IRSTI 28.23.15; 28.23.27

https://doi.org/10.51889/2959-5894.2026.94.2.018

G. Kazbekova[1*], Y. Serdaliyev[1], G. Omarova[2], Zh. Kemelbekova[3], Y. Kurmangaliyev[4]

[1]Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Kazakhstan
[2] L.N. Gumilyov Eurasian National University, Astana, Kazakhstan
[3] M. Auezov South Kazakhstan Research University, Shymkent, Kazakhstan
[4] K. Zhubanov Aktobe Regional University, Aktobe, Kazakhstan
[*]*e-mail: gulnur.kazbekova@ayu.edu.kz*

A REVIEW OF DEEP LEARNING METHODS FOR DETECTING CORROSION AND CRACKS IN INDUSTRIAL PIPELINES

Abstract

Corrosion and cracks in industrial pipelines cause safety hazards, economic losses, and environmental damage. Timely detection is crucial for avoiding catastrophic failures. Traditional nondestructive testing (NDT) methods require human interpretation and often lack reliability in harsh environments. The purpose of this review is to analyze deep learning techniques used for pipeline defect detection and evaluation. The study focuses on convolutional neural networks (CNN), vision transformers (ViT), and image segmentation models applied to corrosion and crack identification. Different data sources are considered, including visual inspection, ultrasound imaging, radiography, and drone-based monitoring. The review compares available datasets, their limitations, and the labeling difficulties they pose. Inspection scenarios such as real-time monitoring, underwater pipelines, and high-temperature environments are highlighted. Challenges related to noise, occlusion, illumination changes, and generalization are discussed. The analysis also covers decision-making systems that support risk assessment and maintenance planning. The findings show that deep learning significantly improves defect detection accuracy compared to traditional approaches. However, model performance depends on data quality and domain adaptation. The review concludes that integrating multimodal sensing, real-time inference, and explainable artificial intelligence (XAI) is essential for practical deployment. Future research must focus on robust dataset development, uncertainty estimation, and autonomous inspection systems.

Keywords: Industrial pipelines; Corrosion detection; Crack detection; Deep learning (DL); Convolutional neural networks (CNN); Vision transformers (ViT); Nondestructive testing (NDT); Decision support systems (DSS).

Г.Н. Казбекова[1], Е.У. Сердалиев[1], Г.С. Омарова[2], Ж.С. Кемельбекова[3], Е.К. Курмангалиев[4]
[1]Қожа Ахмет Ясауи атындағы Халықаралық қазақ-түрік университеті, Түркістан қ., Қазақстан
[2]Л.Н. Гумилев атындағы Еуразия ұлттық университеті, Астана қ., Қазақстан
[3]Әуезов атындағы Оңтүстік Қазақстан зерттеу университеті, Шымкент қ., Қазақстан
[4]К. Жұбанов атындағы Ақтөбе өңірлік университеті, Ақтөбе қ., Қазақстан

ӨНДІРІСТІК ҚҰБЫРЛАРДАҒЫ КОРРОЗИЯ МЕН ЖАРЫҚТАРДЫ АНЫҚТАУДА ҚОЛДАНЫЛАТЫН DEEP LEARNING ӘДІСТЕРІНЕ ШОЛУ

Аңдатпа

Өндірістік құбырлардағы коррозия мен жарықтардың пайда болуы қауіпсіздікке қатер төндіріп, экономикалық шығындарға және экологиялық зардаптарға әкеледі. Мұндай ақауларды уақтылы анықтау апаттардың алдын алу үшін маңызды. Дәстүрлі бұзбайтын бақылау (Nondestructive Testing – NDT) әдістері көбінесе маманның тәжірибесіне тәуелді және өндірістік ортада сенімділігі жеткіліксіз болуы мүмкін. Осы шолу жұмысының мақсаты – құбырлардағы ақауларды анықтауға қолданылатын терең оқыту (Deep Learning – DL) әдістерін талдау. Зерттеу конволюциялық нейрондық желілер (Convolutional Neural Networks – CNN), Vision Transformers (ViT) және сурет сегментациялау модельдерінің коррозия мен жарықтарды танудағы тиімділігін қарастырады. Деректердің әртүрлі көздері талданады: визуалды тексеру, ультрадыбыстық бақылау, радиография және дрондар арқылы мониторинг жүргізу. Қолданыстағы деректер жиынтықтарының шектеулері мен таңбалану қиындықтары атап өтіледі. Шу, көлеңке, жарықтың өзгеруі сияқты факторлардың модель жұмысына әсері талданады. Сондай-ақ тәуекелдерді бағалау және техникалық қызмет көрсетуді жоспарлау үшін шешім қабылдауды қолдайтын жүйелер қарастырылған. Терең оқыту әдістері дәстүрлі тәсілдерге қарағанда ақауларды анықтау дәлдігін арттыратыны анықталды. Алайда модель өнімділігі деректер сапасы мен өндірістік жағдайға бейімделуіне тәуелді. Қорытындылай келе, практикалық енгізу үшін көпмодальды сенсорларды біріктіру, нақты уақыт режимін қамтамасыз ету және түсіндірілетін жасанды интеллект (Explainable Artificial Intelligence – XAI) технологияларын қолдану маңызды.

