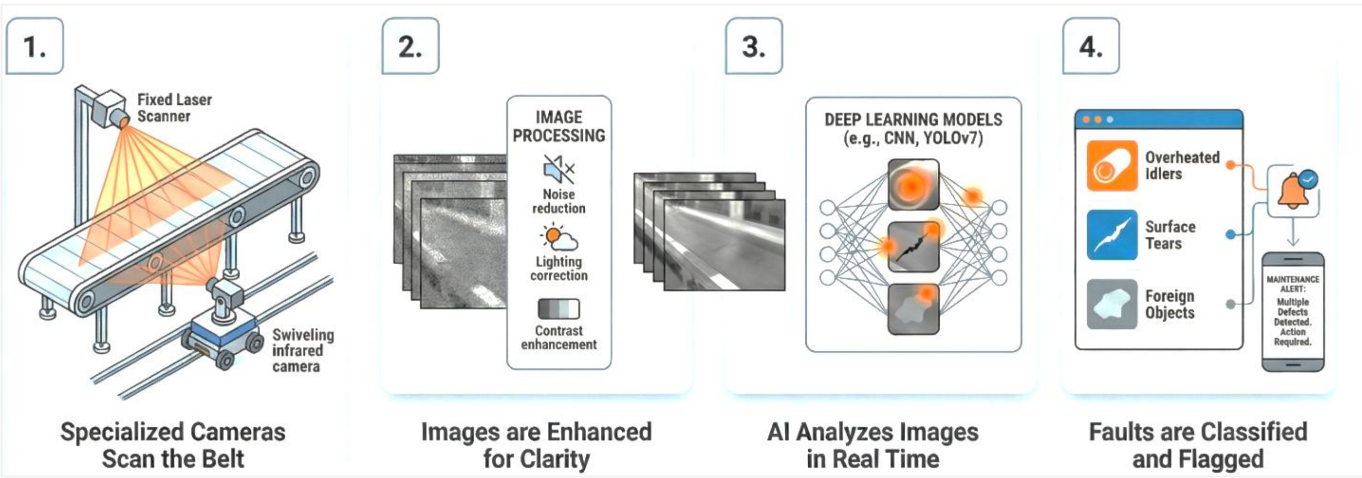

Figure 7. Vision-based conveyor monitoring workflow. RGB, thermal infrared, and laser/structured-light systems acquire belt and idler observations, followed by preprocessing and automated localization or classification. The outputs support fault flagging and maintenance alerting.

It is also noteworthy that the technique of CV is particularly effective for faults that have considerable geometric structure. Initial online machine vision techniques showed the feasibility of belt inspection in actual operating environments [6], followed by improved longitudinal tear detection using algorithmic and geometrical techniques such as structured illumination and laser techniques [15,44]. Most importantly, the technique of CV is also effective in situations of low visibility. Detection of tears in harsh environments (uneven illumination and complex backgrounds) is an important example of the effectiveness of the technique[29]. Similarly, belt deviation detection is naturally aligned with boundary tracking and geometrical constraints, achieving near-ceiling performance in controlled environments [56].

Thermal CV extends monitoring to fault modes that are not reliably detectable in RGB, such as overheat faults caused by friction or idler/bearing degradation [53]. It also aids in developing scalable acquisition concepts such as UAV-based thermography or robotic/UGV acquisition, as discussed in Carvalho et al. [14] and Siami et al. [17,77]. Lastly, multimodal computer vision, using both RGB and thermal, as well as sometimes laser geometry, makes computer vision more robust by using additional information when available in [22,42].

4.6 Edge computing and IoT architecture

Edge computing and IoT architectures translate algorithmic advances into deployable conveyor monitoring by addressing three persistent field constraints—latency, bandwidth, and intermittent connectivity—that limit cloud-only solutions; in many safety-critical contexts, sub-second response is required to reduce downtime and enable timely intervention, consistent with the high proportion of studies reporting real-time operation (57.3%, Figure 5C). In our evidence base, IoT/Edge is reported as a primary methodological stream in 6.7% of studies (n=5/75), with an additional 1.3% (n=1/75) explicitly combining computer vision with IoT/Edge (Figure 5A), indicating that a distinct subset of the literature prioritizes architecture and deployment (edge preprocessing/inference near the belt, event-driven transmission, and cloud storage/analytics) rather than offline benchmarking alone [24,25,43,78].

The most common architecture is based on a layered pipeline (Figure 8). The physical layer comprises the instrumented components of the conveyor system, such as the belt, rollers, and drive systems, which are equipped with one or more detection modes, most often cameras, but sometimes accompanied by vibration/acoustic or temperature sensors when early warning is desired [79,80]. The edge layer is responsible for controlling acquisition, preprocessing, and local inference, converting high-throughput raw data into a dense set of decision artifacts such as defect class, confidence level, timestamp, and the image of the area of interest, which can be transmitted in real time over the network. The cloud/server layer is used for historical recording, dashboards, reporting, and sometimes retraining and version management, as shown in recent studies [27].

