The Use of Artificial Intelligence (AI) Systems in Evaluating the Technical Condition of Buildings and Structures

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**Abstract.** This article aims to explore the application and review of modern Machine Learning (ML) algorithms, data collection methods, and the integration of Artificial Intelligence (AI), ML, and Structural Health Monitoring (SHM) systems in assessing the technical condition of buildings and structures, as well as to highlight the significance of implementing this system in Uzbekistan.

**Keywords:** Machine Learning (ML) algorithms, Artificial Intelligence (AI), Structural Health Monitoring (SHM), technical condition of buildings and structures.

# INTRODUCTION

Research indicates [1] that the majority of building failures in our republic occur due to ground-foundation deformations. Such deformations alter the stress-strain state in the upper structural components of buildings, leading to deviations from vertical and horizontal planes, manifesting as cracks and other types of damage. The practice of using artificial intelligence (AI) is increasingly being adopted to detect, systematize, and analyze these damage symptoms.

AI can rapidly analyze large volumes of data, reduce human errors, and facilitate safe and efficient building management. For instance, it can predict stresses, damages, or malfunctions in engineering systems or optimize energy consumption. In the era of advancing digital technologies, the widespread application of these technologies in the field of technical safety of buildings and structures ensures result accuracy of nearly 90% while reducing repair costs by 20–30%.

The inclusion of AI-based methods for analyzing the technical condition of buildings and structures in the “Roadmap for Improving the System of Ensuring Seismic Safety and Enhancing the Earthquake Resistance of Buildings and Structures,” as outlined in Annex 1 of the Decree of the President of the Republic of Uzbekistan dated April 17, 2024, No. PQ-161, titled “On Measures to Enhance the Earthquake Resistance of Buildings and Structures and Improve Seismic Risk Monitoring Activities,” underscores the special recognition of this issue at the governmental level.

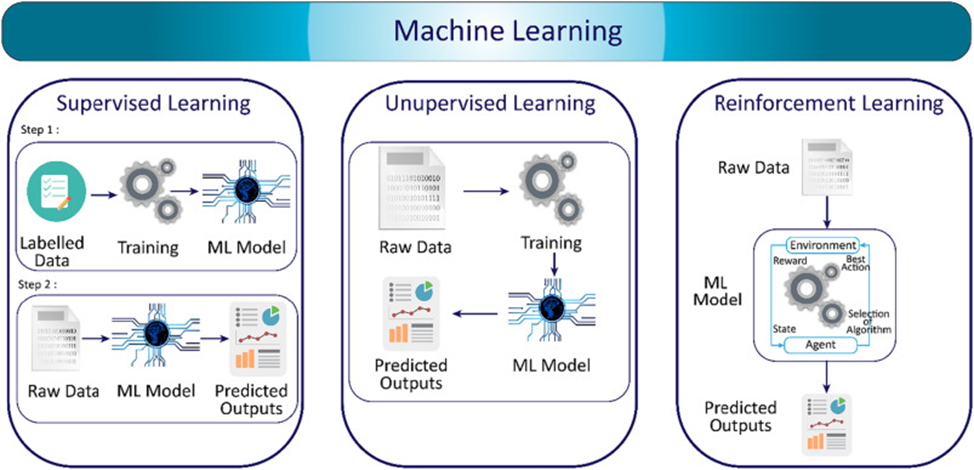
# MAIN PART

Machine Learning as a Key Component of Artificial Intelligence in Assessing the Technical Condition of Buildings and Structures One of the primary components of artificial intelligence (AI) in evaluating the technical condition of buildings and structures is Machine Learning (ML) algorithms. These algorithms analyze data obtained from sensors installed at critical points of a building and visual imagery to identify structural issues, predict failures, and enhance the quality of technical maintenance.

Machine Learning (ML) is a branch of Artificial Intelligence (AI) in which a computer conducts observations based on a specific dataset and creates a model used to solve problems based on input data [2].

ML differs from traditional programming. In traditional programming, rules are explicitly defined through precise instructions in a programming language, and there is no learning from data. In contrast, machine learning uses data to create predictive models, which are then applied to process previously unseen data.

One of the primary methods of classifying ML models is based on the level of supervision during the training process. On this basis, ML models are primarily divided into supervised learning, unsupervised learning, and reinforcement learning types (Figure1).



**FIGURE 1.** Types of ML Models Based on the Level of Supervision in the Training Process [1]

**Supervised Learning**

In supervised learning, the dataset includes both predictive factors and outcomes (referred to as "labels"). As shown in step 1 of variant v in Figure 1, a supervised ML model is first trained using a labeled dataset, and then the trained model can be used to make predictions on previously unseen data. The two most common tasks in supervised learning are classification and regression. In classification tasks, a specific category label is predicted, while in regression tasks, a continuous value is predicted [1].

