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A Review of the Development and Application of Artificial Intelligence in the Safety Inspection of Chemical Storage Tanks

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***Abstract*—Chemical storage tanks undergo long-term corrosion, fatigue, and medium attack; failure of their floors, shells, or welds can readily trigger leakage, fire, and explosion, making safety inspection a core element of process safety. In recent years, artificial intelligence (AI), and deep learning in particular, has profoundly reshaped the inspection paradigm. This paper systematically reviews the latest progress from 2021 to 2026 along several directions: corrosion and surface-defect recognition based on computer vision and deep learning; intelligent diagnosis from acoustic-emission and non-destructive-testing signals; intelligent sensing of leakage and hazardous gases; multi-source fusion, structural health monitoring, and risk assessment; digital twins and predictive maintenance; and unmanned-platform inspection. Key methods, representative results, and performance boundaries are summarized, and challenges such as data scarcity, model interpretability, edge deployment, and standardization are discussed. AI is shown to be moving tank-safety inspection from single-point defect detection toward a multimodal, full-lifecycle, online assurance system, while engineering trustworthiness and large-scale deployment remain to be addressed.**

***Index Terms*—Artificial intelligence; Deep learning; Chemical storage tank; Safety inspection; Corrosion recognition; Acoustic emission; Leak detection**

I. Introduction

Chemical storage tanks are critical infrastructure in petrochemical, energy-reserve, and hazardous-chemical logistics systems, and they typically hold flammable, explosive, toxic, or highly corrosive media. Over long service periods, the tank floor, shell, welds, and ancillary components are continuously subjected to the coupled effects of electrochemical corrosion, stress fatigue, medium attack, and environmental factors; corrosion is widely regarded as one of the principal causes of failure. Once perforation, cracking, or large-area wall thinning occurs, leakage, environmental contamination, and even fire or explosion can readily follow [1], [2]. Timely, accurate, and low-risk assessment of a tank's structural integrity is therefore a core task for ensuring process safety and reliable asset operation.

Conventional tank inspection relies mainly on periodic out-of-service internal inspection, manual visual examination, and routine non-destructive testing (NDT) methods such as magnetic-particle, ultrasonic, and magnetic-flux-leakage testing. Although mature, these methods generally entail substantial production losses, high cleaning and purging costs, long inspection cycles, and pronounced safety risks associated with confined-space operation; moreover, manual interpretation depends heavily on inspector experience and is difficult to keep consistent and traceable [3], [4]. Against a backdrop of ever-expanding oil-and-gas and chemical assets and increasingly stringent safety and environmental requirements, these limitations have become more acute.

At the same time, AI—deep learning in particular—has achieved breakthroughs in image recognition, signal processing, and predictive modeling, and has been widely applied in the oil and gas industry, structural health monitoring (SHM), and industrial defect detection [5]–[7]. Data-driven methods can automatically extract defect-related features from images, acoustic-emission waveforms, sensor time series, and heterogeneous multi-source data, enabling a paradigm shift from "passive discovery" to "active prediction" and offering a new route to resolving the cost–risk–accuracy trilemma of tank inspection.

Building on this, the present paper focuses on the latest research from 2021 to 2026 and systematically reviews the development and application of AI in the safety inspection of chemical storage tanks. We first analyze tank failure modes and the limitations of conventional inspection; we then review key techniques and representative results from the perspectives of computer vision, acoustic-emission and NDT signals, leakage and gas sensing, multi-source fusion and risk assessment, and unmanned-platform inspection; and we finally discuss outstanding challenges and future trends, with the aim of providing a reference for related research and engineering practice.

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TABLE I
COMPARISON BETWEEN CONVENTIONAL AND AI-BASED TANK-INSPECTION METHODS.

Dimension	Conventional inspection	AI / intelligent inspection
Primary means	Manual visual inspection, magnetic-particle testing, ultrasonic thickness gauging, magnetic flux leakage, out-of-service internal inspection	Computer vision / deep learning, intelligent AE diagnosis, multimodal fusion, unmanned-platform inspection
Mode of operation	Frequently requires shutdown, tank cleaning and medium purging, or close-proximity confined-space work	Supports in-service, external / online / edge detection, reducing human entry
Defect interpretation	Relies on inspector experience; consistency and traceability are limited	Data-driven automatic feature extraction; results are more consistent and reproducible
Efficiency & coverage	Point-by-point scanning and long cycles; concealed defects are easily missed	Real-time or batch processing, high coverage, early warning
Main advantages	Mature technology, well-established standards, intuitive results	Automated, low-risk, online-capable, predictive
Main limitations	High cost, high operational risk, strong subjectivity	Depends on high-quality data; cross-scene generalization and interpretability need improvement