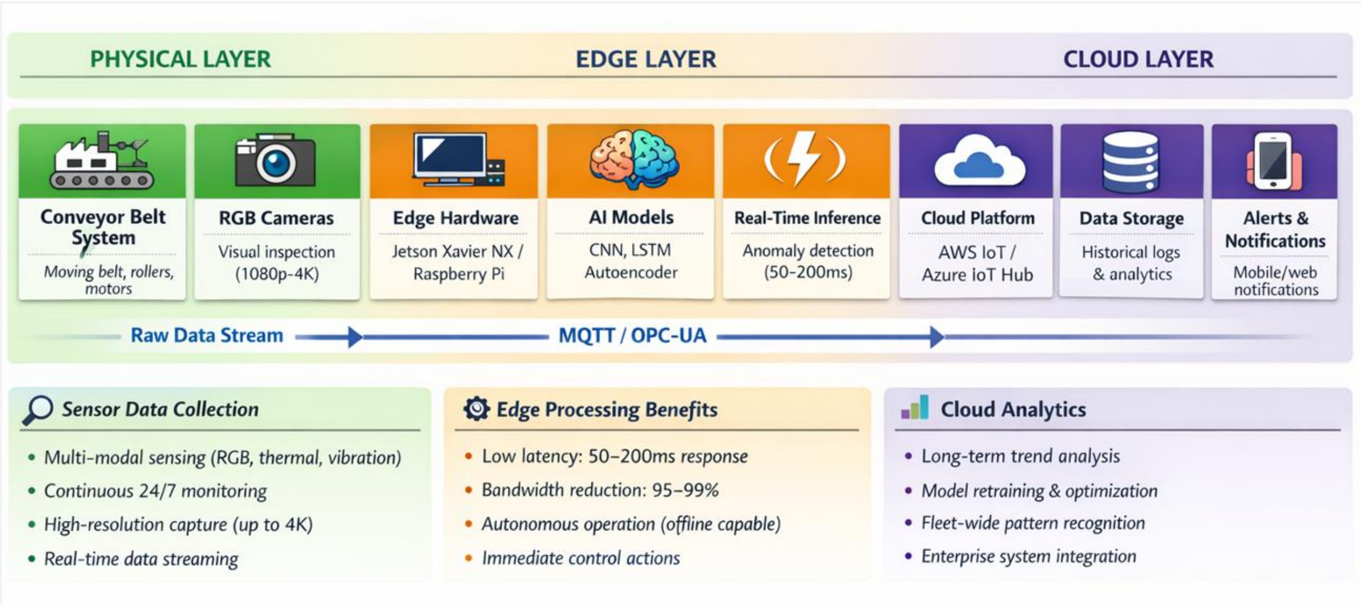

Figure 8. Edge–cloud architecture for real-time conveyor anomaly detection. Multimodal sensors acquire continuous streams that are processed locally for low-latency inference and event-driven alerting. Alerts and summarized logs are transmitted to cloud services for storage, dashboards, long-term analytics, and model maintenance.

The reviewed studies highlight diverse but convergent hardware patterns for edge inference. GPU-enabled embedded devices are frequently used when high-resolution

https://doi.org/10.3390/xxxxx

vision workloads must run online; for example, Jetson-class deployment is reported for real-time object detection pipelines optimized for embedded execution [43]. Other systems prioritize reliability and deterministic integration by coupling industrial PCs with PLCs (Programmable Logic Controller), enabling continuous monitoring with local control actions and robust industrial interfacing [78]. There are also sensor-centric edge nodes, which include Arduino/MCU-based systems for distributed monitoring, where cost, power, and ease of installation are the dominant constraints for the design [24,58]. In the context of monitoring rotating components, sensor nodes embedded close to the bearings/idlers demonstrate the use of IoT technology in facilitating in-situ condition monitoring [79].

Model design is closely related to edge feasibility. Several studies have focused on hardware-aware efficiency, using efficient design and runtimes to meet hardware constraints without compromising operational usefulness. This includes "hardware-friendly" detection pipelines for operational on-belt inference [59], as well as edge-aware implementations on industrial PC/GPU platforms [39]. The communication is typically event-driven rather than using full-resolution streaming, reducing the load and maintaining traceability and operational maintenance signals [27,78].

5. Critical Analysis and Research Gaps

5.1 Evidentiary and Reporting Gaps

Individual studies report strong performance in controlled settings: deep learning achieves high accuracy in belt-damage detection [5,28], thermal segmentation [42], and reconstruction-based anomaly scoring [26].Set against the appraisal in Section 3.2, this needs a caveat: only 17.3% of studies were rated low risk of bias, ground-truth reliability was fully demonstrated in 16.0%, and statistical uncertainty in just 4.0%. Two similar accuracy figures are not necessarily comparable if one study reports how its ground truth was established and the other does not.

Validation shows this clearest: laboratory (50.7%) and single-site (45.3%) settings dominate, multi-site validation appears in only 4.0% of studies, and facilities vary widely in belt material, speed, load, dust, and lighting [30,32]. Reported accuracy may therefore not transfer without recalibration, which argues for multi-site, longitudinal validation across belt aging and seasonal conditions.

Deployment reporting follows the same pattern: 57.3% of studies claim real-time operation, but communication protocols, PLC/SCADA integration, and alerting logic are often omitted , so systems with similar accuracy may differ sharply in operational value without this being visible in the literature. Explicit reporting of compute placement, runtime constraints, and alert logic would close this.

Cost and reproducibility fare worse: 61.3% of studies give no cost information, source code is available for only 4.0%, and public datasets for 8.0%, leaving procurement comparisons and independent verification largely infeasible.