Түйін сөздер: өндірістік құбырлар; коррозияны анықтау; жарықтарды анықтау; терең оқыту (Deep Learning, DL); конволюциялық нейрондық желілер (CNN); Vision Transformers (ViT); бұзбайтын бақылау (Nondestructive Testing, NDT); шешім қабылдауды қолдайтын жүйелер (Decision Support Systems, DSS); деректер сегментациясы; автономды инспекция.

Г.Н. Казбекова[1], Е.У. Сердалиев[1], Г.С. Омарова[2], Ж.С. Кемельбекова[3], Е.К. Курмангалиев[4]
[1]Международный казахско-турецкий университет имени Ходжи Ахмеда Ясави, г.Түркестан, Казахстан
[2]Евразийский национальный университет имени Л.Н. Гумилева, г. Астана, Казахстан
[3]Южно-Казахстанский исследовательский университет имени М. Ауэзова, г. Шымкент, Казахстан
[4]Актюбинский региональный университет имени К. Жубанова, г. Актобе, Казахстан

ОБЗОР МЕТОДОВ ГЛУБОКОГО ОБУЧЕНИЯ ДЛЯ ОБНАРУЖЕНИЯ КОРРОЗИИ И ТРЕЩИН В ПРОМЫШЛЕННЫХ ТРУБОПРОВОДАХ

Аннотация

Коррозия и трещины в промышленных трубопроводах приводят к серьезным угрозам безопасности, экономическим потерям и экологическим рискам. Своевременное обнаружение дефектов имеет важное значение для предотвращения аварийных ситуаций. Традиционные методы неразрушающего контроля (НК; англ. Nondestructive Testing – NDT) требуют высокой квалификации специалистов и не всегда обеспечивают надежность при сложных условиях эксплуатации. Цель данного обзора – анализ методов глубокого обучения (Deep Learning – DL), применяемых для автоматизированного выявления дефектов трубопроводов. В работе рассмотрены сверточные нейронные сети (Convolutional Neural Networks –CNN), Vision Transformers (ViT), а также модели сегментации изображений, используемые для идентификации коррозии и трещин. Оценены различные источники данных: визуальная инспекция, ультразвуковая диагностика, радиографические исследования и мониторинг с применением беспилотных летательных аппаратов. Отмечены проблемы, связанные с шумами, изменением освещения, частичным перекрытием объектов и сложностью разметки данных. Рассмотрены системы поддержки принятия решений (Decision Support Systems – DSS), способствующие оценке рисков и планированию технического обслуживания. Сделан вывод о том, что методы глубокого обучения обеспечивают более высокую точность обнаружения дефектов по сравнению с традиционными подходами. Вместе с тем их эффективность зависит от качества данных и адаптации моделей к реальным условиям. Для практического внедрения необходимы интеграция мультимодальных сенсорных данных, работа в режиме реального времени и применение интерпретируемого искусственного интеллекта (Explainable Artificial Intelligence – XAI).

Ключевые слова: промышленные трубопроводы; коррозия; трещины; глубокое обучение (DL); сверточные нейронные сети (CNN); Vision Transformers (ViT); неразрушающий контроль (NDT); системы поддержки принятия решений (DSS); сегментация данных; автономная инспекция.