II. FAILURE MODES OF CHEMICAL STORAGE TANKS AND THE LIMITATIONS OF CONVENTIONAL INSPECTION

Tank corrosion is generally classified as external or internal. External corrosion mostly originates from aging of the protective coating and from electrochemical action between the floor and the foundation, and is relatively easy to detect and address. Internal corrosion includes vapor-phase corrosion at the tank roof, corrosion in the gas–liquid fluctuation zone, and floor corrosion; among these, internal floor corrosion is the most concealed and the most hazardous, and roughly half of out-of-service inspections reveal no obvious defects, which implies considerable blindness and waste [3]. Beyond corrosion, weld defects, fatigue cracks, and interlaminar damage in composite materials likewise threaten tank integrity [8].

In terms of inspection techniques, acoustic emission (AE) can passively "listen" to corrosion activity and localize active regions without opening the tank, whereas magnetic flux leakage and ultrasonics are suited to wall-thickness and thinning assessment. However, conventional implementations often require close-proximity operation, point-by-point scanning, or out-of-service internal inspection, making it difficult to reconcile efficiency, coverage, and operational safety [4]. The signals and images these methods produce are characterized by strong noise, non-stationarity, and multi-source coupling, so manually designed features and threshold-based criteria struggle to reliably distinguish defects from interference. It is against this background that data-driven intelligent methods offer an opportunity to raise the level of inspection automation and to reduce dependence on expert experience [1]. Table I contrasts conventional and AI-based inspection methods across several key dimensions, including primary means, mode of operation, defect interpretation, efficiency and coverage, and their respective advantages and limitations.

III. KEY AI TECHNIQUES FOR TANK SAFETY INSPECTION

A. *Corrosion and Surface-Defect Recognition Based on Computer Vision and Deep Learning*

Visual inspection is the most mature direction for AI in tank safety. For external corrosion of above-ground tanks, researchers have trained lightweight convolutional networks such as EfficientNet using transfer learning and fine-tuning to classify multiple corrosion categories, achieving about 94% recognition performance on roughly 5,000 industrial images and confirming the feasibility of embedding automated visual tools into tank-inspection workflows [9]. For pixel-level assessment, encoder–decoder networks based on UNet and ResNet34 can semantically segment corroded regions of steel structures and maintain good generalization on external images from unseen scenes [10].

Real-time object-detection frameworks represented by YOLO have been widely used for steel surface-defect and metal-corrosion recognition. Early work improved YOLOv3 for steel-strip surface-defect detection [11]; for highly corrosive marine and coastal environments, researchers introduced an efficient vision-transformer backbone and a normalized Wasserstein distance loss into YOLOv5 to enhance the detection of small-scale pitting against complex backgrounds [12]. To meet industrial-deployment needs, a lightweight improved YOLOv11 model substantially reduced the parameter count and computational load while maintaining accuracy [13], and an improved YOLOv8 was used to recognize corrosion grades on typical equipment such as substation apparatus [14]. To reconcile localization with fine-grained segmentation, a two-stage approach first localizes equipment regions by object detection and then extracts corrosion pixels by semantic segmentation, striking a balance between real-time performance and accuracy [15].

Concerns over data and trustworthiness have spawned new research branches. Zero-shot segmentation uses bounding-box prompts to reduce dependence on pixel-level annotation, improving the transferability of industrial inspection [16]; to address the “black-box” problem, researchers combined explainable-AI techniques such as Grad-CAM with CNNs to visualize the decision basis of binary corrosion classification, enhancing the credibility of the results [17]. Systematic reviews have summarized the learning paradigms and localization methods of surface-defect detection and noted the evolving role of deep learning in corrosion detection, prediction, and material-degradation analysis [2], [6].

B. Intelligent Diagnosis Based on Acoustic Emission and NDT Signals

Acoustic emission (AE) is an important passive monitoring means for assessing floor corrosion in in-service tanks. For cavern and buried oil tanks with high explosion-proof requirements, researchers designed an independent-channel explosion-proof AE detection system that localizes floor corrosion sources and assesses integrity through time-difference and sound-speed modeling, with results consistent with out-of-service inspection [3]. Because AE signals are often mixed with interference from mechanical friction, external impact, and condensate drip-back, machine-learning-based pattern recognition has been used to distinguish valid corrosion signals from noise sources; combining AE with machine learning also enables leak localization in pipelines and vessels [18].