5.2 Scientific and Technical Research Gaps

The gaps above concern how existing studies were designed, validated, and reported. A different question is whether the underlying modeling techniques have kept pace with what industrial deployment actually needs. We examined the full extraction dataset for seven capabilities that adjacent prognostics-and-health-management research already treats as standard: remaining-useful-life (RUL) estimation, physics-informed modeling, principled sensor-fusion architectures, domain adaptation for cross-site transfer, calibrated uncertainty quantification, explainable AI, and digital-twin integration (Table 3). Four are entirely absent from the 75 studies, and the remaining three, physics-informed modeling, explainability, and digital-twin integration, each appear in exactly one study, always as a secondary component rather than the study's focus.

Independent support for this gap analysis comes from several review works (i.e, [33–35]), despite their different scope and methods. Rios-Colque et al. [34] the closest in scope to this review, reach nearly the same conclusion on prognosis, arguing that conveyor-monitoring research should move beyond reactive fault detection toward systems that estimate remaining useful life. Rzeszowska et al. [33] devote a dedicated section to explainable AI and digital-twin integration as priority directions, citing the same digital-twin study identified here as the field's only example. Rojas et al. [35] raise explainability as an open research question and mention physics-informed prognostics in passing. All three also discuss multi-sensor fusion, but as a growing and beneficial trend rather than an architecture that needs to become more principled, which is the more specific claim Table 3 makes. None of the three identify the absence of calibrated uncertainty quantification. On these last two points, the gap analysis here extends beyond what has previously been reported in this literature.

Table 3. Scientific and technical research gaps in intelligent conveyor belt fault detection

Research Gap	Current State of the Evidence	Consequence for the Field	Required Development Direction
Diagnosis-to-prognosis disconnect	No study estimates RUL or degradation trajectory (0/75); all report detection of an already-present fault	Detects that a fault exists, not when intervention is needed	RUL/degradation-trajectory models built on existing detection outputs (e.g., survival analysis, trend extrapolation)
Absence of physics-informed modeling	Only 1/75 studies uses a physics-based component [68]; the rest rely entirely on data-driven pattern recognition	Detectors may not extrapolate beyond their training distribution	Hybrid architectures coupling learned detectors with belt/cord/rubber degradation mechanics
Fusion without a fusion architecture	16/75 studies combine modalities, but all via feature concatenation or rule-based combination, not principled fusion	Unclear whether reported gains reflect genuine complementary information or just added features	Principled fusion (attention-based or Bayesian) with explicit per-modality weighting
No cross-site transfer technique	No study applies domain adaptation or transfer learning for cross-site loss (0/75); 1/75 flags distribution shift as unresolved	The transferability gap (Section 3.3) has no corresponding technical solution in progress	Domain-adaptation methods designed to close source-to-target performance gaps
No calibrated uncertainty in outputs	No study reports calibrated confidence (0/75); "Bayesian" appears only as a training-algorithm name, not uncertainty quantification	Model outputs carry no confidence measure, blocking automated decision-making	Calibrated uncertainty (ensembles, conformal prediction) to flag low-confidence cases
Limited model transparency	Only 1/75 studies applies post-hoc explainability (class-activation mapping) [5]	Operators cannot verify why a model flagged an anomaly, limiting trust	Routine explainability reporting (Grad-CAM, SHAP) for safety-relevant faults
Isolated diagnostics, no system-level integration	Only 1/75 studies integrates a digital twin [3]; the rest evaluate detection in isolation	Detection is disconnected from plant-level decision-making	Closer integration with digital-twin or system-level operational models

The more significant priorities are the modelling gaps in Table 3, which require new scientific work rather than better documentation. These include linking detection to prognosis through degradation-trajectory and RUL-estimation models based on existing field outputs, incorporating physics-informed constraints and mechanistic models of belt fatigue, splice degradation and steel-cord wear so that detectors can extrapolate beyond the conditions on which they were trained, replacing feature concatenation with fusion architectures that explicitly weight the reliability of each modality, applying domain adaptation techniques rather than just pre-trained weight initialisation to close performance gaps between sites, and building uncertainty and explainability into detection pipelines where possible in connection with digital twin or system-level models so that outputs can be trusted, understood and acted upon rather than merely reported.

This review has three main limitations. Firstly, the search was limited to English-language, peer-reviewed studies found in IEEE Xplore, Scopus, ACM Digital Library, and the MDPI platform. This means that relevant work published in other languages or outside these databases may have been missed. Secondly, the outcomes and metrics reported in the studies varied so much that it wasn't possible to combine them into a single analysis. As a result, the analysis remained descriptive, not statistical, and no meta-analysis was conducted. Finally, we assessed methodological quality with a checklist we developed for this review, not an externally validated tool. We assigned ratings independently and then came to a consensus, but there's still some subjectivity in the appraisal.