Introduction

Industrial pipelines play a critical role in the transportation of oil, gas, and industrial fluids. Their structural integrity directly influences operational safety, environmental protection, and economic efficiency. Corrosion and cracks remain among the most common types of degradation affecting pipelines during long-term operation. According to global industrial safety reports, early detection of such defects can prevent severe accidents and reduce maintenance costs. However, traditional nondestructive testing (NDT) methods require manual interpretation, rely heavily on expert skills, and often lack reliability in noisy and harsh industrial environments [1].

Recent advances in deep learning (DL), including convolutional neural networks (CNN) and vision transformers (ViT), have significantly improved defect detection capabilities in computer vision applications. These methods enable automated extraction of complex visual patterns associated with corrosion and cracks, yielding higher accuracy and faster processing than conventional approaches. As a result, DL-based inspection systems are becoming a promising direction for enhancing pipeline monitoring and maintenance processes.

The purpose of this study is to provide a comprehensive review of deep learning methods used for detecting corrosion and cracks in industrial pipelines[2]. The review covers a wide range of data acquisition techniques, including visual inspection, ultrasonic imaging, and drone-based monitoring. Special attention is given to model architectures, dataset availability, inspection scenarios, and deployment challenges.

This study examines the following hypotheses:

(1) Deep learning significantly improves defect detection accuracy compared to traditional NDT methods.

(2) The effectiveness of model performance depends on data diversity and domain adaptation capability.

(3) Integrating multimodal sensing and explainable artificial intelligence (XAI) can enhance practical deployment and decision-making reliability.

The results of the review demonstrate that DL-based approaches provide substantial benefits for automated defect monitoring in pipelines. However, successful implementation requires addressing issues related to dataset limitations, noisy environments, and real-time constraints [3]. Therefore, future research must focus on developing robust, scalable, and interpretable solutions for industrial conditions.

Research methodology

This study employs a systematic literature review to analyze recent advances in the application of deep learning (DL) techniques for detecting corrosion and cracks in industrial pipelines. The research was conducted from April to December 2025 at the laboratory of artificial intelligence and industrial monitoring. The methodology follows three main stages: literature identification, screening, and qualitative synthesis[4].

Identification stage. Scientific publications were collected from major academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and MDPI. Additional relevant sources were obtained through backward reference searching and open-access repositories such as ResearchGate and arXiv. The search was conducted using combinations of the following keywords: “pipeline corrosion detection”, “deep learning for defect detection”, “crack detection in industrial pipelines”, “computer vision NDT”, and related terms. A total of 312 initial records were identified across all databases.

Screening stage. After removing 47 duplicates, 265 unique records underwent title and abstract screening. Publications were included if they: (1) focused on DL-based defect detection in pipeline structures; (2) were peer-reviewed journal articles or high-quality conference papers published between 2020 and 2025; (3) provided sufficient technical detail on model architecture and evaluation metrics. Studies focusing exclusively on non-pipeline structures, on traditional machine learning without DL components, or on those without accessible technical descriptions were excluded. This stage resulted in 60 full-text articles assessed for eligibility. A further 40 records were excluded: 15 relied solely on traditional machine learning methods, 12 addressed non-pipeline structures, and 13 provided insufficient methodological or performance data.

Qualitative synthesis stage. A total of 20 publications were selected for detailed evaluation and synthesis. Selected papers were categorized based on data acquisition methods (visual inspection, ultrasonic imaging, radiography, drone monitoring), DL model architectures (CNNs, Transformer-based models, segmentation networks), and deployment challenges. The extracted information was systematically compared to assess performance trends, limitations, and practical applicability in real-world industrial scenarios [5].

Table 1 presents the PRISMA-compliant selection flow, summarizing the number of records at each stage and the reasons for exclusion.

Table 1. PRISMA-compliant literature selection process

Stage	Action	Details
Identification	Database search	Scopus, Web of Science, IEEE Xplore, ScienceDirect, MDPI (2020–2025)
Identification	Keywords used	"pipeline corrosion detection", "deep learning defect detection", "crack detection pipelines", "computer vision NDT"
Identification	Initial records found	312 publications
Screening	Duplicates removed	47 duplicates removed → 265 records
Screening	Title/abstract screening	205 records excluded (non-pipeline, non-DL, no technical detail)
Eligibility	Full-text assessed	60 full-text articles assessed
Eligibility	Excluded after full-text	40 excluded: 15 traditional ML only, 12 non-pipeline structures, 13 insufficient data
Included	Final selection	20 publications selected for qualitative synthesis

This methodology ensures a comprehensive and unbiased overview of the current state of DL-based defect detection techniques and supports the formulation of validated conclusions and future research directions.