In guided-wave and non-destructive imaging, externally mounted magnetostrictive guided-wave transducers use horizontally polarized shear waves together with total-focusing-method imaging to non-invasively screen internal corrosion of tank shells and floors from outside the tank and to estimate defect width, thereby greatly reducing the risk of opening the tank and of confined-space work during preliminary screening [4]. Infrared thermography combined with ensemble learning can improve the detectability of subsurface defects [19], while hybrid frameworks using continuous-wavelet-transform images and deep belief networks have been applied to feature extraction and classification of pipeline leak signals [20]. This body of work shows that intelligent diagnosis in the signal domain is becoming complementary to image-domain methods.

C. Intelligent Sensing of Leakage and Hazardous Gases

Leakage is one of the most dangerous failure consequences for tanks and their associated pipeline networks, and intelligent sensing methods have developed rapidly. Supervised classification based on two-dimensional convolutional networks can identify pipeline leaks from spectrograms of accelerometer signals, while semi-supervised deep learning, combined with the Industrial Internet of Things (IIoT), achieves low-cost online detection at the edge [21], [22]. Multimodal methods fuse thermography with gas-sensing data and adopt an optimized deep-forest classifier, attaining about 98.9% accuracy on simulated data with a small model footprint that facilitates real-time deployment on platforms such as soft robots [23].

To address the difficulty of modeling small-hole leaks, a spatiotemporal neural network improves detection and localization by modeling the time-varying structure of pipeline networks [24]; distributed acoustic sensing (DAS) uses optical fiber to achieve long-distance, continuous monitoring of leak-induced vibration [25]. On the optical side, combining infrared thermography with computer vision can automatically detect and localize gas / air leak points, and this approach has been further applied to detection and localization assessment at end-of-line leakage stations [26], [27]. A systematic review has summarized the principles, challenges, and latest progress of acoustic, optical-gas-imaging, and multimodal-fusion methods [28].

D. Multi-Source Sensor Fusion, Structural Health Monitoring, and Risk Assessment

Structural health monitoring emphasizes long-term, online state sensing of tanks. For glass-fiber-reinforced polymer and polyethylene composite tanks, researchers used elastic waves excited by piezoelectric (PZT) sensors to penetrate interlaminar interfaces, actively detecting interlayer and weld damage, and verified the feasibility of passively acquiring AE signals with PZT, thereby providing a route to early damage identification in chemical storage tanks [8]. A systematic review of machine learning and SHM has surveyed emerging paradigms such as data-driven monitoring, UAV-assisted inspection, and digital twins, together with their role in damage identification [7].

In risk assessment and full-lifecycle management, models such as gradient boosting, support vector machines, and neural networks have been used to predict coastal atmospheric chloride deposition and corrosion risk, enabling life assessment from publicly available environmental variables [29]; a method based on a mask region-based convolutional network trained on synthetic data can identify defects in fasteners such as corroded bolts [30]. Systematic reviews of integrity assessment and remaining-life prediction for corroded pipelines and vessels further indicate broad prospects for data-driven models in predictive maintenance [1], [2]. To provide an overview, Table II consolidates representative AI studies across the technical routes reviewed in this section, summarizing their methods, application targets, and key results. Complementarily, Fig. 1 provides a qualitative cross-route comparison along six dimensions—detection accuracy, real-time capability, low deployment cost, robustness, interpretability, and low annotation dependence—highlighting the distinct strengths and trade-offs of computer vision / deep learning, acoustic emission / NDT, leakage and gas sensing, and multi-source fusion / SHM.

IV. Unmanned Platforms and Intelligent Inspection

Unmanned platforms are becoming an important vehicle for deploying AI tank inspection in practice. UAVs and robots equipped with high-resolution cameras can enter tank interiors or approach tank exteriors for scanning and, combined with image preprocessing, segmentation, and deep-learning

TABLE II
REPRESENTATIVE AI STUDIES FOR TANK SAFETY INSPECTION.