6. Conclusions

This review shows that intelligent fault detection for belt conveyor systems has advanced substantially between 2010 and 2025, with strong technical potential across a broad range of sensing and modelling approaches. Across 75 empirical studies, detection performance is often strong, and deep learning now dominates the field: CNN-based models were the most frequently reported high-performing approach for vision-driven tasks such as surface damage, tear hazards, belt deviation, and foreign-object detection, while temporal architectures such as LSTM and GRU proved better suited to acoustic and vibration time-series tasks. No single sensor or algorithm is universally optimal; reliable performance instead depends on matching sensing modality to fault physics, vision or laser systems for surface defects, thermal sensing for overheating and fire risk, acoustic or vibration sensors for rotating components, and magnetic or other NDT methods for internal steel-cord and splice inspection. Beyond this technical synthesis, the review’s more significant finding is that the field has optimized detection while leaving prediction largely unexplored: none of the 75 studies estimate remaining useful life, and physics-informed modelling, principled sensor fusion, calibrated uncertainty, and explainability each appear in at most one study.

The field should not yet be considered mature from an industrial deployment perspective, and the path forward has two distinct components. Most studies still rely on laboratory or single-site validation, and decision-critical reporting on false alarms, latency, computational burden, uncertainty, reproducibility, and cost remains inconsistent. This gap is to be closed largely by the adoption of validation and reporting practices that are already supported by the field. The more significant issue concerns the underlying science: moving from detection to prediction will require modelling of degradation and remaining useful life, physics-informed constraints, principled multi-sensor fusion and calibrated explainable inference.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/doi/s1, Figure S1: Comparison of reported classification accuracy across machine-learning and deep-learning model families; Table S1: Database-specific search strategies and search yields; Table S2: PRISMA 2020 Checklist; Table S3: Study-level customized JBI-inspired methodological appraisal ratings ; Table S4: Comparison of sensing modalities used for intelligent conveyor monitoring.

Author Contributions: Conceptualization, M.A. and R.D.; methodology, M.A. and R.D.; formal analysis, M.A.; visualization, M.A.; writing—full original draft preparation, M.A.; writing—review and editing, all co-authors.; project administration, C.M., E.S., and R.D.; funding acquisition, C.M., E.S., and R.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data extraction form and extracted dataset supporting the findings of this review are available from the corresponding author upon reasonable request.

Acknowledgments: The authors gratefully acknowledge the institutions and funding bodies that supported this research. We also extend a special thanks to reviewers for insightful suggestions. During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-5.6 version) for language editing and improvement of clarity and structure. The authors have reviewed and edited the output and take full responsibility.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
JBI	Joanna Briggs Institute
CNN	Convolutional Neural Network
YOLO	You Only Look Once
ResNet	Residual Network
U-Net	U-shaped Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
AI	Artificial Intelligence
IIoT	Industrial Internet of Things
ML	Machine Learning
NDT	Non-Destructive Testing
IoT	Internet of Things
RF	Random Forest
SVM	Support Vector Machine
DL	Deep Learning
VGG	Visual Geometry Group
RNN	Recurrent Neural Network
CV	Computer Vision
ROI	Region of Interest
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
GPU	Graphics Processing Unit
PLCs	Programmable Logic Controllers
MCU	Microcontroller Unit

