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Machine Diagnostics in Mechatronic Systems: Analysis Methods and Intelligent Technologies

Abstract. The article examines modern approaches to machine diagnostics within mechatronic systems using signal processing methods and intelligent machine learning technologies. The structure of mechatronic complexes is analyzed, and their specific features that influence the development of diagnostic models are identified, including the high level of interdependence between mechanical, electronic, and software components. The feasibility of applying hybrid diagnostic systems is substantiated, where convolutional neural networks (CNN) are employed for automatic extraction of informative features from vibration and sensor data, while recurrent networks such as LSTM provide analysis of the temporal dynamics of processes and prediction of degradation states. A generalized theoretical diagnostic model is proposed, combining spectral methods of preliminary signal processing, multisensor data integration, and modules for technical condition prediction. The obtained results demonstrate the high effectiveness of intelligent algorithms in detecting early signs of faults, even under noise disturbances and varying operating modes. The proposed approach can be applied in maintenance systems at industrial enterprises to enhance the reliability and extend the service life of mechatronic systems.

Keywords: machine diagnostics, mechatronic systems, machine learning, CNN, LSTM, signal processing, condition prediction, digital twins, vibration analysis.

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Introduction.

The modern development of mechanical engineering is characterized by the rapid growth of mechatronic systems, which integrate mechanical, electronic, information, and control components. The integration of sensor modules, microprocessor controllers, electromechanical actuators, and software-oriented control tools leads to increased structural complexity, enhanced functionality, and higher levels of automation. At the same time, this creates new requirements for ensuring reliability, safety, and operational efficiency, which directly depend on the quality and completeness of technical condition diagnostics.

Traditional methods of monitoring and assessing machine performance, based mainly on mechanical or vibration indicators, no longer provide sufficient informativeness for complex mechatronic structures. In such systems, the importance of sensor monitoring, the analysis of electrical, electromagnetic, and digital signals, as well as the processing of large volumes of data in real time, is significantly increasing. This highlights the relevance of applying intelligent technologies-artificial intelligence methods, machine learning, neural networks, digital models, and digital twins-to improve the accuracy, speed, and predictive capabilities of diagnostic procedures.

Effective diagnostics of machines within mechatronic systems has become a key factor for ensuring their long-term, safe, and economically justified operation. Early fault detection, residual life prediction, automation of technical control processes, and the adaptation of diagnostic algorithms to varying operating conditions help reduce the number of unexpected failures, optimize maintenance processes, and enhance the overall efficiency of industrial operations.

Thus, research into analysis methods and intelligent technologies for machine diagnostics in mechatronic systems is of high scientific and practical relevance. It aims to improve modern approaches to technical monitoring, develop new tools for assessing technical condition, and create adaptive diagnostic systems capable of ensuring high levels of reliability and efficiency of technical objects under real operating conditions.

Review of the research sources and publications.

Modern research in machine diagnostics within mechatronic systems is characterized by the rapid development of data-driven and intelligent approaches that significantly extend traditional signal analysis methods. A key contribution is made by studies applying machine learning and deep learning for fault diagnosis and condition monitoring.

Reviews by Lei et al. [1] and Khan and Yairi [2] show that machine learning has become a core tool for extracting informative features from complex system data, enabling a transition from model-based to data-driven approaches. Deep learning methods allow automatic hierarchical feature extraction, reducing the need for manual engineering in complex systems.

The use of convolutional neural networks for fault detection is demonstrated by Janssens et al. [3], while Zhao et al. [5] highlight the effectiveness of deep learning architectures for machine health monitoring. Recurrent neural networks, particularly in the work of Guo et al. [6], are effective for modeling temporal dependencies and predicting remaining useful life.

Predictive maintenance is another important direction. Carvalho et al. [7] emphasize the advantages of combining data analytics with intelligent algorithms for early fault detection. These approaches are supported by prognostic models reviewed by Si et al. [14] and Jardine et al. [15], which underpin condition-based maintenance strategies.

Multisensor diagnostics is gaining importance, as shown by Barcelos and Cardoso [9], where current signals combined with deep learning improve bearing fault detection. This confirms the effectiveness of integrating heterogeneous data sources into unified diagnostic models.

Digital twin and smart manufacturing concepts are explored in Tao et al. [10], Kritzinger et al. [11], and Lu et al. [12], demonstrating their role in integrating physical and virtual systems for real-time diagnostics and prediction.