Technical route	**Representative reference**	**Method / model**	**Application target**	**Key result / feature**
Vision · classification	Alviz-Meza et al. [9]	EfficientNet transfer learning	External corrosion of above-ground tanks	≈5,000 images; recognition rate ≈94%
Vision · segmentation	Das et al. [10]	UNet + ResNet34	Steel-structure corrosion	Pixel-level segmentation; cross-scene generalization
Vision · detection	Yu et al. [12]	Improved YOLOv5	Highly corrosive coastal environments	Improved detection of small-scale pitting
Vision · lightweight	Zhang et al. [13]	ELS-YOLO (improved YOLO)	Steel surface defects	Comparable accuracy with markedly fewer parameters
Acoustic emission	Hua et al. [3]	Explosion-proof AE + time-difference localization	Oil-tank floor corrosion	Localization consistent with out-of-service inspection
Guided-wave NDT	Vinogradov et al. [4]	Magnetostrictive guided wave + TFM imaging	Tank shells / floors	External, non-invasive preliminary screening
Leakage · multimodal	Zhang & Zhang [23]	Thermography + gas + deep forest	Pipeline-network leakage	Simulated accuracy ≈98.9%; lightweight model
Structural health monitoring	Dziendzikowski et al. [8]	PZT elastic-wave active detection	Composite chemical tanks	Interlayer and weld damage identification
Risk assessment	Terrados-Cristos et al. [29]	Gradient boosting / SVM / neural networks	Coastal corrosion risk	Environmental-variable-based life assessment

algorithms, can achieve autonomous recognition and severity grading of defects such as corrosion and cracks, markedly shortening inspection cycles and avoiding human entry into confined spaces [10]. Coupling externally mounted guided-wave transducers with unmanned inspection allows tanks to undergo preliminary corrosion screening without shutdown or opening, further reducing operational risk [4].

For complex scenes such as marine and coastal environments, lightweight YOLO-series models provide an algorithmic basis for real-time corrosion detection on airborne or platform-side hardware [12], [13]. At the same time, edge deployment of models has become critical: combining semi-supervised learning with IIoT edge computing enables detection algorithms to run on resource-constrained field devices, supporting the transition from "periodic inspection" to "continuous monitoring" [21]. The synergy of unmanned platforms, external sensing, and edge AI can be expected to drive tank inspection toward automation and routine, continuous operation.

V. DISCUSSION

Taken together, the four technology routes surveyed above have matured largely in parallel rather than in concert, and this fragmentation appears to be a central obstacle to progress. The metrics reported in the literature—recognition rates near 94% [9] or simulated accuracies of about 98.9% [23]—are obtained on heterogeneous, often private or synthetic datasets under inconsistent protocols, and cannot be meaningfully compared across studies; this is why the comparison in Fig. 1 is expressed as qualitative ratings rather than absolute scores. The principal frontier thus appears to lie less in marginally higher accuracy than in establishing standardized, openly shared datasets and evaluation criteria that make claims reproducible and auditable.

A structural imbalance is also evident in the research effort. The vision literature concentrates on external and surface corrosion—the visible and tractable problem—whereas the most hazardous failure mode, concealed internal floor corrosion, is exactly where vision is least effective and where acoustic-emission and guided-wave methods become indispensable [3], [4]. Effort has thus tended to follow the problem that is easiest to instrument rather than the one that dominates risk. Because tank inspection is safety-critical and regulated, with an asymmetric cost of missed defects, false negatives rather than average accuracy should arguably govern model acceptance; explainability tools such as Grad-CAM [17] are then necessary but not sufficient, requiring calibrated uncertainty estimates, robustness under distribution shift, and a traceable decision record.

Looking forward, the surveyed evidence suggests that these routes are best treated as complementary rather than competing. A promising direction is principled multimodal fusion that pairs vision with signal-domain sensing so that visible

