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REVIEW ARTICLE

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Real-time monitoring of tunnel structures using digital twin and artificial intelligence: A short overview

Mohammad Afrazi[1] | **Danial Jahed Armaghani**[2] | **Hossein Afrazi**[3] | **Hadi Fattahi**[4] | **Pijush Samui**[5]

[1]Mechanical Engineering Department, New Mexico Institute of Mining and Technology, Socorro, USA

[2]School of Civil and Environmental Engineering, University of Technology Sydney, Sydney, Australia

[3]Department of Civil, Water and Environmental Engineering, Shahid Bahonar University of Kerman, Kerman, Iran

[4]Faculty of Earth Sciences Engineering, Arak University of Technology, Arak, Iran

[5]Department of Civil Engineering, National Institute of Technology Patna, Patna, India

Correspondence

Danial Jahed Armaghani, School of Civil and Environmental Engineering, University of Technology Sydney, Sydney 2006, Australia.
Email: Danial.jahedarmaghani@uts.edu.au

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Abstract

Tunnels are essential components of contemporary infrastructure, yet guaranteeing their safety, longevity, and efficiency remains a persistent challenge. Recent breakthroughs in artificial intelligence (AI) and digital twin (DT) technology provide innovative solutions for the real-time monitoring of tunnel systems, suggesting proactive maintenance tactics and improved safety protocols. This review paper offers a comprehensive examination of the application of AI and DT methodologies in tunnel surveillance. We explore the core concepts of AI and DT and their applicability to structural monitoring, encompassing machine learning, computer vision, and sensor integration. Through the utilization of these AI-powered technologies, engineers are equipped with unparalleled insights into the state and behavior of tunnels, facilitating the early identification of irregularities and the optimization of maintenance timelines. We discuss the array of AI techniques utilized for the immediate monitoring of tunnel systems, emphasizing their foundations, benefits, and practical uses. Numerous studies have showcased the effectiveness and adaptability of AI-based monitoring systems in various tunnel settings. Moreover, we address the hurdles and constraints inherent in AI and DT methodologies and suggest strategies for overcoming them, such as data augmentation, interpretable AI, edge computing, and continuous monitoring. Ultimately, the incorporation of AI and DT technologies into tunnel surveillance signifies a paradigm shift, offering substantial advantages over conventional techniques. By adopting AI-driven monitoring systems, tunnel operators can augment safety, prolong the lifespan of infrastructure, and decrease operational expenses, molding the future of subterranean infrastructure management.

KEYWORDS

artificial intelligence, digital twin, machine learning, monitoring, real-time, tunnelling

Highlights

- Comprehensive examination of artificial intelligence (AI) and digital twin (DT) methodologies specifically tailored for tunnel surveillance.
- Emphasis on the transformative potential of AI and DT in revolutionizing tunnel monitoring, addressing the challenges of conventional methods.
- Detailed exploration of core AI concepts like machine learning and computer vision, highlighting their applicability in real-time monitoring.
- Discussion of practical uses, benefits, and challenges of AI-based monitoring systems in tunnel settings.
- Comparing and explaining the DT method in detail and its practical applications in tunneling.
- Suggestions for overcoming hurdles through strategies such as data augmentation, interpretable AI, edge computing, and continuous monitoring, paving the way for improved infrastructure management.

1 | INTRODUCTION

Tunnels are indispensable components of modern infrastructure, acting as crucial pathways for transportation networks, underground utilities, and communication systems. They are essential for facilitating the movement of people and goods through urban areas and enabling the transmission of essential services across vast distances, playing a critical role in societal functioning (Huat et al., 2023; Shahrour et al., 2021). Therefore, ensuring the safety, durability, and efficiency of these underground passageways is of paramount importance. Traditionally, the monitoring of tunnels and other underground structures has depended on periodic inspections by human inspectors, complemented by manual data collection and analysis (Farahani et al., 2020; Xu & Yang, 2020; Yang & Xu, 2021). While these methods have been adequate in the past, they are inherently limited by factors such as subjectivity, labor intensity, and the potential for human error. Moreover, the intermittent nature of these inspections means that issues may go undetected for extended periods, increasing the risk of structural deterioration and potential hazards.

In the context of tunneling, artificial intelligence (AI) includes a wide range of technologies and methodologies designed to enable systems to perform tasks that typically require human intelligence. Machine learning (ML), a subset of AI, focuses on developing algorithms that can learn from data and make predictions or decisions without being explicitly programmed. ML techniques are widely used in tunnel monitoring for tasks such as anomaly detection, predictive maintenance, and pattern recognition based on historical sensor data. Deep learning (DL), a subfield of ML, uses neural networks with multiple layers to learn hierarchical representations of data (Barkhordari, Fattahi, et al., 2024). In tunneling applications, DL algorithms, such as convolutional neural networks (CNNs), are often employed for image analysis tasks, such as crack detection and defect classification in tunnel structures based on visual data captured by cameras. While AI encompasses a broader range of techniques beyond ML and DL, these subsets play pivotal roles in enhancing safety, efficiency, and maintenance practices within tunneling infrastructure (Afrazi et al., 2022; Tan et al., 2025). The following figure illustrates the differences between these three approaches (Figure 1).

In recent years, AI has significantly advanced the fields of tunneling and structural monitoring (Ali et al., 2023; Asteris et al., 2022; Wang et al., 2023). It offers real-time evaluations, predictive analytics, and strategies for proactive maintenance. Utilizing AI algorithms like ML (Xu et al., 2019), computer vision (Chen et al., 2020), and sensor fusion, engineers and stakeholders can obtain unique insights into the state and behavior of tunnel structures. These AI-powered monitoring systems facilitate ongoing data collection, analysis, and interpretation, enabling the early identification of anomalies, the recognition of potential risks, and the enhancement of maintenance schedules.

The incorporation of AI technologies into tunnel monitoring marks a significant shift, providing a multitude of advantages over conventional approaches. Real-time monitoring capabilities equip decision-makers with immediate data, allowing for rapid responses to emerging problems and the mitigation of risks to tunnel safety and functionality (Afrazi & Yazdani, 2021; Zeng et al., 2020). Moreover, AI-powered systems can utilize extensive data from sensors, cameras, and other monitoring tools to create predictive models and refine maintenance strategies, significantly extending the lifespan of tunnel infrastructure and lowering operational expenses.

In parallel, a digital twin (DT) acts as a dynamic virtual replica of physical objects, processes, or systems, utilizing real-time data from sensors and Internet of Things (IoT) devices to simulate behavior, monitor performance, and forecast future conditions. In the context of tunneling, DTs are crucial for improving design, construction, maintenance, and operational processes. They allow engineers to simulate tunnels and underground structures, optimizing designs for safety, efficiency, and cost-effectiveness before construction. During the construction phase, DTs support project

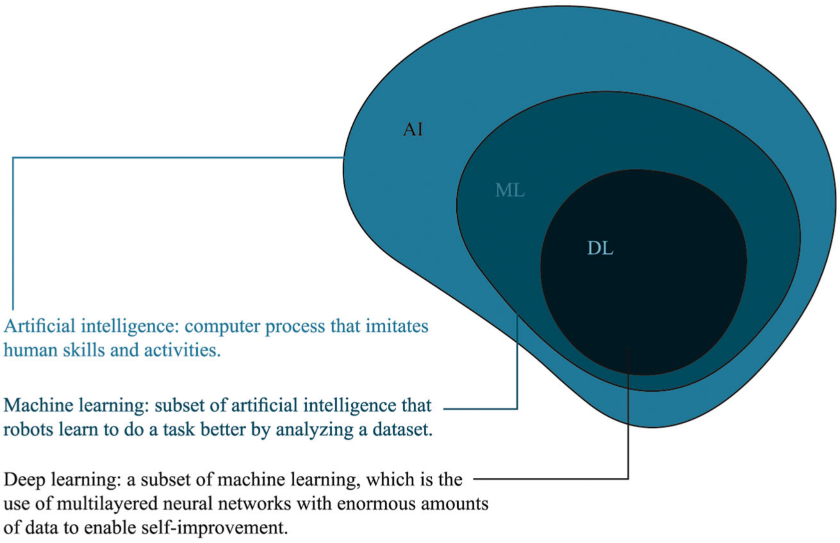

FIGURE 1 Relationship between artificial intelligence (AI), machine learning (ML), and deep learning (DL).

management by offering real-time monitoring of progress, resource usage, and adherence to timelines, ensuring successful project completion through data-driven decision-making.