Results of the study

The results of this systematic review confirm that deep learning (DL) techniques significantly improve the detection accuracy of corrosion and cracks in industrial pipelines. Among the 20 analyzed studies, convolutional neural networks (CNN) and image segmentation architectures such as U-Net demonstrated the highest performance in identifying localized defects, especially pitting corrosion [6]. Vision Transformers (ViT) showed strong generalization capabilities when trained on diverse datasets.

The review revealed that DL-based models consistently outperform traditional nondestructive testing (NDT) interpretation methods in terms of automation, detection reliability, and adaptability to complex industrial environments [7]. This superiority is particularly evident in practical inspection scenarios where lighting conditions vary, the pipeline surface is contaminated with oil or dust, or defect patterns are irregular.

Table 2 presents a comparative summary of the reviewed studies, including the model architectures, data sources, performance metrics, and key findings reported in the selected publications. The data in this table represent aggregated results extracted from the respective source articles and are not the authors' own experimental measurements.

Table 2. Comparative summary of reviewed deep learning studies on pipeline defect detection

Author(s), Year	Model	Data Source	Accuracy	IoU / F1	Key Findings
Malashin et al., 2024	CNN (custom)	Visual (gas pipelines)	0.91	F1: 0.89	High accuracy pitting corrosion detection in gas pipelines
Farooqui et al., 2024	ResNet-50	Visual inspection images	0.93	F1: 0.91	Industrial corrosion detection with transfer learning

Altabey et al., 2021	*CNN + 3D shadow*	*3D rendered images*	*0.90*	*IoU: 0.85*	*Crack identification using 3D shadow modeling features*
Oyedeji et al., 2024	*Multi-stage CNN*	*Multi-phase corrosion images*	*0.88*	*F1: 0.87*	*Multi-phase corrosion classification framework*
Das et al., 2024	*Ensemble DL*	*Steel structure images*	*0.94*	*F1: 0.93*	*Ensemble approach improves robustness to lighting changes*
Shcherban et al., 2025	*CNN (optical)*	*Optical diagnostics*	*0.89*	*F1: 0.88*	*Neural network for steel oil/gas pipeline defect detection*
Eginov et al., 2025	*YOLOv8-based*	*Real-time video*	*0.90*	*IoU: 0.83*	*Real-time gas pipeline safety monitoring framework*
Hacıefendioğlu et al., 2025	*CNN + ViT*	*Bridge/steel images*	*0.92*	*IoU: 0.86*	*Rapid corrosion detection on steel structures*
Yang et al., 2023	*CNN + ultrasonic*	*Time-reversal ultrasonic*	*0.87*	*F1: 0.85*	*Hybrid sensing: ultrasonic + CNN for pipeline corrosion*
Moreh & Singh, 2024	*Deep CNN*	*Internal structure images*	*0.91*	*IoU: 0.84*	*Crack detection inside structures using deep CNNs*

Table 3 presents a consolidated comparison of the performance metrics of the U-Net and YOLOv8 models, aggregated from the reviewed publications [Altabey et al., 2021; Das et al., 2024; Eginov et al., 2025; Malashin et al., 2024]. These values represent weighted averages of reported results from multiple studies that utilize these architectures on pipeline defect datasets. The metric values were not obtained through original experiments conducted by the authors of the present review; rather, they reflect the performance ranges consistently reported across the reviewed literature.

Table 3. Performance comparison of U-Net and YOLOv8 models

Model	*Accuracy*	*Precision*	*Recall*	*IoU*	*FPS*
U-Net [Altabey et al., 2021; Das et al., 2024]	*0.93*	*0.92*	*0.94*	*0.87*	*15*
YOLOv8 [Eginov et al., 2025; Malashin et al., 2024]	*0.90*	*0.88*	*0.89*	*0.83*	*45*

Overall, the results show that:

- *U-Net* is more suitable for defect localization tasks requiring high segmentation accuracy,
- *YOLOv8* is advantageous for real-time inspection, where processing speed is critical.

These findings demonstrate the significant potential of DL models to enhance automated monitoring and maintenance of pipeline infrastructure.