**Unsupervised Learning**

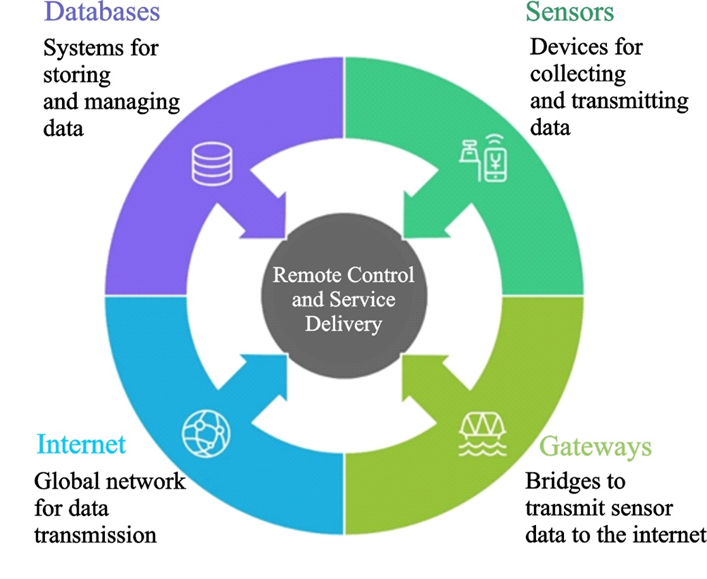
Unsupervised learning uses unlabeled datasets to identify hidden relationships or internal structures within the data. It is widely applied in tasks such as clustering, anomaly detection, novelty detection, visualization, and dimensionality reduction.

**Reinforcement Learning**

Reinforcement learning is an ML method that trains a model by rewarding desired behaviors and penalizing undesired ones. The learning system, called a reinforcement learning agent, observes the environment and performs actions that result in rewards or penalties. The primary goal is to find the optimal sequence of actions, known as a "policy," that maximizes cumulative rewards over time. The policy determines which action to take in each situation.

As observed above, the use of AI significantly reduces errors and shortcomings associated with human factors. Specialized algorithms analyze input data through neural networks in a structured manner to generate predictive outputs. Selecting the appropriate algorithm type is, of course, a critical step in this process. Integrating this process into a real-time monitoring system for assessing the technical condition of buildings and structures enables continuous real-time predictive data generation, early detection of stresses, defects, and flaws in structures, extension of the service life of buildings and structures, and reduction of maintenance costs.

In real-time monitoring of the technical condition of buildings and structures, implementing a Structural Health Monitoring (SHM) system (Figure 2) allows for the analysis of data collected in real time from sensors installed at critical points of buildings and structures using ML algorithms. This enables early detection of structural changes and, when necessary, precise determination of the remaining service life of buildings and structures, thereby enhancing these capabilities.



**FIGURE 2.** Diagram of the Structural Health Monitoring (SHM) System

The effective operation of this monitoring system is achieved through the use of “smart sensors.” These sensors are intelligent, capable not only of measuring physical quantities but also of processing them and transmitting data via the internet for analysis. Each sensor is considered a smart object, and the entire SHM system is a practical implementation of the Internet of Things (IoT) paradigm [15, 16]. Implementing the SHM system based on the IoT paradigm enables the application of new technologies to enhance the efficiency and reliability of the monitoring system. Typically, IoT systems utilize wireless networks to exchange data between smart objects (sensors), allowing sensors to be installed at designated monitoring points by specialists [14].

# RESULTS AND DISCUSSION

There are three main stages for applying Machine Learning (ML) in SHM and damage detection. First, data is collected using appropriate sensors. Next, relevant features are extracted from the collected data. Finally, these features are processed to evaluate results that provide insights into the condition of the structural system. Research on applying ML to SHM typically focuses on classification techniques and anomaly detection to identify issues at an early stage [3]. AI-based SHM techniques are currently used in developed countries for the following purposes: general SHM [4], multi-level damage detection [5], corrosion detection [6], distinguishing voids from defects on concrete surfaces [7], crack detection in concrete [8], concrete deterioration [9], crack detection in metal [10], visible and invisible damages [11], road pavement crack detection [12], and condition assessment of masonry buildings [13].

This method can be used to predict the condition of building and structure components based on operational data collected and transmitted by sensors, utilizing ML algorithms. The effectiveness of predictions in implementing such systems depends on the correct selection of the ML algorithm.

# CONCLUSION

This article examines the use of AI systems, particularly ML algorithms, in assessing the technical condition of buildings and structures, their integration into Structural Health Monitoring (SHM) systems, and their effectiveness. The widespread application of ML algorithms in studying the properties of construction materials such as concrete, metal, and wood, as well as predicting structural strength and performance, significantly contributes to improving the quality of technical maintenance for buildings and structures in the context of Uzbekistan.

**FUTURE SCOPE**

Machine Learning (ML) algorithms could be optimized in future, which include deep learning models, thus monitoring Structural Health Monitoring (SHM) in Uzbekistan could be more accurate. Personalised algorithms can identify micro-damages such as cracks with a precision higher than 90 percent, depending on available, local material and situations.