Moreover, DTs facilitate ongoing monitoring of tunnel infrastructure, identifying anomalies and potential hazards early to extend the structure's lifespan (Sakr et al., 2024). By amalgamating data from various sensors, including strain gauges and accelerometers, DTs offer insights into the health of the structure and forecast maintenance requirements. They also enhance tunnel operations by simulating scenarios and evaluating data from IoT devices to boost energy efficiency, traffic flow, and overall safety within the tunnel environment. In emergency situations, DTs bolster response efforts by offering real-time situational awareness, simulating evacuation scenarios, and assisting decision-making for emergency responders, thereby improving resilience and reducing risks to human safety (Omrany et al., 2023).

This review paper offers a thorough examination of the methods and progress in real-time monitoring of tunnel structures utilizing AI and DT. Through a detailed review of existing research, we will explore the array of AI and DT-based methodologies used for structural monitoring, their applications across diverse tunnel settings, and their capacity to revolutionize the management and maintenance of underground infrastructure. Our objective is to underscore the advantages, constraints, and future prospects of AI- and DT-driven tunnel monitoring systems. Due to the emerging nature of DT applications in this field, specific case studies and datasets are currently scarce but represent a critical avenue for future research.

2 | TRADITIONAL METHODS OF TUNNEL MONITORING

Tunnel monitoring has historically depended on a range of conventional techniques to evaluate structural integrity and guarantee the safety of underground infrastructures. These techniques commonly encompass manual inspections (Sjölander et al., 2023), visual surveys (Sjölander et al., 2023), and the application of instrumentation like inclinometers, crack gauges, and strain gauges. Manual inspections involve visual examinations conducted by trained individuals who scrutinize tunnel surfaces for indications of stress, fracturing, or deformation. Instrumentation-based monitoring hinges on sensors strategically positioned within the tunnel to gauge parameters such as deformation, strain, and groundwater levels (Afrazi et al., 2024; Armaghani & Azizi, 2021; He, Armaghani, Bhatawdekar, et al., 2021). The subsequent figure illustrates the traditional approach to tunnel monitoring (Figure 2).

While these traditional methods have played a crucial role in identifying structural issues and directing maintenance efforts, they are not without their limitations and challenges. Initially, manual inspections are laborious, time-consuming, and prone to human error. The subjective aspect of visual assessments can result in variations in data interpretation, potentially missing early indicators of deterioration. Moreover, reaching certain areas of the tunnel for inspection can be difficult, especially in extensive or intricate underground networks.

Instrumentation-based monitoring, although more objective and accurate than manual inspections, encounters its own array of challenges. Traditional sensors often have limited reach and may not offer a complete understanding of the tunnel system's structural health. Furthermore, these sensors necessitate regular maintenance and calibration, which can be expensive and disruptive to tunnel operations. In some instances, sensor malfunctions or data inaccuracies may occur, leading to unreliable monitoring outcomes and potential safety risks (Flah et al., 2021; Ramirez et al., 2022).

Moreover, conventional monitoring techniques are primarily reactive, meaning they are structured to detect issues only after they have manifested. This reactive strategy can lead to delays in identifying structural problems, potentially jeopardizing the safety and integrity of tunnel structures. Additionally, the data gathered from traditional monitoring methods may not offer real-time insights, complicating the ability to respond swiftly to emerging threats or anomalies.

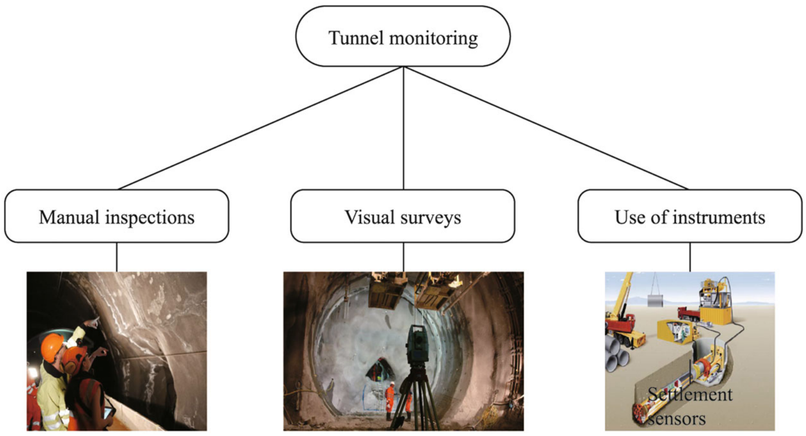

FIGURE 2 Traditional tunnel monitoring.

3 | FUNDAMENTAL PRINCIPLES OF AI AND DT

3.1 | Introduction to AI and its relevance to structural monitoring

AI has emerged as a pivotal force in the field of structural monitoring, marking a significant shift in our approach to evaluating and managing tunnel infrastructures (Dong et al., 2022; Putra, 2021; Sofi et al., 2022; Zinno et al., 2022). Its ability to process and interpret vast quantities of data in real-time, identifying patterns that might not be immediately discernible to human operators, holds the promise to significantly improve our capacity to forecast, prevent, and address structural challenges (He et al., 2023, 2024; Zhou et al., 2022).

In the sphere of tunnel monitoring, AI systems can act as intelligent aids, persistently analyzing sensor data to identify anomalies, forecast potential failures, and refine maintenance schedules (Blasch et al., 2021; Coccia et al., 2021; Mukhopadhyay et al., 2021). This transition allows tunnel operators to transition from reactive to proactive maintenance strategies, prioritizing safety, efficiency, and cost-effectiveness by leveraging AI.

The reactive approach involves reacting to observed damage after it has occurred, providing a limited window for the formulation of mitigation strategies before the damage escalates to unacceptable levels. This time constraint often results in rushed or incomplete mitigation efforts, driven by the urgency of the situation. In contrast, the proactive approach is defined by the anticipation of potential sources of degradation and the preemptive execution of measures designed to either prevent or mitigate damage before it begins. The distinction between reactive and proactive methods is illustrated in the subsequent figure.

3.2 | Basic principles of AI technologies

3.2.1 | ML

ML is central to many AI-driven tunnel monitoring systems, offering the ability to derive valuable insights from extensive datasets without the need for explicit programming. ML algorithms can be trained on historical sensor data to identify patterns that signal structural deterioration, enabling the early identification of potential problems before they escalate into expensive repairs or safety risks (Armaghani et al., 2024; Barkhordari, Barkhordari et al., 2024; Chopra et al., 2018).

Supervised learning algorithms, for example, can be utilized to predict tunnel behavior based on labeled data, such as historical instances of structural damage and corresponding sensor readings. Conversely, unsupervised learning techniques can uncover hidden patterns in unlabeled data, potentially unveiling emerging threats or vulnerabilities that were not previously recognized. Reinforcement learning approaches can enhance maintenance strategies by learning from past actions and their results, iteratively refining decision-making processes to ensure long-term structural integrity.

3.2.2 | Computer vision

Computer vision is crucial in tunnel monitoring, enabling automated analysis of visual data captured by cameras within tunnel environments (Attard et al., 2018; Chen et al., 2021). By employing computer vision techniques, such as object detection, image segmentation, and anomaly detection, AI systems can identify and locate structural defects, cracks, or deformations in real-time, facilitating quick response and intervention (Chi et al., 2013; Koch et al., 2015; Li, Li, Chen, et al., 2024; Wu et al., 2021).