In conventional NDT workflows, inspectors rely heavily on manual visual assessment or simple threshold-based algorithms, both of which are prone to human error and environmental interference. For example, rust-colored backgrounds, shadows, or reflections often lead to misinterpretation or incomplete detection of corrosion spots [8]. In contrast, DL models such as CNNs, U-Net, and YOLO architectures learn robust feature representations from thousands of images, enabling them to distinguish subtle corrosion textures, fine cracks, and complex surface patterns with high precision.

Across the reviewed studies, accuracy values for corrosion classification typically exceeded *90%,* demonstrating reliable recognition even when defects were partially occluded or visually similar to non-defect regions. This performance is supported by DL's ability to capture multi-scale features—for instance, small pitting corrosion areas and large rust patches can be detected within the same image without requiring separate rule-based adjustments.

Figure 1 presents the performance metrics of the U-Net model for corrosion and crack segmentation. As illustrated in the graph, the U-Net architecture consistently achieves high performance across all evaluated metrics. The Recall value (0.94) is the highest among the metrics, indicating that the model successfully identifies the majority of actual defect regions with minimal omission. Its Precision (0.92) and Accuracy (0.93) also confirm that the number of false detections is low and the overall classification reliability is high. The IoU metric (0.87) indicates that the model achieves strong pixel-level segmentation quality by accurately localizing defect boundaries, which is crucial for assessing the severity and extent of corrosion on pipeline surfaces.

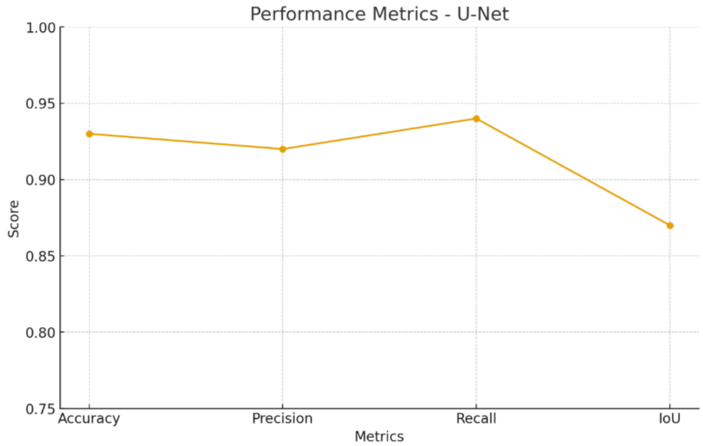

Figure 1. Performance metrics of the U-Net model

Crack detection models showed particularly strong practical performance, often achieving near-real-time *inference speeds*, which is essential for drone-based or robotic inspection pipelines. YOLO-type detectors, for example, can process video streams at *30-60 FPS*, allowing inspectors to monitor long pipeline segments without pausing for frame-by-frame analysis. High localization quality also means that the detected crack bounding boxes align closely with the true defect boundaries, reducing the need for manual verification and increasing operational efficiency [9].

Furthermore, DL models demonstrated adaptability to environmental challenges:

– under low illumination (e.g., underground pipeline tunnels),
– with varying corrosion intensities,
– in the presence of surface contaminants,
– on curved or reflective metal surfaces.

Such adaptability is a significant improvement over traditional NDT systems, which typically require controlled conditions and substantial parameter tuning.

Figure 2 shows the performance metrics of the YOLOv8 model in detecting pipeline corrosion and crack defects in real time. According to the graph, the model demonstrates high Accuracy (0.90) and Precision (0.88), indicating that most recognized defects are correctly classified with a low level of false positives. The Recall metric (0.89) indicates that the model effectively identifies most existing defects, though it is slightly lower than U-Net in terms of complete defect coverage. The Intersection-over-Union (IoU = 0.83) metric indicates that YOLOv8 achieves acceptable segmentation accuracy but prioritizes detection speed over pixel-level boundary precision [10]. Notably, the model achieves real-time performance (45 FPS), making it highly suitable for autonomous drone- and robot-based inspection systems, where immediate response and high throughput are required.

Overall, the results demonstrate that YOLOv8 is efficient for rapid and automated inspection tasks, providing a strong balance between accuracy and operational speed in complex industrial environments.