Widespread Internet of Things (IoT) by the enhanced smart sensor technology in SHM systems has the potential to allow real-time assessment of vibration, temperature, and humidity. The implementation of these in the various climate of Uzbekistan will enhance structural evaluation regarding data.

With fully automated SHM systems having AI, data will be collected and damage classified much easier and without many mistakes. This is critical in tracking the ageing infrastructure in Uzbekistan which dates 1970s-1980s.

Existing field-testing focuses on the long-term field validation of AI-based SHM systems in the seismic region in Uzbekistan which will test the validity at real-world scenarios and real-life earthquakes and cyclic situations.

Supervised, unsupervised and reinforcement learning may be combined to make SHM more flexible. Such models will be able to forecast structural lives through examination of the degradation trends of the buildings in Uzbekistan.

Learning the building behaviors through the seismic process of AI with Finite Element Modeling (FEM) allows computer simulations to simulate building behavior in the event of an earthquake, and optimize the design of buildings in the seismic plagued regions of Uzbekistan according to the new safety requirements set out by the government.

AI would provide a way of accessing the strength of eco-friendly materials in dynamic loading, which would act towards sustainability targets of Uzbekistan and maintain safety of structures.

Real-time dashboards powered by AI technology will allow predicting a structural failure before it occurs, start proactive maintenance and save the costs of repair going to Uzbekistan infrastructure.

Partnership of AI, material and structural specialists can lead to emergence of sensor-integrated smart materials to enable real-time SHM that can be fronted by the concerns of the environment of Uzbekistan.

The introduction of standards on a national and international level of AI-based SHM will prevent inconsistency and guarantee safety in the Uzbekistan infrastructure, according to the seismic safety laws.

# REFERENCES

1. The President of the Republic of Uzbekistan, “On Measures to Enhance the Earthquake Resistance of Buildings and Structures and Improve Seismic Risk Monitoring Activities,” Decree No. PQ-161 (17 April 2024).
2. S. K. Baduge, S. Thilakarathna, J. S. Perera, M. Arashpour, P. Sharafi, B. Teodosio, A. Shringi, and P. Mendis, Autom. Constr. **141**, 104440 (2022). https://doi.org/10.1016/j.autcon.2022.104440
3. O. Abdeljaber, O. Avci, M. S. Kiranyaz, B. Boashash, H. Sodano, and D. J. Inman, Neurocomputing **275**, 1308–1317 (2018). https://doi.org/10.1016/j.neucom.2017.09.034
4. Y. Bao, Z. Tang, H. Li, and Y. Zhang, Struct. Health Monit. **18**, 401–421 (2019). https://doi.org/10.1177/1475921718757405
5. Y.-J. Cha, W. Choi, and O. Büyüköztürk, Comput.-Aided Civ. Infrastruct. Eng. **32**, 361–378 (2017). https://doi.org/10.1111/mice.12263
6. M. R. Jahanshahi and S. F. Masri, J. Comput. Civ. Eng. **27**, 345–357 (2013). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000212
7. F. Wei, G. Yao, Y. Yang, and Y. Sun, Autom. Constr. **107**, 102920 (2019). https://doi.org/10.1016/j.autcon.2019.102920
8. S. German, I. Brilakis, and R. DesRoches, Adv. Eng. Inform. **26**, 846–858 (2012). https://doi.org/10.1016/j.aei.2012.07.003
9. C. V. Dung, H. Sekiya, S. Hirano, T. Okatani, and C. Miki, Autom. Constr. **102**, 217–229 (2019). https://doi.org/10.1016/j.autcon.2019.02.013
10. R. Ali and Y.-J. Cha, Constr. Build. Mater. **226**, 376–387 (2019). https://doi.org/10.1016/j.conbuildmat.2019.07.246
11. A. Zhang, K. C. P. Wang, Y. Fei, Y. Liu, S. Tao, C. Chen, J. Q. Li, and B. Li, J. Comput. Civ. Eng. **32**, 04018041 (2018). https://doi.org/10.1061/(ASCE)CP.1943-5487.0000735
12. N. Wang, X. Zhao, P. Zhao, Y. Zhang, Z. Zou, and J. Ou, Autom. Constr. **103**, 53–66 (2019). https://doi.org/10.1016/j.autcon.2019.03.007
13. R. S. Olivito and F. Lamonaca, IEEE Instrum. Meas. Mag. **21**(6), 30–35 (2018). <https://doi.org/10.1109/MIM.2018.8573586>
14. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, Future Gener. Comput. Syst. **29**, 1645–1660 (2013). https://doi.org/10.1016/j.future.2013.01.010
15. F. Lamonaca, C. Scuro, P. F. Sciammarella, D. L. Carnì, and R. Olivito, in Proc. IEEE Int. Workshop on Metrology for Industry 4.0 and IoT, pp. 73–78 (2018). https://doi.org/10.1109/METROI4.2018.8428308
16. A. T. Khotamov, Methodology for assessment of housing stock wear and scientific foundations of monitoring system in urban planning, Ph.D. dissertation, Tashkent (2021).