Object detection algorithms can identify specific features of interest within images, such as cracks or displacement joints, allowing for precise identification and characterization of structural anomalies. Image segmentation techniques can divide images into meaningful sections, enabling detailed analysis of structural components and their condition. Anomaly detection methods can highlight deviations from normal visual patterns, alerting operators to potential safety hazards or structural issues that demand immediate attention.

3.2.3 | Sensor fusion

A crucial aspect of AI-driven tunnel monitoring systems is sensor fusion, which enables the integration of data from multiple sensors to offer a comprehensive view of structural health and performance. By combining data from various sources, such as accelerometers, strain gauges, temperature sensors, and environmental sensors, AI systems can overcome the limitations of individual sensors and enhance overall monitoring capabilities (Das et al., 2021; Fakharian et al., 2024; Li et al., 2021; Shaffiee Haghshenas et al., 2022; Zhang et al., 2022).

For instance, merging data from accelerometers and strain gauges can provide insights into structural deformation and dynamic behavior during tunnel excavation or operation. Similarly, integrating temperature and humidity measurements with structural data can help evaluate the influence of environmental factors on tunnel integrity. Sensor fusion techniques can enhance the reliability and robustness of monitoring systems by cross-validating sensor outputs, mitigating sensor failures or inaccuracies, and providing a more accurate representation of the monitored environment.

3.3 | Basic principles of DT technologies

DT technologies transform tunnel monitoring by creating virtual counterparts of physical structures. These counterparts are continuously updated with real-time sensor data, offering a dynamic simulation of structural behavior and performance (Baghalzadeh Shishehgarkhaneh et al., 2022; Huat et al., 2024; Pang et al., 2024). DTs incorporate physics-based models, real-time sensor data, and historical records to provide a comprehensive understanding of tunnel conditions.

DTs enable predictive maintenance by forecasting potential issues based on real-time and historical data, facilitating proactive interventions to prevent structural failures. They optimize tunnel performance by analyzing data to enhance operational efficiency and extend infrastructure lifespan. Additionally, DTs serve as decision support tools, aiding operators, engineers, and stakeholders in making informed decisions regarding maintenance, repairs, and upgrades.

The integration of AI technologies enhances the intelligence of DTs, enabling advanced analytics for predictive modeling, visual inspection, and comprehensive data analysis. This synergy improves the accuracy of structural health assessments and predictive capabilities, advancing safety, efficiency, and sustainability in tunnel management. In summary, DT technologies offer a holistic approach to tunnel monitoring, merging real-time data integration, physics-based modeling, and advanced analytics to revolutionize infrastructure management practices.

4 | AI TECHNIQUES FOR REAL-TIME MONITORING

4.1 | Interpretability in AI for tunnel monitoring

Interpretability in AI models is essential for ensuring trust and usability, particularly in safety-critical applications like tunnel monitoring. This involves elucidating how models reach their predictions, which is vital for nonspecialist stakeholders such as maintenance personnel and policymakers. Techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are employed to explain model outputs. For example, SHAP assigns importance scores to input features, helping operators understand which parameters (e.g., strain gauge data, temperature variations) significantly influence anomaly detection. Similarly, feature visualization in CNNs allows the identification of patterns leading to defect classification. Such approaches enhance transparency and foster trust in AI-driven systems.

4.2 | Detailed exploration of AI techniques utilized for tunnel monitoring

AI techniques have become pivotal tools in the realm of real-time monitoring for tunnel structures, providing a sophisticated range of methods to guarantee the safety, reliability, and efficiency of underground infrastructures (Chen et al., 2023; Hajihassani et al., 2014; Jahed Armaghani & Azizi, 2021a, 2021b). These AI-powered systems utilize sophisticated algorithms and data analytics to continuously process sensor data streams, identify anomalies, forecast potential structural problems before they worsen, and refine maintenance strategies. This section offers a thorough analysis of numerous AI methods employed for tunnel monitoring, discussing their advantages, mechanisms, and foundational principles (Eng et al., 2023).

4.3 | Utilization of ML algorithms

ML algorithms are a vital part of AI-powered tunnel monitoring systems. These algorithms are adept at autonomously learning patterns, relationships, and trends from historical sensor data, enabling the creation of predictive models and intelligent decision-making processes. In tunnel monitoring applications, ML techniques such as supervised learning, unsupervised learning, and reinforcement learning are commonly applied, as depicted in Figure 3.

Supervised learning, as depicted in Figure 4, is an ML approach where the algorithm learns from labeled data, linking inputs with their corresponding outputs. This enables the algorithm to generalize patterns and relationships, making predictions or classifications on unseen data. Common algorithms encompass regression for continuous outputs and classification for discrete ones. Supervised learning algorithms, including support vector machines (Jahed Armaghani et al., 2023), decision trees (He, Armaghani, Masoumnezhad, et al., 2021), random forests (Zhou et al., 2019), and neural networks (Asteris et al., 2019), as shown in Figure 4, are employed to classify sensor data and identify patterns indicative of structural anomalies. By training these algorithms on labeled historical data, tunnel operators can develop predictive models capable of detecting deviations from normal operating conditions in real-time. Supervised learning methods learn from examples, where the input data (e.g., sensor readings) are associated with corresponding output labels (e.g., normal or anomalous conditions) (Figure 5).

Unsupervised learning is a subset of ML where algorithms analyze data without the need for labeled examples. Its goal is to uncover patterns and structures within data to offer insights. The primary methods include outlier detection (identifying unusual data points), clustering (grouping similar data points), and dimensionality reduction (simplifying data visualization). In the field of geotechnical engineering, these techniques assist in monitoring works, classifying rock types, and enhancing data analysis. Unsupervised learning techniques, such as clustering algorithms and anomaly detection methods, allow for the identification of hidden patterns or outliers in unlabeled sensor data, enabling the discovery of previously unknown structural issues or

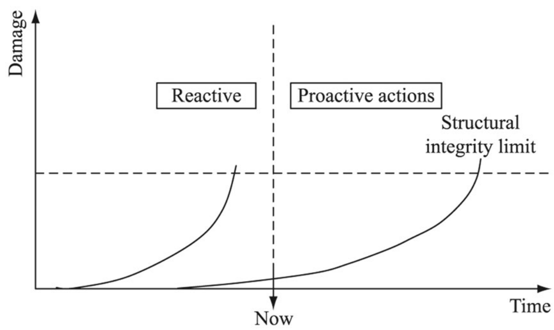

FIGURE 3 Comparing reactive and proactive methods in structural integrity. Adopted from NUREG/CR-6923.

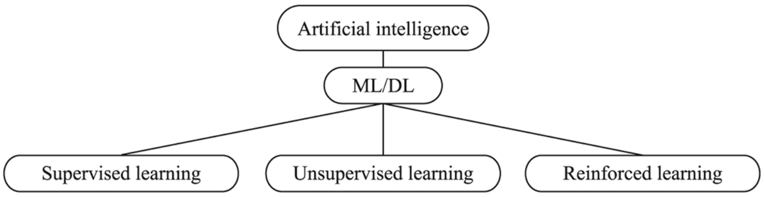

FIGURE 4 The fields of artificial intelligence (AI), machine learning (ML), and deep learning (DL) in a specific context, adopted from Marcher et al. (2021).

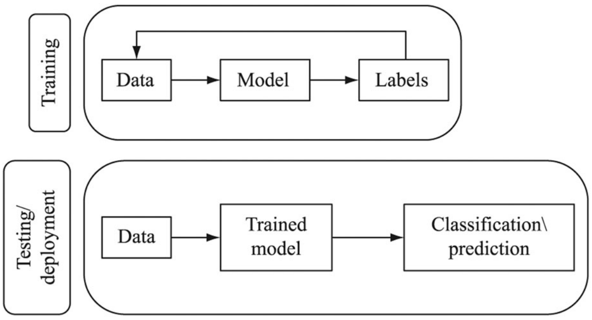

FIGURE 5 Principle of supervised learning, adopted from Marcher et al. (2021).