References

1. Kiangala, K.S.; Wang, Z. An Effective Predictive Maintenance Framework for Conveyor Motors Using Dual Time-Series Imaging and Convolutional Neural Network in an Industry 4.0 Environment. *IEEE Access* **2020**, *8*, 121033–121049, doi:10.1109/ACCESS.2020.3006788.
2. Liu, X.; Pei, D.; Lodewijks, G.; Zhao, Z.; Mei, J. Acoustic Signal Based Fault Detection on Belt Conveyor Idlers Using Machine Learning. *Adv. Powder Technol.* **2020**, *31*, 2689–2698, doi:10.1016/j.apt.2020.04.034.
3. Pulcini, V.; Modoni, G. Machine Learning-Based Digital Twin of a Conveyor Belt for Predictive Maintenance. *Int. J. Adv. Manuf. Technol.* **2024**, *133*, 6095–6110, doi:10.1007/s00170-024-14097-3.
4. Ban, Y.; Liu, C.; Yang, F.; Guo, N.; Ma, X.; Sui, X.; Huang, Y. Failure Identification Method of Sound Signal of Belt Conveyor Rollers under Strong Noise Environment. *Electronics* **2024**, *13*, doi:10.3390/electronics13010034.
5. Chen, Y.; Zhou, M.; Hu, F.; Gao, L.; Wang, K. YOLOv8-LDH: A Lightweight Model for Detection of Conveyor Belt Damage Based on Multispectral Imaging. *Measurement* **2025**, *245*, 116675, doi:10.1016/j.measurement.2025.116675.
6. Yang, Y.; Miao, C.; Li, X.; Mei, X. On-Line Conveyor Belts Inspection Based on Machine Vision. *Optik* **2014**, *125*, 5803–5807, doi:10.1016/j.ijleo.2014.07.070.
7. Hu, Y.; Zhang, Y.; Shen, J.; Wang, G. Real-Time Conveyor Belt Damage Detection Method Based on Improved YOLO. *Eng. Res. Express* **2025**, *7*, 025513, doi:10.1088/2631-8695/adc8fd.
8. Liu, W.; Tao, Q.; Wang, N.; Xiao, W.; Pan, C. YOLO-STOD: An Industrial Conveyor Belt Tear Detection Model Based on Yolov5 Algorithm. *Sci. Rep.* **2025**, *15*, 1659, doi:10.1038/s41598-024-83619-6.
9. P.V.S.Anusha Edge Machine Learning-Enabled Predictive Fault Detection System for Conveyor Belt Maintenance Optimization in Industrial Settings. *J. Electr. Syst.* **2024**, *20*, 2031–2041, doi:10.52783/jes.4003.
10. Liu, Y.; Miao, C.; Li, X.; Ji, J.; Meng, D.; Wang, Y. A Dynamic Self-Attention-Based Fault Diagnosis Method for Belt Conveyor Idlers. *Machines* **2023**, *11*, 216, doi:10.3390/machines11020216.
11. Bzinkowski, D.; Rucki, M.; Chalko, L.; Kilikevicius, A.; Matijosius, J.; Cepova, L.; Ryba, T. Application of Machine Learning Algorithms in Real-Time Monitoring of Conveyor Belt Damage. *Appl. Sci.* **2024**, *14*, doi:10.3390/app142210464.
12. Rucki, M.; Kilikevicius, A.; Bzinkowski, D.; Ryba, T. Identification of Rubber Belt Damages Using Machine Learning Algorithms. *Appl. Sci.* **2025**, *15*, 10449, doi:10.3390/app151910449.
13. Alharbi, F.; Luo, S.; Zhao, S.; Yang, G.; Wheeler, C.; Chen, Z. Belt Conveyor Idlers Fault Detection Using Acoustic Analysis and Deep Learning Algorithm With the YAMNet Pretrained Network. *IEEE Sens. J.* **2024**, *24*, 31379–31394, doi:10.1109/JSEN.2024.3439509.
14. Carvalho, R.; Nascimento, R.; D'Angelo, T.; Delabrida, S.; Bianchi, A.G.C.; Oliveira, R.A.R.; Azpúrua, H.; Garcia, L.G.U. A UAV-Based Framework for Semi-Automated Thermographic Inspection of Belt Conveyors in the Mining Industry. *Sensors* **2020**, *20*, doi:10.3390/s20082243.
15. Li, J.; Miao, C. The Conveyor Belt Longitudinal Tear On-Line Detection Based on Improved SSR Algorithm. *Optik* **2016**, *127*, 8002–8010, doi:10.1016/j.ijleo.2016.05.111.
16. Szrek, J.; Wodecki, J.; Błażej, R.; Zimroz, R. An Inspection Robot for Belt Conveyor Maintenance in Underground Mine—Infrared Thermography for Overheated Idlers Detection. *Appl. Sci.* **2020**, *10*, doi:10.3390/app10144984.
17. Siami, M.; Barszcz, T.; Wodecki, J.; Zimroz, R. Automated Identification of Overheated Belt Conveyor Idlers in Thermal Images with Complex Backgrounds Using Binary Classification with CNN. *Sensors* **2022**, *22*, doi:10.3390/s222410004.
18. Xianguo, L.; Lifang, S.; Zixu, M.; Can, Z.; Hangqi, J. Laser-Based on-Line Machine Vision Detection for Longitudinal Rip of Conveyor Belt. *Optik* **2018**, *168*, 360–369, doi:10.1016/j.ijleo.2018.04.053.
19. Muralidharan, V.; Ravikumar, S.; Kangasabapathy, H. Condition Monitoring of Self Aligning Carrying Idler (SAI) in Belt-Conveyor System Using Statistical Features and Decision Tree Algorithm. *Measurement* **2014**, *58*, 274–279, doi:10.1016/j.measurement.2014.08.047.