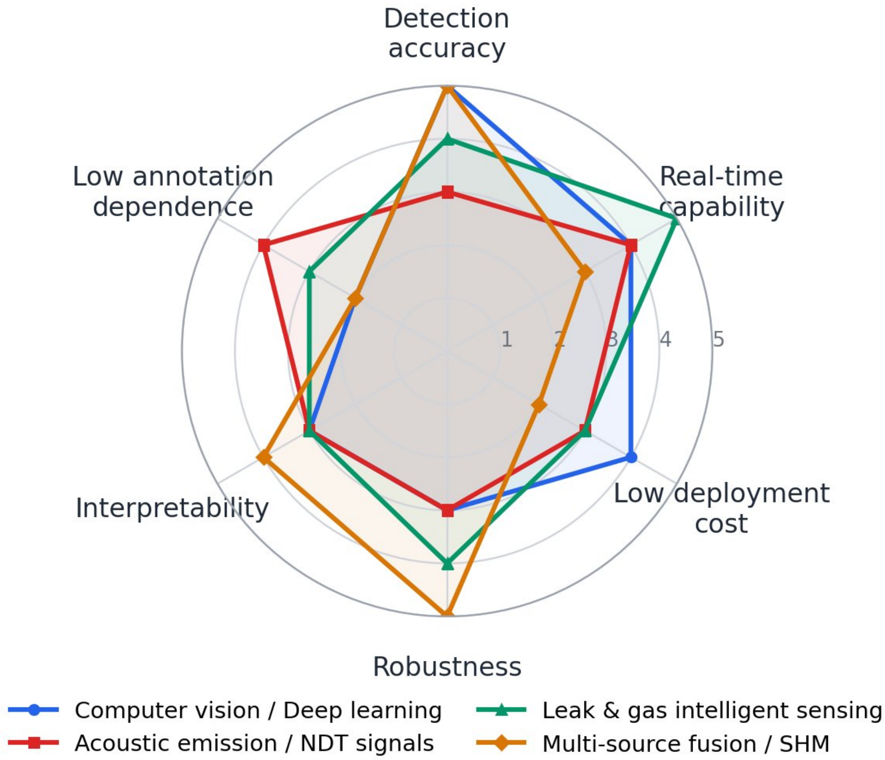

Fig. 1. Comprehensive performance comparison of the four AI-based inspection technology routes for storage-tank safety. Scores (1–5) are qualitative relative ratings synthesized from the reviewed literature for cross-route comparison, rather than absolute quantitative metrics.

and concealed defects fall within a single assurance framework [28], reinforced by physics-informed, mechanism–data hybrid models that offset scarce labels and improve cross-scene generalization [12]. Combined with digital-twin-based structural health monitoring [7] and evaluation benchmarks aligned with existing inspection codes, such integration would move the field from isolated, single-point demonstrations toward the full-lifecycle, predictive assurance envisioned in the integrity-assessment literature [1], [2]. In the near term, this also implies a shift of emphasis from model architecture toward data curation, annotation standards, and shared validation campaigns conducted on in-service tanks under realistic operating conditions.

VI. Challenges and Future Trends

Despite these fruitful achievements, AI-based tank safety inspection still faces several challenges. The first is data scarcity and annotation cost: high-quality tank data with real defect labels are difficult to obtain, which constrains model training and evaluation [6], [10]. The second is distribution shift and generalization: differences in tank material, coating, illumination, and corrosion morphology are substantial, so cross-scene generalization needs improvement [12]. The third is interpretability and engineering trustworthiness: safety-critical scenarios require model decisions to be traceable and auditable, making explainable AI and uncertainty quantification prerequisites for deployment [2], [17].

As for trends, multimodal fusion (vision, AE, thermography, gas sensing, etc.) is expected to overcome the blind spots of any single technique and to improve robustness under complex operating conditions [28]; edge and online deployment will support real-time, continuous safety monitoring [21]; and the integration of digital twins with SHM can enable full-lifecycle state prediction and predictive maintenance of tanks [7]. In addition, self-supervised and foundation models, methods that fuse physical mechanisms with data-driven approaches, and standardized datasets and evaluation systems aligned with industrial standards and regulations will be important directions for scaling AI tank inspection toward trustworthy, large-scale deployment [1], [4].

VII. Conclusion

The safety inspection of chemical storage tanks is undergoing a profound transition from manual experience to data intelligence. Research over the past five years shows that deep learning has made significant progress in the visual recognition of corrosion and surface defects, in the intelligent diagnosis of AE and NDT signals, in the multimodal sensing of leakage and hazardous gases, and in SHM, risk assessment, and predictive maintenance, and that—through unmanned platforms and edge computing—it is gradually moving toward automation, online operation, and routine use. Overall, AI has driven tank inspection from single-point, offline defect discovery toward a multimodal, full-lifecycle, predictive safety-assurance system. Nevertheless, data scarcity, cross-scene generalization, model interpretability and engineering trustworthiness, and alignment with industry standards and regulations remain key bottlenecks limiting large-scale deployment. In the future, as technologies such as multimodal fusion, digital twins, self-supervised learning, and foundation models mature, and as standardized data and evaluation systems are established, AI is poised to play a more central and trustworthy role in ensuring the inherent safety of chemical storage tanks.

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