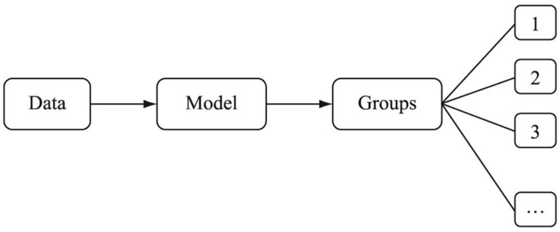

FIGURE 6 Principle of unsupervised learning, adopted from Marcher et al. (2021).

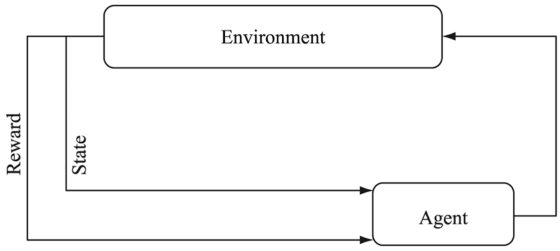

FIGURE 7 Principle of reinforcement learning, adopted from Marcher et al. (2021).

abnormal behaviors. The subsequent figure illustrates the principles of unsupervised learning.

Reinforcement learning approaches enable AI systems to autonomously learn optimal control policies through trial-and-error interactions with the tunnel environment, facilitating adaptive and proactive maintenance strategies, as depicted in Figures 6 and 7).

4.4 | Computer vision methods

Computer vision techniques are essential for visual monitoring systems in tunnels, utilizing cameras to capture images or videos of the tunnel's surroundings. Sophisticated image processing methods, such as CNNs (Tuama et al., 2016), feature extraction algorithms, and image segmentation techniques, are used to analyze visual data and extract valuable information about the structural condition and integrity. CNNs, especially, have shown remarkable effectiveness in tasks like object detection, image classification, and semantic segmentation in tunnel monitoring scenarios. These DL architectures can automatically detect and locate structural flaws, cracks, or distortions in images, facilitating quick identification and evaluation of anomalies. Moreover, feature extraction algorithms can extract key features or attributes from images, enabling the quantification and analysis of structural characteristics such as displacement, distortion, or corrosion. Image segmentation techniques further divide images into separate areas, aiding in detailed examination and interpretation of structural elements and flaws.

4.5 | Integrating sensor data for enhanced monitoring

Sensor fusion methods are crucial for merging data from various sensors placed within tunnel structures, offering a thorough understanding of their health and performance. By merging information from a range of sensor types, including accelerometers, strain gauges, temperature sensors, and environmental sensors, AI-powered systems can evaluate structural conditions in real-time and identify deviations from expected performance (Ding et al., 2024; Jiang et al., 2022). The combination of data from different sensors enhances monitoring capabilities, allowing tunnel operators to gain a more complete understanding of structural health and integrity. For example, integrating accelerometer data with strain gauge readings can offer insights into structural deformation and dynamic behavior during tunnel excavation or operation (Fakharian et al., 2023; Ghanizadeh et al., 2023; Mao et al., 2024). Similarly, merging temperature and humidity data with structural information can help assess the influence of environmental factors on tunnel integrity. Sensor fusion methods enable AI-powered monitoring systems to pinpoint potential risks, optimize maintenance schedules, and more effectively mitigate safety hazards by cross-verifying sensor data, compensating for sensor failures or inaccuracies, and providing a more accurate depiction of the monitored environment (Ding et al., 2024).

In applications, AI technologies for tunnel monitoring are frequently implemented as unified systems that integrate ML algorithms, computer vision techniques, and sensor fusion strategies. These unified systems harness the synergistic capabilities of different AI technologies to deliver robust and comprehensive monitoring solutions tailored to the specific needs of underground infrastructure. Tunnel operators can ensure the long-term safety and reliability of tunnel structures, enhance maintenance processes, and gain actionable insights into the structural health of their tunnels by employing AI.

5 | DT TECHNIQUES FOR REAL-TIME MONITORING

5.1 | Overview of DT technology

DT technology has emerged as a potent instrument for the immediate monitoring of tunnel infrastructure, providing a virtual depiction of physical assets that reflects their state and performance. A DT comprises three main elements: a virtual replica of the actual tunnel structure, the immediate incorporation of data from sensors and IoT devices, and sophisticated analytics for evaluating performance and facilitating decision-making (Hu et al., 2021; Li, Li, Rui, et al., 2024; Wu et al., 2022).

5.2 | Components of a DT system

A DT system for tunnel monitoring typically consists of the following components.

5.2.1 | Virtual model

The virtual model acts as the digital counterpart to the physical tunnel structure, encompassing its geometry, materials, and structural characteristics. Sophisticated modeling methods, including finite element analysis (FEA) and computational fluid dynamics (CFD), are utilized to generate precise simulations of how the tunnel behaves under different loadings and environmental conditions.

5.2.2 | Real-time data integration

Data from sensors positioned within the tunnel, such as strain gauges, accelerometers, temperature sensors, and environmental monitors, are persistently transmitted into the DT system. IoT devices ensure smooth integration of this sensor data, allowing for thorough monitoring of the structural health and performance.

5.2.3 | Advanced analytics

Complex analytics algorithms within the DT framework process the collected sensor data, scrutinizing patterns, identifying anomalies, and forecasting possible problems. Techniques like ML, statistical modeling, and data fusion are used to derive practical insights from the extensive sensor data, facilitating proactive maintenance plans and informed decision-making.

5.3 | Applications of DT in tunnel monitoring

DT technology offers several applications in tunnel monitoring, including the following.

5.3.1 | Predictive maintenance

By virtually replicating the behavior of tunnel structures in real-time and comparing it with sensor data, DTs can anticipate maintenance requirements before problems worsen. Predictive maintenance models utilize historical data and sophisticated analytics to foresee possible breakdowns, streamline maintenance schedules, and reduce downtime.

5.3.2 | Performance optimization

DTs facilitate performance enhancement by simulating various operational scenarios and evaluating their effects on tunnel behavior. By examining sensor data and simulating alterations in operational conditions, operators can pinpoint opportunities for efficiency enhancements, energy conservation, and risk reduction.

5.3.3 | Scenario analysis and decision support

DTs support scenario analysis and decision-making by offering a virtual space for hypothesis testing and assessing alternative approaches. Operators can simulate the outcomes of maintenance activities, environmental adjustments, or emergency situations, facilitating informed choices and efficient risk management.

6 | AI AND DT APPLICATIONS IN REAL-TIME TUNNEL STRUCTURE MONITORING

6.1 | Structural health monitoring

Ensuring the structural integrity and safety of tunnel constructions/structures is crucial. AI-powered methods enable proactive maintenance strategies, offering innovative solutions for early detection of structural problems and continuous monitoring. Two primary facets of structural health monitoring supported by AI include the following.

6.1.1 | Detecting deformations, cracks, and other structural issues

AI algorithms, particularly those based on computer vision and ML, are adept at scrutinizing sensor data to spot minute deformations, fractures, and other structural irregularities in tunnel infrastructure. By evaluating data from sensors like strain gauges, accelerometers, and cameras, AI systems can spot alterations in structural behavior that might signal potential problems. These algorithms can autonomously analyze sensor data flows, discern patterns that suggest structural deterioration, and notify operators about anomalies instantly. Through ongoing surveillance and examination, AI-powered systems facilitate the early identification of structural flaws, enabling prompt intervention and maintenance (Dang et al., 2022; Liu et al., 2023; Sharma et al., 2021).