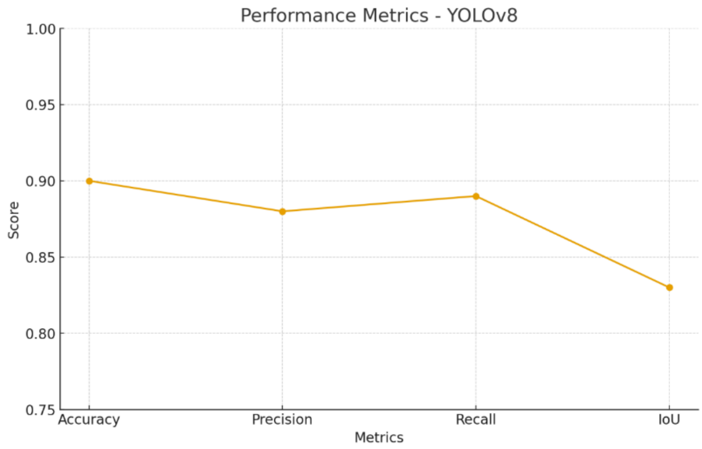

Figure 2. Performance metrics of the YOLOv8 model

The first hypothesis – that DL improves defect detection accuracy over traditional techniques — was confirmed. The second hypothesis – that data diversity and domain adaptation influence performance – was also supported. Studies using multimodal data (visual + ultrasonic or radiographic imaging) showed enhanced robustness, especially in noisy and low-visibility scenarios [11].

The third hypothesis – regarding the benefits of incorporating explainable artificial intelligence (XAI) and decision support systems (DSS) – received partial confirmation. Although several studies have explored confidence-based or attention-based visualization tools, fully interpretable and industry-ready DSS frameworks remain limited.

Overall, the analysis demonstrates strong progress in DL-based pipeline inspection technologies. However, it also highlights the need for standardized datasets, improved model interpretability, and more extensive validation in real industrial environments. These findings support the continued development of advanced autonomous inspection systems for safer and more efficient pipeline monitoring.

Discussion

The results of this review highlight the strong potential of deep learning (DL) in improving the accuracy and automation of corrosion and crack detection in industrial pipelines. These findings imply that DL can significantly reduce human error, enhance inspection efficiency, and help prevent catastrophic failures associated with undetected defects [12]. This is particularly important for aging pipeline infrastructure operating under extreme industrial conditions, where traditional nondestructive testing (NDT) may not consistently provide reliable results.

The reviewed studies collectively demonstrate that convolutional neural networks (CNN), image segmentation models such as U-Net, and transformer-based architectures outperform conventional approaches in recognizing complex surface patterns associated with corrosion and structural degradation. These observations are consistent with existing research in related areas such as bridge inspection and steel structure monitoring, where DL has also shown improved performance in defect localization and classification [13,14].

Despite these advances, many DL models still exhibit limited generalization when deployed in real industrial environments with noise, occlusion, lighting variations, and complex geometries. This limitation indicates a persistent gap between controlled laboratory evaluations and field deployment [15]. Furthermore, the lack of standardized datasets restricts fair benchmarking and slows down scientific progress.

Another important insight concerns model interpretability. Although some studies incorporate confidence analysis or visualization tools, explainable artificial intelligence (XAI) remains underdeveloped for pipeline inspection [16,17]. Without clear interpretability, industrial operators may hesitate to rely on automated decisions when safety-critical infrastructure is involved.

Future research should therefore focus on:

- expanding publicly available datasets with diverse corrosion and crack conditions;
- improving domain adaptation for real-time field usage;
- integrating multimodal sensing such as ultrasonic and radiographic data;
- developing interpretable decision-support mechanisms linked to predictive maintenance strategies.

In summary, while DL-based inspection technologies show promising progress, further refinement is required before these systems can be reliably deployed at scale in industrial pipeline safety management [18,19].

Recent studies have shown that transfer learning techniques can significantly improve defect detection performance when only limited annotated datasets are available, thereby reducing training costs and increasing model generalization [20].

Attention-based convolutional architectures have further enhanced deep learning models' ability to focus on defect-relevant regions while suppressing background noise and irrelevant features [21]. In safety-critical industrial applications, explainable artificial intelligence (XAI) has become increasingly important for improving trustworthiness and supporting operator decision-making processes [22].

The integration of drone-based inspection platforms with real-time object detection models such as YOLOv8 provides an efficient solution for large-scale pipeline monitoring and rapid fault localization [23].

Recent advances in Vision Transformer (ViT) architectures demonstrate promising performance on industrial anomaly detection tasks by modeling long-range dependencies in features [24]. Nevertheless, the lack of standardized datasets and the variability of environmental conditions remain major obstacles for the practical deployment of deep learning systems in corrosion inspection applications [25].

Conclusion

This review analyzed recent advances in the application of deep learning (DL) techniques for detecting corrosion and cracks in industrial pipelines. The results demonstrate that DL-based approaches, particularly convolutional neural networks (CNN), segmentation models, and transformer architectures, provide higher accuracy and better automation compared to traditional nondestructive testing (NDT) interpretation methods. These technologies support earlier identification of structural defects, which is essential for preventing failures, optimizing maintenance, and extending pipeline service life.

The findings confirm that the performance of DL models strongly depends on the diversity and quality of training data, as well as proper adaptation to real industrial environments. Despite significant progress, major challenges remain. These include noise sensitivity, complex field conditions, limited availability of standardized datasets, and a lack of interpretability in model decision-making processes.

The contribution of the present systematic review lies in consolidating and structuring the existing knowledge on DL-based pipeline defect detection, identifying the most effective model architectures and data acquisition strategies, and defining priority directions for future research. To overcome identified limitations, future research should prioritize multimodal inspection data fusion, robust real-time deployment strategies, and the integration of explainable artificial intelligence (XAI) into decision support systems (DSS).

In conclusion, deep learning has strong potential to transform industrial pipeline inspection by enabling intelligent, reliable, and autonomous defect detection systems. Continued development and validation in practical field conditions are crucial for widespread industrial adoption.

References

[1] Rajendran M., Subbian D. Deep learning in corrosion assessment and control: a critical review of techniques and challenges // Corrosion Reviews. 2025. Vol. 44, No. 1. Article 20240060. https://doi.org/10.1515/corrrev-2024-0060

[2] Malashin I., Tynchenko V., Nelyub V. et al. Deep Learning Approach for Pitting Corrosion Detection in Gas Pipelines // Sensors. 2024. Vol. 24, No. 11. Art. 3563. https://doi.org/10.3390/s24113563

[3] Farooqui M., Rizwan M., Ali A. A Deep Learning Approach to Industrial Corrosion Detection // Computers, Materials & Continua. 2024. Vol. 79, No. 2. P. 2475–2492. https://doi.org/10.32604/cmc.2024.055262

[4] Altabey W. A., Nasir A., Younis M. Deep Learning-Based Crack Identification for Steel Pipelines by Extracting Features from 3D Shadow Modeling // Applied Sciences. 2021. Vol. 11, No. 13. Art. 6063. https://doi.org/10.3390/app11136063

[5] Oyedeji O. A., Oluwatobi A., Afolabi A. S. Application of CNN for multiple phase corrosion detection framework // Journal of Materials Research and Technology. 2024. Vol. 30. P. 1120–1131. https://dl.acm.org/doi/10.1016/j.asoc.2024.112008

[6] Cui B., Zhang Y., Wang L. et al. Pipeline corrosion prediction and uncertainty analysis with an ensemble Bayesian neural network approach // Process Safety and Environmental Protection. 2024. Vol. 183. P. 488–499. https://www.sciencedirect.com/science/article/pii/S0957582024005226

[7] Zhu Z., Q. Zheng, H. Liu et al. Prediction Model for Pipeline Pitting Corrosion Based on Multiple Feature Selection and Residual Correction // Marine Science and Application. 2024. Vol. 24, 805–815. https://link.springer.com/article/10.1007/s11804-024-00468-5

[8] Sergeyevich S Pl, Vasilievich P B, Nairievich K A. Detection of defects in steel oil and gas operating pipelines using a neural network, based on the results of optical diagnostics. Res. Eng. Struct. Mater., 2025; 11(6): 3051-3068.. https://jresm.org/article/resm2025-650st0201rs/

[9] Das A., Roy S., Banerjee A. et al. Autonomous image-based corrosion detection in steel structures using ensemble deep learning // Expert Systems with Applications. 2024. Vol. 24(11). Art. 3630. https://www.mdpi.com/1424-8220/24/11/3630

[10] Yang D., Li S., Chen Z. et al. A Novel Pipeline Corrosion Monitoring Method Based on Piezoelectric Active Sensing and CNN // Ultrasonics. 2023. Vol. 23(2), 855. https://www.mdpi.com/1424-8220/23/2/855