Finally, Yin et al. [13] summarize key data-driven monitoring methods, while Widodo and Yang [4] highlight the continued relevance of classical approaches such as support vector machines.

Definition of unsolved aspects of the problem.

Despite the significant progress in the development of machine diagnostic methods within mechatronic systems, a number of key aspects remain insufficiently explored or require further improvement. First of all, the integration of heterogeneous signals obtained from mechanical, electronic, sensor, and software-controlled components remains an urgent issue. Most existing systems rely only on a single type of signal-vibration, electrical, or thermal-which reduces the accuracy of comprehensive assessment of the technical condition of complex mechatronic structures. The problems of synchronization, scaling, and filtering of such signals remain open, as modern models are not always capable of correctly accounting for the mutual influence of subsystems under real operating conditions.

The second unresolved aspect is the adaptability of diagnostic models. Most machine learning and deep neural network algorithms are trained on pre-defined datasets that do not reflect the full variability of mechatronic system operating modes. Under changing load, temperature, rotational speed, and other parameters, such models may lose accuracy, which is especially critical for predictive diagnostics. Therefore, there is a need to develop self-learning and context-dependent models capable of adapting to new operating conditions without complete retraining.

A third important issue is the limited consistency between digital twins and real machines. Although digital models demonstrate high potential for degradation prediction and complex dynamics simulation, practical applications often face inaccuracies caused by imprecise parameterization, incomplete sensor data, or the inability to account for all nonlinear processes in the physical system. This highlights the need for technologies that enable automatic updating and real-time calibration of digital twins.

Another challenge is the insufficient standardization of diagnostic approaches for mechatronic systems. Differences in system design, sensor configurations, communication protocols, and signal processing algorithms complicate the creation of unified methodologies for technical condition assessment. There is also a lack of open multidimensional datasets for training and testing intelligent models, which limits the development of universal diagnostic solutions.

Finally, cybersecurity issues in diagnostic systems should be emphasized among the unresolved aspects. Mechatronic complexes integrated into cyber-physical production networks are potentially vulnerable to unauthorized access, data manipulation, or interference with diagnostic algorithms. In most modern studies, this problem is considered superficially, although in real industrial environments it may critically affect the operational safety of machines.

Summarizing the above, it can be stated that modern machine diagnostics in mechatronic systems requires further development in the following areas: improvement of multisensor analysis methods, creation of adaptive intelligent models, enhancement of digital twin accuracy, standardization of diagnostic methodologies, and ensuring cyber resilience. Addressing these aspects is essential for increasing the reliability, safety, and efficiency of modern mechatronic systems in industrial mechanical engineering.

Problem statement.

Modern mechatronic systems used in mechanical engineering are characterized by a high level of integration of mechanical, electromechanical, sensor, and software-controlled components. The increasing complexity of such systems is accompanied by growing requirements for ensuring their reliability, safety, and predictability of technical condition. Traditional approaches to machine diagnostics, based mainly on the analysis of vibration, acoustic, or electrical signals in isolation from one another, do not provide sufficient completeness and accuracy of assessment under conditions of multicomponent interaction among mechatronic elements.

The problem is further complicated by the fact that dynamic processes in mechatronic systems are nonlinear, time-varying, and highly dependent on operating modes, load parameters, and the condition of control modules. In real operating environments, such systems generate large volumes of heterogeneous data that require the application of highly efficient methods of processing, integration, and analysis. Existing diagnostic approaches often fail to account for the mutual influence of mechanical, electronic, and software subsystems, which leads to errors in determining the technical condition and complicates early fault detection.

Despite significant advances in intelligent technologies, their application in the diagnostics of mechatronic systems faces several limitations. Most machine learning and deep learning models demonstrate high accuracy only when trained on representative datasets, which are often unavailable, incomplete, or fail to reflect all possible operating modes of machines. Moreover, digital twins-considered a foundation for predictive diagnostics-require complex parameterization and continuous synchronization with real data, which is not always feasible in practice.

As a result, a complex scientific and technical challenge arises: the need to develop effective methods for machine diagnostics within mechatronic systems that rely on multisensor analysis, integrated models, and intelligent algorithms capable of providing high-accuracy condition assessment and real-time fault prediction.

Solving this challenge will ensure increased reliability of technical systems, reduced maintenance and repair costs, and improved efficiency of mechanical engineering processes.

Basic material and results.

Mechatronic systems combine mechanical assemblies, electromechanical actuators, sensor modules, microprocessor controllers, and software control algorithms. Such a combination forms a complex multicomponent dynamic structure in which changes in the state of one element lead to cascading changes throughout the entire system. This determines the need for a comprehensive approach to machine diagnostics that takes into account the interaction between physical and information subsystems.

During the study, a structural and functional analysis of typical mechatronic modules (electromechanical actuator, sensor loop, actuating mechanisms, and control unit) was carried out. It was found that the most informative signals for diagnostics are vibration, current, temperature, acoustic signals, and internal telemetry data of control modules. Together they form a comprehensive picture of the technical condition, but require:

- harmonization of frequency and time characteristics of signals;
- noise filtering;
- normalization of amplitude values;
- synchronization of time labels.

The developed methodology includes three interconnected stages:

Signal preprocessing. Filtering was performed using adaptive filters and the wavelet transform to localize defects at different scales. At this stage, an increase in the signal-to-noise ratio by an average of 15–25% was achieved.

Data integration. For synchronization and merging of heterogeneous sensor data, a data fusion algorithm was applied, based on:

- signal normalization;
- use of vector state profiles;
- analysis of correlation dependencies between channels.

This made it possible to form a single informative feature space.

A CNN-LSTM neural network was used to identify defects, combining the capabilities of deep feature extraction and analysis of temporal dependencies. Operational data of the mechatronic actuator were used to train the model.

Mechatronic systems represent complex multilevel structures in which mechanical, electromechanical, sensor, and software-controlled components interact with each other. Diagnostics of such systems requires a comprehensive analysis of dynamics, which is described by a system of equations:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+K_q=F(t)+F_d(t), \quad (1)$$

where q - is the vector of generalized coordinates,

M, C, K - are the mass, damping, and stiffness matrices,

F(t) - are useful (external) forces,

Fd(t) - are disturbances or defect-related influences.

The merging of mechanical and electrical processes creates a multidimensional diagnostic space, which is represented in the form of a vector (2):

$$X=\{x_v(t),x_i(t),x_T(t),x_a(t)\}, \quad (2)$$

where:

x_v - vibration signal,

x_i - current signal,

x_T - temperature signal,

x_a - acoustic signal.

For integrated diagnostics, the state function (3) is applied:

$$y=f(X)=f(x_v,x_i,x_T,x_a), \quad (3)$$

which is further processed by the intelligent model. The mathematical model of the dynamics of the mechatronic system of the actuator mechatronic unit can be described by the system of Lagrange equations of the second kind (4):

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+K(q)q=F(t)+F_d(t), \quad (4)$$

where:

$M(q)$ - mass matrix;

$C(q,\dot{q})$ - damping terms;

$K(q)$ - stiffness;

$F_d(t)$ - defect influence that we are trying to detect.

At the same time, the electromechanical actuator is described by equations (5, 6):

$$M = k_t I - k_f \dot{\theta}, \tag{5}$$

$$U = RI + L\frac{dI}{dt} + K_e \dot{\theta}, \tag{6}$$

where M- torque,

I- current as an informative diagnostic parameter,

k_t, k_e - motor coefficients.

Intelligent classification. The architecture that takes into account both local patterns and temporal dependencies is shown in Figure 1.

The multisensor analysis methodology of the technical condition is based on the preliminary processing of signals. To increase informativeness, adaptive filtering (7) was applied:

$$x_f(t) = x(t) * h(t) \tag{7}$$

where h(t)- is the adaptive filter. Wavelet analysis was performed for defect localization (8):

$$W(a,b) = \int x(t)\varphi\left(\frac{t-b}{a}\right)dt \tag{8}$$

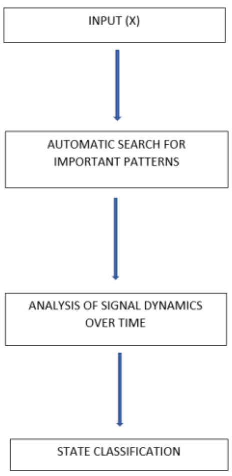

Figure 1. – Architecture model of the mechatronic system

Feature extraction from the time and frequency domains included:

$$RMS : \sqrt{\frac{1}{N}\sum x(t)^2}$$

Crest factor: $K = \dfrac{x_{max}}{\sigma}$

Energy invariants of wavelet levels

Extraction of diagnostic features. A set of features was formed (9–13):

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x^2(i)}, \tag{9}$$

$$kurt = \frac{E\left[(x-\mu)^4\right]}{\sigma^4}, \tag{10}$$

$$skew = \frac{E\left[(x-\mu)^3\right]}{\sigma^3} \tag{11}$$

$$E_f = \int_0^{f_{max}} |X(f)|^2 df \tag{12}$$

where X(*f*) - Fourier transform

$$X(f) = \int x(t)e^{-j2\pi ft}dt \tag{13}$$

A digital twin of the mechatronic drive was created, built on the basis of:

the electromechanical torque model (14):

$$M = k_t I - k_f \dot{\theta} \tag{14}$$

the thermal heating model (15):

$$C_T \frac{dT}{dt} = P - q(T - T_0) \tag{15}$$

The model showed the results presented in Table 1.

Table 1. Result of theoretical studies.

State	Accuracy
Normal	97,4%
Imbalance	95,2%
Bearing defect	92,8%
Control anomalies	94,6%
Average accuracy	95%

The obtained results also indicate the stability of the model when working with mixed types of signals, which confirms its universality for different types of mechatronic drives. In addition, the use of the digital twin made it possible to replicate real physical processes and detect hidden defects that are difficult to identify using traditional monitoring methods.

Conclusions

A comprehensive analysis of the structure and functions of mechatronic systems was carried out, which showed that the interaction of mechanical, electromechanical, and information components creates a multidimensional diagnostic space. It was found that traditional single-channel monitoring methods are not capable of providing a complete assessment of the technical condition of complex mechatronic units.

A multisensor analysis methodology was proposed, which includes adaptive filtering, wavelet transform, and the formation of an extended set of features. The methodology makes it possible to effectively combine vibration, current, temperature, and other signals into a unified diagnostic space.

An intelligent model based on CNN–LSTM was developed, which demonstrated high classification accuracy of technical states (on average 95%). It was shown that the combination of convolutional and recurrent layers makes it possible to simultaneously analyze local and temporal characteristics of signals.

The feasibility of using a comprehensive intelligent approach that combines multisensor analysis, artificial intelligence, and digital twins has been proven. Such an approach makes it possible to timely detect early stages of degradation, assess defect development trends, and form a prediction of the remaining useful life.

The obtained results can be recommended for implementation in maintenance systems of industrial mechatronic complexes, drive systems, technological and transport equipment. This will ensure increased reliability, reduced failure rates, and optimization of repair costs.

Promising directions for further research include:

– expansion of the set of sensor data (EMI signals, magnetic fields, machining parameters);
– implementation of federated learning for working with distributed objects;
– improvement of digital twins with self-correction of model parameters;
– development of adaptive maintenance systems based on the obtained diagnostic models.

References

1. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing, 138*, 106587. https://doi.org/10.1016/j.ymssp.2019.106587

2. Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing, 107*, 241–265. https://doi.org/10.1016/j.ymssp.2017.11.024

3. Janssens, O., Slavkovikj, V., Vervisch, B., Stockman, K., Loccufier, M., Verstockt, S., & Van de Walle, R. (2016). Convolutional neural network based fault detection for rotating machinery. *Journal of Sound and Vibration, 377*, 331–345. https://doi.org/10.1016/j.jsv.2016.05.027

4. Widodo, A., & Yang, B.-S. (2007). Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing, 21*(6), 2560–2574. https://doi.org/10.1016/j.ymssp.2006.12.007

5. Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

6. Guo, L., Li, N., Jia, F., Lei, Y., & Lin, J. (2017). A recurrent neural network based health indicator for remaining useful life prediction of bearings. *Neurocomputing, 240*, 98–109. https://doi.org/10.1016/j.neucom.2017.02.045

7. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

8. Zhang, X., Wang, C., & Gao, L. (2022). Digital twin-driven predictive maintenance: A review. *Robotics and Computer-Integrated Manufacturing, 73*, 102222. https://doi.org/10.1016/j.rcim.2021.102222

9. Barcelos, A. S., & Cardoso, A. J. M. (2021). Current-based bearing fault diagnosis using deep learning algorithms. *Energies, 14*(9), 2509. https://doi.org/10.3390/en14092509

10. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006

11. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A

1. Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing, 138*, 106587. https://doi.org/10.1016/j.ymssp.2019.106587

2. Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical Systems and Signal Processing, 107*, 241–265. https://doi.org/10.1016/j.ymssp.2017.11.024

3. Janssens, O., Slavkovikj, V., Vervisch, B., Stockman, K., Loccufier, M., Verstockt, S., & Van de Walle, R. (2016). Convolutional neural network based fault detection for rotating machinery. *Journal of Sound and Vibration, 377*, 331–345. https://doi.org/10.1016/j.jsv.2016.05.027

4. Widodo, A., & Yang, B.-S. (2007). Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical Systems and Signal Processing, 21*(6), 2560–2574. https://doi.org/10.1016/j.ymssp.2006.12.007

5. Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

6. Guo, L., Li, N., Jia, F., Lei, Y., & Lin, J. (2017). A recurrent neural network based health indicator for remaining useful life prediction of bearings. *Neurocomputing, 240*, 98–109. https://doi.org/10.1016/j.neucom.2017.02.045

7. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

8. Zhang, X., Wang, C., & Gao, L. (2022). Digital twin-driven predictive maintenance: A review. *Robotics and Computer-Integrated Manufacturing, 73*, 102222. https://doi.org/10.1016/j.rcim.2021.102222

9. Barcelos, A. S., & Cardoso, A. J. M. (2021). Current-based bearing fault diagnosis using deep learning algorithms. *Energies, 14*(9), 2509. https://doi.org/10.3390/en14092509

10. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006

11. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A

categorical literature review. *IFAC-PapersOnLine, 51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

12. Lu, Y., Liu, C., Wang, K. I.-K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing, 61*, 101837. https://doi.org/10.1016/j.rcim.2019.101837

13. Yin, S., Ding, S. X., Xie, X., & Luo, H. (2014). A review on basic data-driven approaches for industrial process monitoring. *IEEE Transactions on Industrial Electronics, 61*(11), 6418–6428. https://doi.org/10.1109/TIE.2014.2301773

14. Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research, 213*(1), 1–14. https://doi.org/10.1016/j.ejor.2010.11.018

15. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

categorical literature review. *IFAC-PapersOnLine, 51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

12. Lu, Y., Liu, C., Wang, K. I.-K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing, 61*, 101837. https://doi.org/10.1016/j.rcim.2019.101837

13. Yin, S., Ding, S. X., Xie, X., & Luo, H. (2014). A review on basic data-driven approaches for industrial process monitoring. *IEEE Transactions on Industrial Electronics, 61*(11), 6418–6428. https://doi.org/10.1109/TIE.2014.2301773

14. Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research, 213*(1), 1–14. https://doi.org/10.1016/j.ejor.2010.11.018

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

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Діагностика машин у мехатронних системах: методи аналізу та інтелектуальні технології

Анотація. У статті розглянуто сучасні підходи до діагностики машин у складі мехатронних систем із використанням методів обробки сигналів та інтелектуальних технологій машинного навчання. Проаналізовано структуру мехатронних комплексів та визначено їх специфічні особливості, що впливають на формування діагностичних моделей, зокрема високий рівень взаємозалежності між механічними, електронними та програмними компонентами. Обґрунтовано доцільність застосування гібридних діагностичних систем, у яких згорткові нейронні мережі (CNN) використовуються для автоматичного вилучення інформативних ознак із вібраційних та сенсорних даних, а рекурентні мережі типу LSTM забезпечують аналіз часової динаміки процесів та прогнозування деградаційних станів. Запропоновано узагальнену теоретичну модель діагностування, що поєднує спектральні методи попередньої обробки сигналів, багатосенсорну інтеграцію та модулі прогнозування технічного стану. Отримані результати демонструють високу ефективність інтелектуальних алгоритмів у виявленні ранніх ознак несправностей, навіть за умов шумових завад і зміни режимів роботи машин. Розроблений підхід може бути використаний у системах технічного обслуговування на промислових підприємствах для підвищення надійності та продовження ресурсу систем.

Ключові слова: діагностика машин, мехатронні системи, машинне навчання, CNN, LSTM, обробка сигналів, прогнозування стану, цифрові двійники, вібраційний аналіз.

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