6.1.2 | Predictive maintenance through AI analysis

AI-powered predictive maintenance models leverage historical sensor data and ML algorithms to forecast the future state of tunnel structures. By scrutinizing patterns in sensor data and relating them to historical instances of structural deterioration or failure, these models can forecast upcoming maintenance requirements before they evolve into serious problems. Predictive maintenance algorithms can pinpoint trends in structural decline, estimate the remaining service life, and fine-tune maintenance schedules to lessen downtime and cut repair expenses. By incorporating AI-powered predictive maintenance tactics into tunnel management processes, operators can anticipate maintenance needs, prolong asset lifespans, and boost the overall safety and dependability of tunnels.

6.2 | Geotechnical monitoring

Geotechnical monitoring is vital for evaluating soil stability and displacement around tunnel structures, reducing geotechnical hazards, and guaranteeing the long-term stability of underground infrastructure. AI technologies provide sophisticated geotechnical monitoring solutions that facilitate immediate assessment and risk mitigation (Baghbani et al., 2022). Two primary facets of geotechnical monitoring improved by AI include the following.

6.2.1 | Soil stability and movement detection

AI-powered geotechnical monitoring systems employ data from devices like inclinometers, piezometers, and tiltmeters to evaluate soil stability and monitor movement around tunnel structures. By scrutinizing data feeds from these sensors through ML algorithms, AI systems can spot patterns that suggest ground displacement, settlement, or slope instability. These algorithms can discern minor shifts in ground conditions, evaluate the extent and speed of movement, and issue early alerts about potential geotechnical risks. Through ongoing surveillance and examination, AI-driven geotechnical monitoring systems facilitate proactive actions to reduce risks and maintain the stability of tunnel infrastructure (Bardhan & Samui, 2022).

6.2.2 | Risk assessment using AI algorithms

AI-powered risk assessment frameworks merge geotechnical data with ML methodologies to gauge the potential and impacts of geotechnical hazards near tunnel structures. These frameworks scrutinize elements such as soil characteristics, groundwater levels, seismic activity, and past geotechnical occurrences to evaluate the risk landscape of tunnel environments (Haque, 2023; Qi et al., 2023). By determining the likelihood of geotechnical hazards like landslides, subsidence, or groundwater infiltration, AI-driven risk assessment models empower informed decision-making and prioritization of mitigation strategies. By incorporating AI-based risk assessment into tunnel management protocols, operators can proactively identify and mitigate potential geotechnical risks, safeguarding the safety and adaptability of tunnel infrastructure across various geological contexts (Afzal et al., 2021; Lin et al., 2021).

6.3 | DT applications in real-time monitoring of tunnel structure

In the domain of infrastructure management, the importance of real-time monitoring for ensuring safety and durability cannot be overstated. DT technology has become a formidable instrument in this area, providing unmatched insights into the state and performance of a wide range of structures, including tunnels. The implementation of DTs in real-time monitoring of tunnel structures marks a significant leap forward, transforming how engineers and regulatory bodies oversee these vital assets.

Real-time monitoring of tunnel structures involves the ongoing gathering of data from sensors strategically positioned within the tunnel infrastructure. These sensors can monitor a variety of parameters, including temperature, humidity, structural strain, vibration, and air quality. By coupling these sensors with a DT framework, engineers can construct a virtual model of the tunnel and its surrounding environment.

A major advantage of employing DTs in tunnel monitoring is the capacity to simulate different scenarios and foresee potential problems before they become critical. For example, by examining data gathered from sensors embedded in tunnel walls, engineers can evaluate the structural integrity and pinpoint areas susceptible to deterioration or collapse. This forward-thinking strategy allows maintenance teams to act swiftly, minimizing the risk of accidents and costly repairs (Machado & Futai, 2024; Yu et al., 2021, 2023).

Moreover, DTs support predictive maintenance strategies by utilizing ML algorithms to scrutinize historical data and predict future trends. By recognizing patterns and anomalies in the data, maintenance schedules can be refined, reducing downtime and enhancing operational efficiency.

Another significant use of DTs in tunnel monitoring is in emergency response planning. By simulating various emergency situations, such as fires or natural disasters, engineers can devise comprehensive evacuation plans and evaluate the effectiveness of safety measures. This proactive method bolsters the resilience of tunnel infrastructure and elevates safety for both users and emergency personnel (Ye et al., 2023).

Beyond safety and maintenance advantages, DTs also provide valuable insights for long-term planning and design optimization. By regularly updating the DT with real-time data, engineers can assess the performance of different design options and make informed decisions for future infrastructure projects.

Both AI and DT methods are widely used in tunnel infrastructure monitoring. AI is particularly effective in detecting anomalies, such as structural deformations, and in predictive analytics to forecast maintenance needs and extend the life of infrastructure. DTs are applied in optimizing tunnel designs for safety and efficiency, as well as in real-time operational management, such as controlling ventilation or improving traffic flow within tunnels. Together, these technologies offer comprehensive monitoring solutions that enhance safety, operational efficiency, and cost-effectiveness in the management of tunnel infrastructure.

7 | ADVANTAGES AND DISADVANTAGES OF DT AND AI MONITORING METHODS

DT and AI monitoring methods offer several advantages and disadvantages. DT enables real-time monitoring and predictive maintenance by continuously analyzing data from tunnel infrastructure, allowing for early detection of potential issues and proactive maintenance, which helps reduce downtime and avoid unexpected failures. DT also allows scenario simulations, providing valuable insights into risk management and operational optimization. Additionally, DT enhances decision-making by offering real-time data and simulations that support informed choices in project management and long-term planning (Gao et al., 2021). However, implementing DT systems comes with high initial costs, as they require significant investments in sensors, data integration platforms, and computational resources. The quality and integration of data can also be challenging, as DTs rely on accurate data from multiple sources. Moreover, managing and updating DT models to reflect changes in physical infrastructure is complex and requires robust maintenance systems (Jiang et al., 2021).

AI-based monitoring methods also bring numerous advantages, including improved efficiency and speed, as AI algorithms can quickly analyze large datasets to identify structural anomalies and predict potential failures. AI improves the accuracy of monitoring by reducing subjectivity, particularly in detecting cracks, deformations, or other structural issues (Armaghani & Azizi, 2021). Additionally, AI systems are adaptable, learning from changing environmental conditions and infrastructure behavior to enhance monitoring processes. However, AI systems are heavily dependent on data, and their effectiveness relies on the availability and quality of the input data. Furthermore, AI algorithms, especially DL models, can be difficult to interpret, leading to challenges in transparency and trust, especially in critical applications. AI systems also require significant computational resources, which can be a limitation for real-time monitoring in large-scale infrastructure networks (Mahdevari et al., 2012).

However, it should be mentioned that the future of real-time tunnel monitoring with DT and AI will bring advancements in accuracy, efficiency, and predictive maintenance. As sensor technologies evolve, AI models will become better at detecting structural issues and predicting failures before they happen. DTs will enhance operational decision-making through advanced simulations, while edge computing will solve scalability challenges. There will also be a stronger focus on sustainability, with monitoring systems assessing environmental impacts, and cybersecurity will be critical to ensuring infrastructure protection. These developments will result in smarter, more autonomous, and secure tunnel monitoring systems, enhancing safety and sustainability.

8 | CHALLENGES AND LIMITATIONS

8.1 | Examination of challenges and limitations associated with current AI-driven approaches

Despite the numerous benefits of AI-driven approaches for tunnel monitoring, there are several challenges that need to be addressed before they can be effectively implemented and operated.

The primary obstacle is securing and sustaining high-quality data. AI algorithms, for training and validation purposes, heavily rely on extensive, high-quality datasets. However, in the context of tunnel monitoring, acquiring adequate labeled data for training ML models can be difficult due to the scarcity of historical sensor data and the intricate nature of underground environments. Moreover, the data quality can fluctuate because of environmental factors, sensor malfunctions, or calibration problems, resulting in noisy or untrustworthy input data for AI systems (Kuang et al., 2022; Marcher et al., 2020; Zhang et al., 2023, 2024).

A critical challenge in applying AI to tunnel monitoring is the “black-box” nature of many models, especially DL algorithms. This lack of transparency can hinder stakeholders' trust and the practical adoption of these systems. Furthermore, nonspecialists often find it challenging to interpret AI results, which poses a barrier to actionable decision-making. Addressing this issue requires the integration of interpretability tools, enabling users to understand the rationale behind predictions and recommendations.

Another hurdle is the interpretability and explainability of AI models. Although AI algorithms can frequently achieve remarkable outcomes in identifying anomalies or forecasting structural problems, the mechanisms behind these models can be obscure and hard for human operators to understand. This lack of transparency could diminish trust in AI-powered monitoring systems, especially in critical areas like tunnel infrastructure, where safety is paramount. Furthermore, the obscurity of AI models might hinder the identification of potential biases or errors in the decision-making process, raising concerns about accountability and ethical considerations (Chakraborty et al., 2017; Nandi & Pal, 2021; Vishwarupe et al., 2022).

Moreover, the scalability and computational demands of deploying AI-driven tunnel monitoring systems in extensive infrastructure networks present substantial challenges. ML algorithms, especially DL models, typically demand substantial computational power for training and inference, making the real-time processing and analysis of sensor data computationally demanding. Adapting AI systems to manage the intricacies of vast tunnel networks while ensuring acceptable performance and responsiveness is a formidable task, necessitating meticulous optimization of algorithms, hardware infrastructure, and deployment strategies.

8.2 | Strategies for overcoming these challenges and enhancing the effectiveness of AI-based tunnel monitoring systems

To overcome the obstacles and constraints inherent in current AI-driven methodologies for tunnel monitoring, several strategies can be implemented.

8.2.1 | Data augmentation and synthesis

This strategy addresses the shortage of labeled training data by utilizing techniques such as data augmentation and synthesis to produce additional training samples. Techniques for synthetic data generation, including generative adversarial networks (GANs) or physics-based simulations, can augment limited datasets and enhance the resilience of AI models.

8.2.2 | Explainable AI (XAI)

This approach aims to improve the interpretability and explainability of AI models by integrating methods from the field of XAI. Techniques like feature attribution, model visualization, and rule extraction can offer insights into the decision-making process of AI systems, facilitating human operators' understanding and trust in these models.

8.2.3 | Edge computing and distributed AI

This strategy tackles scalability and computational complexity challenges by employing edge computing and distributed AI architectures. Edge computing platforms enable real-time processing and analysis of sensor data at the network edge, minimizing latency and bandwidth needs. Distributed AI frameworks, such as federated learning or ensemble methods, distribute computation across multiple devices or nodes, allowing for efficient training and inference on decentralized infrastructure.

8.2.4 | Continuous monitoring and adaptive learning

This involves establishing a framework for continuous monitoring and adaptive learning, where AI models are continuously updated and refined based on real-time sensor data and feedback from human operators. Incorporating mechanisms for model adaptation and retraining enables AI-driven monitoring systems to adapt to changing environmental conditions, sensor characteristics, and structural dynamics over time.

8.2.5 | Standards and regulations

This strategy involves establishing standards and regulations for the development, deployment, and evaluation of AI-driven tunnel monitoring systems to ensure transparency, reliability, and safety. Regulatory frameworks can address concerns related to data privacy, model accountability, and ethical considerations, promoting trust and confidence in AI technologies among stakeholders (Figure 8).

8.3 | Challenges and limitations of DT technology

DT technology, which involves creating virtual replicas of physical assets or systems, presents both opportunities and challenges in the field of tunnel monitoring. Several challenges and limitations need to be addressed.

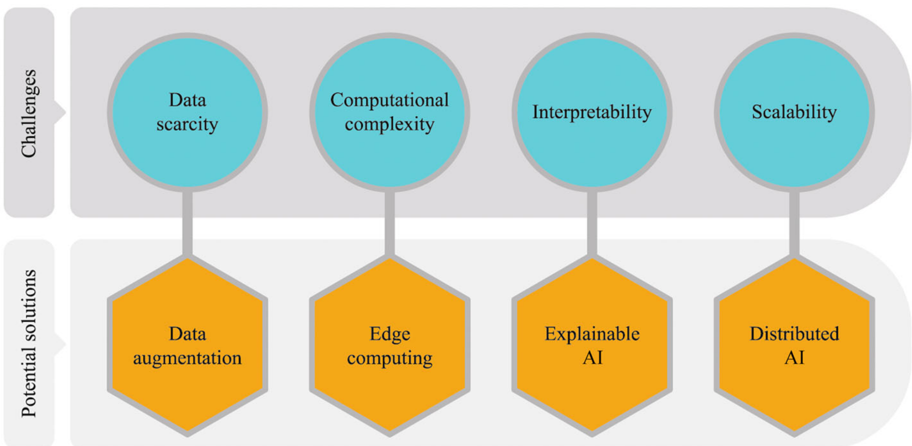

FIGURE 8 Challenges and potential solutions to artificial intelligence (AI) problems.

8.3.1 | Data integration and interoperability

One of the primary challenges is integrating data from multiple sources into the DT environment. Tunnel infrastructure typically includes a range of systems and sensors, each generating data in different formats and at varying frequencies. Ensuring interoperability and seamless integration of data from different sources is crucial for the accuracy and reliability of the DT.

8.3.2 | Model accuracy and validation

The accuracy of DT models significantly relies on the quality of the data used for their development and calibration. Ensuring that DT models accurately represent the complex behavior of tunnel infrastructure requires thorough validation against real-world data. However, validating these models can be challenging due to the limited availability of comprehensive and high-fidelity datasets.

8.3.3 | Computational complexity and resource requirements

Building and maintaining DTs for large-scale tunnel networks can be computationally intensive, requiring significant computational resources and storage capacity. Ensuring real-time or near-real-time performance of DTs, particularly for dynamic monitoring and predictive analytics, necessitates efficient algorithms and robust infrastructure.

8.3.4 | Security and privacy concerns

DTs store and process sensitive data related to tunnel infrastructure, making them potential targets for cyberattacks or unauthorized access. Ensuring the security and privacy of data within the DT environment is paramount to safeguarding critical infrastructure assets and preventing unauthorized manipulation or exploitation.

8.3.5 | Lifecycle management and maintenance

Over time, the physical assets represented by DTs may undergo changes due to aging, maintenance activities, or structural modifications. Ensuring the continuous synchronization and updating of DTs to reflect these changes requires robust lifecycle management processes and mechanisms for maintaining the fidelity and relevance of the virtual replicas.

8.4 | Strategies for overcoming challenges in DT implementation

To tackle the challenges and constraints inherent in DT technology for tunnel monitoring, several strategies can be implemented (Hu et al., 2021; Rathore et al., 2021; Shahzad et al., 2022).

8.4.1 | Standardized data formats and interfaces

Establishing standardized data formats and interfaces for data exchange between different systems and sensors can facilitate seamless integration into the DT environment. Adopting industry-standard protocols and metadata schemas enhances interoperability and simplifies the aggregation, processing, and visualization of heterogeneous data sources.

8.4.2 | Advanced modeling techniques and validation methods

Utilizing advanced modeling techniques, such as physics-based simulations and ML algorithms, can improve the accuracy and fidelity of DT models. Moreover, employing robust validation methods, including cross-validation against historical data and real-world validation through field testing and monitoring, ensures that DTs accurately represent the behavior of tunnel infrastructure under various conditions.

8.4.3 | Cloud computing and edge analytics

Leveraging the scalability and computational power of cloud computing platforms can mitigate the computational complexity and resource requirements associated with DT implementation. Cloud-based solutions allow flexible scaling of computational resources and storage capacity, enabling efficient processing and analysis of large data volumes. Additionally, utilizing edge analytics capabilities enables real-time processing and decision-making at the network edge, reducing latency and enhancing responsiveness for time-critical monitoring tasks.

8.4.4 | Cybersecurity measures and data governance

Implementing strong cybersecurity measures and data governance practices is crucial for protecting DT environments against cyber threats and ensuring the integrity, confidentiality, and availability of data. This includes deploying encryption techniques, access control mechanisms, intrusion detection systems, and regular security audits to detect and mitigate potential vulnerabilities or breaches. Furthermore, establishing clear data governance policies and procedures ensures compliance with regulatory requirements and ethical standards for data handling and usage.

8.4.5 | Dynamic update and maintenance mechanisms

Developing dynamic update and maintenance mechanisms enables the continuous synchronization and

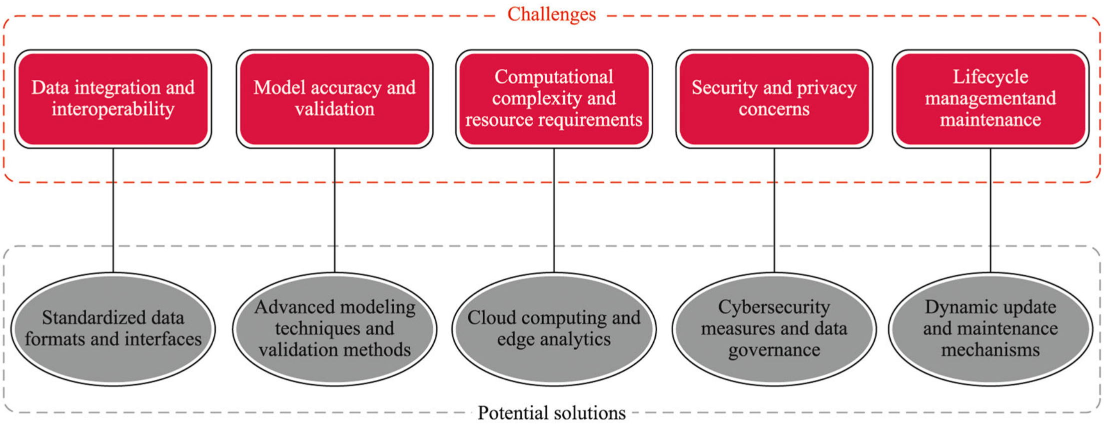

FIGURE 9 Challenges and potential solutions to digital twin (DT) problems.

evolution of DTs to reflect changes in the physical infrastructure. This involves establishing automated workflows for data ingestion, model recalibration, and scenario analysis, allowing DTs to adapt to evolving conditions and operational requirements. Additionally, integrating feedback loops and anomaly detection algorithms enables proactive identification of discrepancies between DT predictions and observed behavior, facilitating timely adjustments and improvements (Figure 9).

9 | FUTURE RESEARCH DIRECTIONS

9.1 | Advanced AI algorithms

Future research should explore advanced AI algorithms, such as graph neural networks (GNNs) for spatially correlated data analysis in tunnel systems, and Transformer models for time-series forecasting in structural health monitoring. These algorithms can offer improved accuracy and adaptability compared to traditional methods.

9.2 | Sensor innovations

Emerging sensor technologies, such as self-powered IoT devices and quantum sensors, could enable more precise, energy-efficient, and reliable monitoring of structural health and environmental conditions. Multimodal sensors that capture a broader range of tunnel parameters, including strain, vibration, temperature, and humidity, are critical for next-generation monitoring systems.

9.3 | Enhanced data fusion techniques

Enhanced data fusion techniques, such as Bayesian inference and advanced multisensor fusion frameworks, are needed to combine heterogeneous data (e.g., from strain gauges, accelerometers, and environmental sensors) for a holistic assessment of tunnel performance. Real-time fusion algorithms could help address the challenges of missing or noisy data in dynamic monitoring environments.

9.4 | DT integration strategies

Dynamic DTs that incorporate real-time AI analytics, physics-based simulations, and adaptive models could significantly improve predictive maintenance and operational efficiency. Integration strategies, such as utilizing edge computing for decentralized data processing or blockchain for secure data sharing, should be explored to enhance scalability and reliability.

9.5 | Sustainability and resilience

Future work should emphasize sustainable monitoring systems by incorporating energy-efficient sensors and green AI techniques that minimize computational overhead. Additionally, resilience-focused research can address the adaptation of monitoring systems to extreme conditions, such as earthquakes or flooding.

10 | CONCLUSION

This review highlights the limitations of conventional tunnel monitoring methods, such as labor-intensive manual inspections and the restricted scope of instrumentation-based approaches. These challenges underscore the need for advanced technologies that offer real-time insights into tunnel health. AI technologies, including ML, computer vision, and sensor fusion, provide effective solutions. ML autonomously detects structural anomalies and predicts maintenance needs, while computer vision automates the identification of structural defects. Sensor fusion integrates data from various sources to provide a comprehensive understanding of tunnel performance.

Simultaneously, DT technology offers a digital reflection of tunnel structures, seamlessly incorporating real-time sensor data and enabling thorough monitoring and performance assessment. By simulating various scenarios and predicting potential issues, DTs equip engineers with the ability to make informed decisions and improve operational efficiency, thereby enhancing safety and resilience across numerous aspects of tunnel monitoring and maintenance.

However, the implementation of AI-driven and DT methodologies in tunnel monitoring is not without its challenges. Concerns such as data quality, AI model interpretability, scalability, and computational complexity need to be addressed to fully leverage these technologies. Approaches like data augmentation, explainable AI, edge computing, continuous monitoring, and regulatory frameworks provide avenues to overcome these obstacles and enhance the efficacy of AI-based monitoring systems.

Future research in tunnel monitoring should prioritize the development of cutting-edge data collection methods, such as advanced sensors and IoT integration, to improve data quality and reliability. Enhancing the interpretability of AI models remains critical for fostering trust and usability, particularly for nonspecialist stakeholders. Sophisticated AI algorithms tailored for real-time decision-making, autonomous inspection, and predictive maintenance can enable proactive management of tunnel integrity. Integrating dynamic DT technology provides opportunities for real-time virtual modeling and system optimization, while addressing challenges such as resilience and cybersecurity. Collaboration between humans and AI through user-friendly systems will further enhance monitoring effectiveness. Lastly, incorporating sustainable practices, such as energy-efficient sensors and green AI techniques, will pave the way for smarter, safer, and more environmentally conscious tunnel infrastructure.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest. All co-authors have seen and agree with the contents of the manuscript, and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

ORCID

Mohammad Afrazi http://orcid.org/0000-0002-0024-1432
Hossein Afrazi http://orcid.org/0009-0007-5543-7399

REFERENCES

Afrazi M, Lin Q, Fakhimi A. Physical and numerical evaluation of mode II fracture of quasi-brittle materials. *Int J Civil Eng*. 2022;20(9):993-1007.

Afrazi M, Razavi M, Monjezi M, Bhatawdekar R, Mohamad ET. Development and evaluation of a computer-aided educational platform for advancing understanding of slope stability analysis. *Civil Eng Infrastruct J*. 2024;57:2.

Afrazi M, Yazdani M. Determination of the effect of soil particle size distribution on the shear behavior of sand. *J Adv Eng Comput*. 2021;5(2):125-134.

Afzal F, Yunfei S, Nazir M, Bhatti SM. A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: cost overrun in construction projects. *Int J Manag Project Bus*. 2021;14(2):300-328.

Ali M, Khan NM, Gao Q, et al. Prediction of coal dilatancy point using acoustic emission characteristics: insight experimental and artificial intelligence approaches. *Mathematics*. 2023;11(6):1305.

Armaghani DJ, Azizi A. Applications of artificial intelligence in tunnelling and underground space technology. Springer; 2021.

Armaghani DJ, Rasekh H, Asteris PG. An advanced machine learning technique to predict compressive strength of green concrete incorporating waste foundry sand. *Comp Concr*. 2024;33(1):77.

Asteris PG, Armaghani DJ, Hatzigeorgiou GD, Karayannis CG, Pilakoutas K. Predicting the shear strength of reinforced concrete beams using artificial neural networks. *Comp Concr Int J*. 2019;24(5):469-488.

Asteris PG, Lourenço PB, Roussis PC, et al. Revealing the nature of metakaolin-based concrete materials using artificial intelligence techniques. *Constr Build Mater*. 2022;322:126500.

Attard L, Debono CJ, Valentino G, Di Castro M. Tunnel inspection using photogrammetric techniques and image processing: a review. *ISPRS J Photogram Rem Sens*. 2018;144:180-188.

Baghalzadeh Shishehgarkhaneh M, Keivani A, Moehler RC, Jelodari N, Roshdi Laleh S. Internet of Things (IoT), building information modeling (BIM), and digital twin (DT) in construction industry: a review, bibliometric, and network analysis. *Buildings*. 2022;12(10):1503.

Baghbani A, Choudhury T, Costa S, Reiner J. Application of artificial intelligence in geotechnical engineering: a state-of-the-art review. *Earth Sci Rev*. 2022;228:103991.

Bardhan A, Samui P. Application of artificial intelligence techniques in slope stability analysis: a short review and future prospects. *Int J Geotech Earthquake Eng*. 2022;13(1):1-23.

Barkhordari MS, Barkhordari MM, Armaghani DJ, Mohamad ET, Gordan B. GUI-based platform for slope stability prediction under seismic conditions using machine learning algorithms. *Archit Struct Constr*. 2024;4:145-156.

Barkhordari MS, Fattahi H, Armaghani DJ, Khan NM, Afrazi M, Asteris PG. Failure mode identification in reinforced concrete flat slabs using advanced ensemble neural networks. *Multiscale Multidiscipl Model Exp Des*. 2024;7:5759-5773. doi:10.1007/s41939-024-00554-9

Bellini Machado L, Massao Futai M. Tunnel performance prediction through degradation inspection and digital twin construction. *Tunnel Undergr Space Technol*. 2024;144:105544.

Blasch E, Pham T, Chong CY, et al. Machine learning/artificial intelligence for sensor data fusion–opportunities and challenges. *IEEE Aerospace Electr Syst Magaz*. 2021;36(7):80-93.

Chakraborty S, Tomsett R, Raghavendra R, et al. *Interpretability of Deep Learning Models: A Survey of Results*. IEEE; 2017:1-6.

Chen IH, Ho S-C, Su M-B. Computer vision application programming for settlement monitoring in a drainage tunnel. *Autom Constr*. 2020;110:103011.

Chen L, Fakharian P, Rezazadeh Eidgahee D, Haji M, Mohammad Alizadeh Arab A, Nouri Y. Axial compressive strength predictive models for recycled aggregate concrete filled circular steel tube columns using ANN, GEP, and MLR. *J Build Eng*. 2023;77:107439.

Chen Y, Wang Y, Li K. *Recognition and Application of Tunnel Water Accumulation Based on Computer Vision*. IOP Publishing; 2021:012043.

Chi J, Liu L, Liu J, Sun C, Zhang W. Computer vision based pose bias detection of shield tunneling machine. In: Sun C, Fang F, Zhou ZH, Yang W, Liu ZY, eds. *Intelligence Science and Big Data Engineering: 4th International Conference, IScIDE 2013*. Springer; 2013:880-886.

Chopra P, Sharma RK, Kumar M, Chopra T. Comparison of machine learning techniques for the prediction of compressive strength of concrete. *Adv Civil Eng*. 2018:5481705.

Coccia R, Corsini A, Bonacina F, et al. An application of data-driven analysis in road tunnels monitoring. In: *Proceedings of the 4th European International Conference on Industrial Engineering and Operations Management*. 2021:1445-1455.

Dang LM, Wang H, Li Y, et al. Automatic tunnel lining crack evaluation and measurement using deep learning. *Tunnel Undergr Space Technol*. 2022;124:104472.

Das R, Dhounchak R, Singh TN. Analysis and prediction of brittle failure in rock blocks having a circular tunnel under uniaxial compression using acoustic emission technique: laboratory testing and numerical simulation. *Int J Geo-Eng*. 2021;12(1):14.

Ding N, Zhou Y, Li D, Zeng K. Real-time deformation monitoring of large diameter shield tunnel based on multi-sensor data fusion technique. *Measurement*. 2024;225:114061.

Dong W, Huang Y, Lehane B, Ma G. An artificial intelligence-based conductivity prediction and feature analysis of carbon fiber reinforced cementitious composite for non-destructive structural health monitoring. *Eng Struct*. 2022;266:114578.

Eng SK, He B, Monjezi M, Bhatawdekar RM. An artificial intelligence approach for tunnel construction performance. *J Soft Comp Civil Eng*. 2023;7(2):138-154.

Fakharian P, Eidgahee DR, Akbari M, Jahangir H, Taeb AA. *Compressive Strength Prediction of Hollow Concrete Masonry Blocks Using Artificial Intelligence Algorithms*. Elsevier; 2023:1790-1802.

Fakharian P, Naderpour H, Sharbatdar MK, Ghasemi SH. *Advancements in Structural Target Reliability: A Comprehensive Examination of Theories and Practical Applications (2013-2024)*. Elsevier; 2024:106930.

Farahani BV, Barros F, Sousa PJ, Tavares PJ, Moreira PMGP. A railway tunnel structural monitoring methodology proposal for predictive maintenance. *Struct Control Health Monitor*. 2020;27(8):e2587.

Flah M, Nunez I, Ben Chaabene W, Nehdi ML. Machine learning algorithms in civil structural health monitoring: a systematic review. *Arch Comp Methods Eng*. 2021;28(4):2621-2643.

Gao Y, Qian S, Li Z, Wang P, Wang F, He Q. *Digital Twin and its Application in Transportation Infrastructure*. IEEE; 2021:298-301.

Ghanizadeh AR, Ghanizadeh A, Asteris PG, Fakharian P, Armaghani DJ. Developing bearing capacity model for geogrid-reinforced stone columns improved soft clay utilizing MARS-EBS hybrid method. *Transport Geotech*. 2023;38:100906.

Hajihassani M, Jahed Armaghani D, Sohaei H, Tonnizam Mohamad E, Marto A. Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Appl Acoust*. 2014;80:57-67.

Haque MF. Nonlinear anisotropic finite element analysis of liquefiable tunnel–sand–pile interaction under seismic excitation. *Deep Undergr Sci Eng*. 2023;2(3):275-285.

He B, Armaghani DJ, Bhatawdekar RM, Lai SH. A review of soft computing techniques in predicting overbreak induced by tunnel blasting. In: *International Conference on Geotechnical Challenges in Mining, Tunneling and Underground Infrastructures*. Springer; 2021:3-13.

He B, Armaghani DJ, Lai SH. Application of a data augmentation technique on blast-induced fly-rock distance prediction. In: Verma AK, Mohamad ET, Bhatawdekar RM, Raina AK, Khandelwal M, Armaghani D, Sarkar K, eds. *Proceedings of Geotechnical Challenges in Mining, Tunneling and Underground Infrastructures. ICGMTU 2021. Lecture Notes in Civil Engineering*, vol 228. Springer; 2023:135-165.

He B, Armaghani DJ, Lai SH, Mohamad ET. Application of an expert extreme gradient boosting model to predict blast-induced air-overpressure in quarry mines. In: Nguyen H, Bui X, Topal E, Zhou J, Choi J, Zhang W, eds. *Applications of Artificial Intelligence in Mining, Geotechnical and Geoengineering*. Elsevier; 2024:269-289.

He Z, Armaghani DJ, Masoumnezhad M, Khandelwal M, Zhou J, Murlidhar BR. A combination of expert-based system and advanced decision-tree algorithms to predict air-overpressure resulting from quarry blasting. *Nat Resour Res.* 2021;30:1889-1903.

Hu W, Zhang T, Deng X, Liu Z, Tan J. