

Слід зазначити, що лабораторія - організатор міжлабораторних порівнянь має відповідати вимогам міжнародного стандарту ISO 15195:2003 Laboratory medicine - Requirements for reference measurement laboratories.

Зобов'язанням клініко-діагностичної лабораторії є проведення аналізу кожної фази життєвого циклу кожного з елементів системи управління якістю. Основою представленого методу розробки такої системи є цикл життя продукту, розкритого для елементів системи, характерних для такого типу лабораторій.

Висновки

На підставі проведеного аналізу міжнародних та вітчизняних нормативних документів, можна сформулювати основні принципи методики впровадження системи управління якістю в клініко-діагностичних лабораторіях, що ґрунтується на загальній методології життєвих циклів:

- класифікувати всі обов'язкові вимоги стандарту ISO 15189:2015 по аргументованим підгрупам (елементам системи управління);
- визначити «життєві цикли» елементів системи та проаналізувати кожний елемент в рамках методики «життєвих циклів»;
- впровадження вимог стандарту по кожному із елементів проводити в логічній послідовності життєвого циклу.

Ключові слова: система управління якістю, стандарт, клініко-діагностична лабораторія, єдність вимірювань, засіб вимірювань.

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UDC 004.895.32

AUTOMATION OF DECISION-MAKING IN NONDESTRUCTIVE TESTING SYSTEMS USING ARTIFICIAL INTELLIGENCE

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Nondestructive testing (NDT) plays a key role in ensuring the quality, reliability and safety of products in a variety of industries, from aircraft to energy to mechanical engineering. Its main advantage is the ability to detect defects and damage without

damaging the object of inspection, which allows for real-time diagnostics and early detection of potentially dangerous deviations. However, the effectiveness of such inspections largely depends on the human factor: operator qualifications, working conditions, fatigue, subjective perception of signals and images, etc.

In the context of the overall digital transformation of industry, more and more attention is being paid to the use of artificial intelligence (AI) as a tool to increase the level of automation in control processes. Unlike traditional analysis systems that are based on predefined rules, modern AI approaches allow systems to learn from large amounts of data, identify hidden patterns, and make decisions with a high degree of accuracy.

Of particular interest is the use of AI in decision-making tasks in NDT systems, i.e. in situations where the system not only detects anomalies or defects but also draws conclusions about their criticality, the need for further action, or even automatically initiates a response. This approach opens up new horizons for the creation of autonomous or semi-autonomous technical diagnostic systems capable of operating in real-time, minimizing human intervention and reducing the likelihood of errors. Therefore, it is relevant to analyze the opportunities and challenges associated with the introduction of AI in decision-making processes in nondestructive testing systems, as well as to review the latest research and examples of practical application of such technologies in industrial settings.

One of the key areas of research is the use of deep learning to analyze ultrasonic data. For example, paper [1] discusses the use of deep neural networks for automated defect detection based on ultrasonic inspection data, which can increase the efficiency and reliability of inspection.

Another promising area is the analysis of thermographic data using AI. The authors of [2-3] investigate the use of AI to process thermographic images, which helps automate the processes of defect detection and decision-making in NDT. The study [Journal of Failure Analysis and Prevention (2024)] considers the use of machine learning for the analysis of acoustic and thermal signals in the time, frequency, and time-frequency domains, which allows for increased accuracy of defect detection and automated decision-making.

Despite the significant achievements, there are certain challenges associated with the implementation of AI in the NDT. These include the need for large amounts of high-quality data to train models, ensure the interpretability of results, and comply with regulatory requirements in critical industries. Thus, current research confirms the potential of AI in automating decision-making processes in NDT, but a number of technical and regulatory barriers need to be overcome for widespread implementation.

Automation of decision-making in nondestructive testing systems using artificial intelligence is achieved through the deep integration of modern machine learning and deep learning algorithms into all stages of the diagnostic process. The main idea is to

create a closed analysis cycle that includes signal acquisition, pre-processing, pattern recognition, and the formation of a conclusion on the presence or absence of defects.

The initial link in such a system is the collection of data from physical sources. The most common sources of signals in NDT are ultrasonic, visual, X-ray, and thermographic sensors that record wave, image, or thermal characteristics of the object under control. These data are usually highly sensitive to noise and artefacts, so they are subject to complex pre-processing that includes filtering, normalization, and spatial or frequency transformation.

The next step is to transfer the processed signals to the analytical module, where intelligent algorithms are implemented. In most modern systems, these are Convolutional Neural Networks (CNN), which demonstrate a high ability to automatically interpret complex patterns. For example, in [4], it was shown that the use of CNNs to analyze ultrasonic images of welded joints allows for a classification accuracy of more than 95%, which is significantly higher than the results of traditional analysis.

Automated systems pay special attention to the model training process. The most important aspects of this stage are the quality of the training set, the representativeness of defects, and the depth of features that the model can detect. The experience of practical implementation of AI solutions shows that models trained on well-balanced samples demonstrate not only high accuracy but also stability to new or partially unknown scenarios. This is a key factor for industrial applications where defect types can be rare, variable, or combined.

The advantages of using artificial intelligence in nondestructive testing systems are becoming increasingly apparent compared to traditional expert assessment methods. Thus, in a study [5] on the detection of defects on ceramic substrates, it was demonstrated that the combination of ResNet and YOLO v3 models allows to achieve a detection accuracy of 99.2% with a complete absence of false positives. This is significantly higher than the efficiency of traditional automatic optical inspection systems, which typically provide an accuracy of 85% and a false positive rate of 75%. Thanks to the introduction of such an intelligent system, the number of personnel required for repeated visual inspection has been reduced from ten to one person, which also had a positive impact on the cost-effectiveness of the process.

In the field of eddy current inspection, the use of deep learning models, in particular GRU, has demonstrated even higher efficiency. For example, in [6], which focused on monitoring the condition of heat exchange tubes, the accuracy of defect detection reached over 99%. This approach proved to be much more effective than traditional methods and expert opinion, which often depend on the operator's experience and do not always provide a stable quality of analysis.

No less illustrative is the example of using the GADF-CNN architecture to detect damage in concrete structures [7]. The proposed model achieved a classification accuracy of 98%, which exceeds the results of such common approaches as the support vector method (88%) and even classical convolutional neural networks (94-

96%). This demonstrates the ability of modern AI models to better take into account the complex spatial and temporal features of signals that are typical of nondestructive testing data.

All of the above examples clearly demonstrate that the introduction of artificial intelligence into the field of nondestructive testing not only increases the accuracy and reliability of defect detection but also significantly reduces the influence of the human factor, speeds up analysis processes, and makes it possible to process large amounts of data in real-time. Due to these advantages, AI-based systems are increasingly replacing traditional methods and becoming an important component of modern approaches to technical diagnostics. Table 1 summarizes the data on modern methods of automation of various nondestructive testing methods. The data sources for Table 1 are works [1 – 7].

Table 1. Efficiency of AI use in different NDT methods

NDT method	Models of artificial intelligence	Accuracy of defect classification, %	Comments
Ultrasonic	CNN (ResNet)	96.3	High fault detection accuracy, even on noisy signals
Radiographic	YOLOv5 + Attention	97.8	Fast real-time processing, maintaining performance while scaling
Thermographic	ResNet50 + Augmentation	94.1	Shows high generalizability on composites
Eddy current	GRU	99.1	A combination of time and frequency response ensures reliable analysis
Visual and optical	GADF + CNN	98.0	Requires less training data compared to classical CNN models

Thus, the review of current research shows a significant increase in the interest of the scientific community in the use of deep learning algorithms, in particular convolutional neural networks, to analyze signals and images obtained from various NDT systems. It has been shown that AI technologies can significantly improve the accuracy of defect detection, reduce the influence of the human factor, and ensure informed decision-making in real-time.

The results demonstrate that the integration of modern deep learning models with the NDT infrastructure allows not only the automation of quality assessment procedures but also the creation of adaptive control systems capable of self-learning and improving performance during operation. Such systems can serve not only as a control tool but also as a source of strategic information for managing the technical condition of facilities.

At the same time, despite the positive dynamics of implementation, there are a number of limitations associated with the need for high-quality labelled datasets, the high computational complexity of individual models, and the need to ensure transparency of algorithmic output. Overcoming these challenges opens up prospects for the creation of fully autonomous NDT systems that can not only diagnose but also predict the development of defects based on historical data and trends.

Keywords: nondestructive testing, deep learning, artificial intelligence.

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УДК 620.179.14

МАГНІТОАНІЗОТРОПНИЙ МОНІТОРИНГ НАПРУЖЕНОГО СТАНУ ПІДЗЕМНИХ ТРУБОПРОВОДІВ

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Україна має розгалужену мережу газо-, нафто-, продуктопроводів. Враховуючи, що термін експлуатації цих споруд становить 30-55 років, проблема забезпечення безаварійної роботи набуває все більшого значення.