20. Ravikumar, S.; Kanagasabapathy, H.; Muralidharan, V. Fault Diagnosis of Self-Aligning Troughing Rollers in Belt Conveyor System Using k-Star Algorithm. *Measurement* **2019**, *133*, 341–349, doi:10.1016/j.measurement.2018.10.001.
21. Roos, W.A.; Heyns, P.S. In-Belt Vibration Monitoring of Conveyor Belt Idler Bearings by Using Wavelet Package Decomposition and Artificial Intelligence. *Int. J. Min. Miner. Eng.* **2021**, *12*, 48–66, doi:10.1504/IJMME.2021.114914.
22. Dąbek, P.; Krot, P.; Wodecki, J.; Zimroz, P.; Szrek, J.; Zimroz, R. Measurement of Idlers Rotation Speed in Belt Conveyors Based on Image Data Analysis for Diagnostic Purposes. *Measurement* **2022**, *202*, 111869, doi:10.1016/j.measurement.2022.111869.
23. Yang, L.; Chen, G.; Liu, J.; Guo, J. Wear State Detection of Conveyor Belt in Underground Mine Based on Retinex-YOLOv8-EfficientNet-NAM. *IEEE Access* **2024**, *12*, 25309–25324, doi:10.1109/ACCESS.2024.3363834.
24. Martinez-Rau, L.S.; Zhang, Y.; Oelmann, B.; Bader, S. On-Device Anomaly Detection in Conveyor Belt Operations. *IEEE Open J. Instrum. Meas.* **2025**, *4*, 1–9, doi:10.1109/OJIM.2025.3613073.
25. Zhou, P.; Sun, L.; Zhou, G.; Ma, T.; Wang, H.; Bi, W.; Ma, G.; Wang, W.; Yan, X. A New Embedded Condition Monitoring Node for the Idler Roller of Belt Conveyor. *IEEE Sens. J.* **2024**, *24*, 10335–10346, doi:10.1109/JSEN.2024.3363905.
26. Bortnowski, P.; Gondek, H.; Król, R.; Marasova, D.; Ozdoba, M. Detection of Blockages of the Belt Conveyor Transfer Point Using an RGB Camera and CNN Autoencoder. *Energies* **2023**, *16*, doi:10.3390/en16041666.
27. Chamorro, J.; Vallejo, L.; Maynard, C.; Guevara, S.; Solorio, J.A.; Soto, N.; Singh, K.V.; Bhate, U.; G.v.v., R.K.; Garcia, J.; et al. Health Monitoring of a Conveyor Belt System Using Machine Vision and Real-Time Sensor Data. *CIRP J. Manuf. Sci. Technol.* **2022**, *38*, 38–50, doi:10.1016/j.cirpj.2022.03.013.
28. Wu, T.; Zhou, H.; Sun, K. Real-Time Damage Detection Network for Mine Conveyor Belts Based on Knowledge Distillation. *Measurement* **2025**, *249*, 116976, doi:10.1016/j.measurement.2025.116976.
29. Wang, G.; Liu, Z.; Zhang, L.; Xiang, L.; Sun, H. Machine Vision-Based Conveyor Belt Tear Detection in a Harsh Environment. *Meas. Sci. Technol.* **2022**, *33*, 084006, doi:10.1088/1361-6501/ac632c.
30. Zhao, A.; Zheng, Q.; Li, L. Application of CycleGAN-Based Low-Light Image Enhancement Algorithm in Foreign Object Detection on Belt Conveyors in Underground Mines. *Sci. Rep.* **2025**, *15*, 27897, doi:10.1038/s41598-025-10779-4.
31. Zhang, M.; Zhang, Y.; Zhou, M.; Jiang, K.; Shi, H.; Yu, Y.; Hao, N. Application of Lightweight Convolutional Neural Network for Damage Detection of Conveyor Belt. *Appl. Sci.* **2021**, *11*, 7282, doi:10.3390/app11167282.
32. Yuan, Y.; Bai, Y.; Meng, W.; Zhou, L.; Wang, M.; Qu, W. Research on Conveyor Belt Damage Detection Method Based on FDEP–YOLOv8. *Sci. Rep.* **2025**, *15*, 36371, doi:10.1038/s41598-025-20391-1.
33. Rzeszowska, A.; Błażej, R.; Jurdziak, L. Detection and Analysis of Conveyor Belt Damage: A Review of Sensing Technologies and Signal-Based Approaches. *Sensors* **2026**, *26*, 4453, doi:10.3390/s26144453.
34. Rios-Colque, P.; Rios-Colque, V.; Rios-Colque, L.; Robles, P.A. Computer Vision-Based Techniques for Conveyor Belt Condition Monitoring: A Systematic Review. *Sensors* **2026**, *26*, 2527, doi:10.3390/s26082527.
35. Rojas, L.; Peña, Á.; Garcia, J. AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management. *Appl. Sci.* **2025**, *15*, 3337, doi:10.3390/app15063337.
36. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. **2021**, doi:10.1136/bmj.n71.
37. Aromataris, E.; Lockwood, C.; Porritt, K.; Pilla, B.; Jordan, Z. JBI Manual for Evidence Synthesis Available online: https://doi.org/10.46658/JBIMES-24-01 (accessed on 1 March 2026).
38. Błażej, R.; Jurdziak, L.; Rzeszowska, A. Sensor-Based Diagnostics for Conveyor Belt Condition Monitoring and Predictive Refurbishment. *Sensors* **2025**, *25*, 3459, doi:10.3390/s25113459.

39. Guo, X.; Liu, X.; Królczyk, G.; Sulowicz, M.; Glowacz, A.; Gardoni, P.; Li, Z. Damage Detection for Conveyor Belt Surface Based on Conditional Cycle Generative Adversarial Network. *Sensors* **2022**, *22*, doi:10.3390/s22093485.
40. Shin, K.S.; Nam, Y.; Suh, Y.-J. Designing a Multivariate Belt Conveyor Idler Stall Detection and Identification System with Scalability Analysis. *Sensors* **2024**, *24*, 7989, doi:10.3390/s24247989.
41. Wang, Y.; Miao, C.; Miao, D.; Yang, D.; Zheng, Y. Hazard Source Detection of Longitudinal Tearing of Conveyor Belt Based on Deep Learning. *PLOS ONE* **2023**, *18*, e0283878, doi:10.1371/journal.pone.0283878.
42. Siami, M.; Barszcz, T.; Wodecki, J.; Zimroz, R. Semantic Segmentation of Thermal Defects in Belt Conveyor Idlers Using Thermal Image Augmentation and U-Net-Based Convolutional Neural Networks. *Sci. Rep.* **2024**, *14*, 5748, doi:10.1038/s41598-024-55864-2.
43. Dwivedi, U.K.; Kumar, A.; Sekimoto, Y. Real-Time Classification of Longitudinal Conveyor Belt Cracks with Deep-Learning Approach. *PLOS ONE* **2023**, *18*, e0284788, doi:10.1371/journal.pone.0284788.
44. Yang, Q.; Li, F.; Tian, H.; Li, H.; Xu, S.; Fei, J.; Wu, Z.; Feng, Q.; Lu, C. A New Knowledge-Distillation-Based Method for Detecting Conveyor Belt Defects. *Appl. Sci.* **2022**, *12*, 10051, doi:10.3390/app121910051.
45. Yang, Y.; Hou, C.; Qiao, T.; Zhang, H.; Ma, L. Longitudinal Tear Early-Warning Method for Conveyor Belt Based on Infrared Vision. *Measurement* **2019**, *147*, 106817, doi:10.1016/j.measurement.2019.07.045.
46. Che, J.; Qiao, T.; Yang, Y.; Zhang, H.; Pang, Y. Longitudinal Tear Detection Method of Conveyor Belt Based on Audio-Visual Fusion. *Measurement* **2021**, *176*, 109152, doi:10.1016/j.measurement.2021.109152.
47. Miao, D.; Wang, Y.; Li, S. Sound-Based Improved DenseNet Conveyor Belt Longitudinal Tear Detection. *IEEE Access* **2022**, *10*, 123801–123808, doi:10.1109/ACCESS.2022.3224430.
48. Bortnowski, P.; Król, R.; Ozdoba, M. Roller Damage Detection Method Based on the Measurement of Transverse Vibrations of the Conveyor Belt. *Maint. Reliab.* **2022**, doi:10.17531/ein.2022.3.12.
49. Alharbi, F.; Luo, S.; Yang, G. TD-CLNet: A Time-Distributed CNN-LSTM Network for Fault Detection in Belt Conveyor Idlers. *Neural Comput. Appl.* **2025**, *37*, 25151–25181, doi:10.1007/s00521-025-11570-2.
50. Li, Z.; Wang, H.; Liang, W.; Yao, L. Audio Fault Diagnosis of Belt Conveyors Based on Improved Variational Modal Decomposition and Improved Adaptive Noise Reduction Convolutional Network in Strong Noise Environments. *Meas. Sci. Technol.* **2024**, *35*, 106126, doi:10.1088/1361-6501/ad5b11.
51. Wijaya, H.; Rajeev, P.; Gad, E.; Vivekanantham, R. Automatic Fault Detection System for Mining Conveyor Using Distributed Acoustic Sensor. *Measurement* **2022**, *187*, 110330, doi:10.1016/j.measurement.2021.110330.
52. Liu, J.; Fu, S.; Liu, F.; Cheng, X. Intelligent Fault Diagnosis of Belt Conveyor Rollers Using a Polar KNN Algorithm with Audio Features. *Eng. Fail. Anal.* **2025**, *168*, 109101, doi:10.1016/j.engfailanal.2024.109101.
53. Dabek, P.; Szrek, J.; Zimroz, R.; Wodecki, J. An Automatic Procedure for Overheated Idler Detection in Belt Conveyors Using Fusion of Infrared and RGB Images Acquired during UGV Robot Inspection. *Energies* **2022**, *15*, doi:10.3390/en15020601.
54. Xiuyu, Y.; Liyong, T.; Feng, C. Thermal Infrared Imaging for Conveyor Roller Fault Detection in Coal Mines. *PLOS ONE* **2024**, *19*, e0307591, doi:10.1371/journal.pone.0307591.
55. Liu, Y.; Miao, C.; Li, X.; Xu, G. Research on Deviation Detection of Belt Conveyor Based on Inspection Robot and Deep Learning. *Complexity* **2021**, *2021*, 3734560, doi:10.1155/2021/3734560.
56. Wu, X.; Wang, C.; Tian, Z.; Huang, X.; Wang, Q. Research on Belt Deviation Fault Detection Technology of Belt Conveyors Based on Machine Vision. *Machines* **2023**, *11*, doi:10.3390/machines11121039.
57. Zhang, M.; Jiang, K.; Cao, Y.; Li, M.; Hao, N.; Zhang, Y. A Deep Learning-Based Method for Deviation Status Detection in Intelligent Conveyor Belt System. *J. Clean. Prod.* **2022**, *363*, 132575, doi:10.1016/j.jclepro.2022.132575.
58. Ni, Y.; Cheng, H.; Hou, Y.; Guo, P. Study of Conveyor Belt Deviation Detection Based on Improved YOLOv8 Algorithm. *Sci. Rep.* **2024**, *14*, 26876, doi:10.1038/s41598-024-75542-7.

59. Zhang, M.; Shi, H.; Yu, Y.; Zhou, M. A Computer Vision Based Conveyor Deviation Detection System. *Appl. Sci.* **2020**, *10*, doi:10.3390/app10072402.
60. Olchówka, D.; Rzeszowska, A.; Jurdziak, L.; Błażej, R. Statistical Analysis and Neural Network in Detecting Steel Cord Failures in Conveyor Belts. *Energies* **2021**, *14*, doi:10.3390/en14113081.
61. Zohra, F.T.; Salim, O.; Masoumi, H.; Karmakar, N.C.; Dey, S. Health Monitoring of Conveyor Belt Using UHF RFID and Multi-Class Neural Networks. *Electronics* **2022**, *11*, 3737, doi:10.3390/electronics11223737.
62. Kirjanów-Błażej, A.; Rzeszowska, A. Conveyor Belt Damage Detection with the Use of a Two-Layer Neural Network. *Appl. Sci.* **2021**, *11*, doi:10.3390/app11125480.
63. Mao, Q.; Ma, H.; Zhang, X.; Zhang, G. An Improved Skewness Decision Tree SVM Algorithm for the Classification of Steel Cord Conveyor Belt Defects. *Appl. Sci.* **2018**, *8*, doi:10.3390/app8122574.
64. Skoczylas, A.; Stefaniak, P.; Anufriiev, S.; Jachnik, B. Belt Conveyors Rollers Diagnostics Based on Acoustic Signal Collected Using Autonomous Legged Inspection Robot. *Appl. Sci.* **2021**, *11*, doi:10.3390/app11052299.
65. Li, W.; Wang, Z.; Zhu, Z.; Zhou, G.; Chen, G. Design of Online Monitoring and Fault Diagnosis System for Belt Conveyors Based on Wavelet Packet Decomposition and Support Vector Machine. *Adv. Mech. Eng.* **2013**, *5*, 797183, doi:10.1155/2013/797183.
66. Hao, X.; Liang, H. A Multi-Class Support Vector Machine Real-Time Detection System for Surface Damage of Conveyor Belts Based on Visual Saliency. *Measurement* **2019**, *146*, 125–132, doi:10.1016/j.measurement.2019.06.025.
67. Li, X.; Li, Y.; Zhang, Y.; Liu, F.; Fang, Y. Fault Diagnosis of Belt Conveyor Based on Support Vector Machine and Grey Wolf Optimization. *Math. Probl. Eng.* **2020**, *2020*, 1367078, doi:10.1155/2020/1367078.
68. Ling, J.; Fu, Z.; Yuan, X. Lightweight Coal Mine Conveyor Belt Foreign Object Detection Based on Improved Yolov8n. *Sci. Rep.* **2025**, *15*, 10361, doi:10.1038/s41598-025-87848-1.
69. Guo, X.; Liu, X.; Gardoni, P.; Glowacz, A.; Królczyk, G.; Incecik, A.; Li, Z. Machine Vision Based Damage Detection for Conveyor Belt Safety Using Fusion Knowledge Distillation. *Alex. Eng. J.* **2023**, *71*, 161–172, doi:10.1016/j.aej.2023.03.034.
70. Pan, C.; Tao, Q.; Pei, H.; Wang, B.; Liu, W. Belt Conveyor Idler Fault Detection Algorithm Based on Improved YOLOv5. *Sci. Rep.* **2025**, *15*, 1926, doi:10.1038/s41598-024-81244-x.
71. Guo, X.; Liu, X.; Zhang, X.; Królczyk, G.M.; Gardoni, P.; Li, Z. A Novel Denoising Approach Based on Improved Invertible Neural Networks for Real-Time Conveyor Belt Monitoring. *IEEE Sens. J.* **2023**, *23*, 3194–3203, doi:10.1109/JSEN.2022.3232714.
72. Ling, J.; Fu, Z.; Yuan, X.; Ling, R. Development of a Deep Learning-Based Foreign Object Detection Algorithm for Coal Mine Conveyor Belts. *Sci. Rep.* **2025**, *15*, 42291, doi:10.1038/s41598-025-22636-5.
73. Li, M.; Lu, C.; Yan, X.; He, R.; Zhao, X. Enhanced Detection of Foreign Objects on Molybdenum Conveyor Belt Based on Anchor-Free Image Recognition. *Appl. Sci.* **2024**, *14*, doi:10.3390/app14167061.
74. Zhang, M.; Shi, H.; Zhang, Y.; Yu, Y.; Zhou, M. Deep Learning-Based Damage Detection of Mining Conveyor Belt. *Measurement* **2021**, *175*, 109130, doi:10.1016/j.measurement.2021.109130.
75. Komorska, I.; Puchalski, A.; Bzinkowski, D. Localization of Conveyor Belt Damages Using a Deep Neural Network and a Hybrid Method for 1D Sequential Data Augmentation. *Appl. Sci.* **2025**, *15*, doi:10.3390/app15126784.
76. Santhi, T.M.; Srinivasan, K. A Duo Autoencoder-SVM Based Approach for Secure Performance Monitoring of Industrial Conveyor Belt System. *Comput. Chem. Eng.* **2023**, *177*, 108359, doi:10.1016/j.compchemeng.2023.108359.
77. Siami, M.; Barszcz, T.; Wodecki, J.; Zimroz, R. Design of an Infrared Image Processing Pipeline for Robotic Inspection of Conveyor Systems in Opencast Mining Sites. *Energies* **2022**, *15*, doi:10.3390/en15186771.
78. Li, Y.; Yang, F.; Dong, J.; Wang, Z.; Yuan, C.; Wang, R. Precision Detection of Micro-Damage on Conveyor Belt Surfaces Using Laser Scanning and Deep Learning Techniques. *Sci. Rep.* **2025**, *15*, 38946, doi:10.1038/s41598-025-22818-1.

79. Luo, B.; Kou, Z.; Han, C.; Wu, J. A "Hardware-Friendly" Foreign Object Identification Method for Belt Conveyors Based on Improved YOLOv8. *Appl. Sci.* **2023**, *13*, doi:10.3390/app132011464.
80. Luo, B.; Kou, Z.; Han, C.; Wu, J.; Liu, S. A Faster and Lighter Detection Method for Foreign Objects in Coal Mine Belt Conveyors. *Sensors* **2023**, *23*, 6276, doi:10.3390/s23146276.