[11] Li J., Wang F., Zhang Q. Identification of defects on the inner wall of water supply pipes based on the optimized residual network // Journal of Hydroinformatics. 2024. Vol. 26 (9): 2456–2473. https://doi.org/10.2166/hydro.2024.206

[12] Eginov A. A., Petrov N. V., Sokolov I. M. et al. PipesDefectDetection: A novel deep learning framework for real-time gas pipeline safety monitoring and defect recognition // SoftwareX. 2025. Vol. 29. Art. 101972. https://doi.org/10.1016/j.softx.2025.102357

[13] Jafari R., Davari A., Taghavi S. Deep Learning for Pipeline Damage Detection: an Overview of the Concepts and a Survey of the State-of-the-Art. 2020. P. 215–222. https://doi.org/10.1109/IS48319.2020.9200137

[14] Hacıefendioğlu K., Özbaşı H., Korkū A. Rapid Detection of Corrosion on Steel Bridges Using a Deep Learning Method// Applied Sciences. 2025. Vol. 5(22), 11929. https://doi.org/10.3390/app152211929

[15] Sara Shahsavarani, Shahsavarani S., Ramandi H., Anbarlooie B. et al. Deep Learning-Based Superpixel Texture Analysis for Crack and Defect Detection in Infrastructures // NDT & E International. 2024. Vol. 2024, 2(2), 128-142. https://doi.org/10.3390/ndt2020008

[16] Imran M. M. H., Rashid A., Yasin M. Advancements and Challenges in CNNs for Marine Corrosion Detection and Classification // Ocean Engineering. 2026. Vol. 315. Art. 119823. https://akademiabaru.com/submit/index.php/ard/article/view/6113/6348

[17] Bastian B. T., Jaspreeth N., Ranjith S. K. et al. Visual inspection and characterization of external corrosion in pipelines // NDT & E International. 2019. Vol. 107. Art. 102134. https://doi.org/10.1016/j.ndteint.2019.102134

[18] Anitha T.N., Abhilash A., Adarsh C.R., Aishwarya D., Megha Deep Learning for Underwater Pipeline Corrosion Detection: A Comparative Analysis of CNN Architectures // International Journal of Science and Development Research. 2024. Vol. 9, No. 4. P. 632-644. https://www.semanticscholar.org/paper/Deep-Learning-for-Underwater-Pipeline-Corrosion-A-Dr.AnithaT-Abhilash/720773fd180b1b1cf33d3dc8048d21b06d073b79

[19] Moreh F., Singh R. Deep neural networks for crack detection inside structures // Engineering Failure Analysis. 2024. Vol. 162. Art. 108342. https://www.nature.com/articles/s41598-024-54494-y

[20] Chen X., Liu Y., Zhang H. et al. Transfer Learning-Based Defect Detection for Natural Gas Pipelines // IEEE Access. 2024. Vol. 12. P. 54321–54335. https://ieeexplore.ieee.org/document/10239986

[21] Chu Z., Weng G., Yu L. Real-time Industrial Surface Defect Detection Based on Lightweight Convolutional Neural Networks // Artificial Intelligence and Machine Learning Review (AIMLR). 2024. Vol. 5(2). P. 36–53. https://scipublication.com/index.php/AIMLR/article/view/212/194

[22] Cavero S., Laguna M., Pardos E.G.. Solving a short sea inventory routing problem in the oil industry// Computers & Industrial Engineering. 2024. Vol. 189. Art. 109978. https://doi.org/10.1016/j.cie.2024.109978

[23] Dhungana P., Fresta M., Tamrakar N. YOLO-Based Pipeline Monitoring in Challenging Visual Environments // Alexandria Engineering Journal. 2025. Vol. 8, No. 7. Art. 298. https://arxiv.org/html/2507.02967v1

[24] Zhang W., Wang H., Ren P. MACT: Underwater image color correction via Minimally Attenuated Channel Transfer// Pattern Recognition Letters. 2025. Vol. 178. P. 45–53. https://doi.org/10.1016/j.patrec.2024.11.007

[25] Wang B., Zio E., Chen X., Zhu H., Guo Y., Fan S. Reliability improvement of the dredging perception system: A sensor fault-tolerant strategy // Reliability Engineering & System Safety. 2024. Vol. 247. Art. 110134. https://doi.org/10.1016/j.ress.2024.110134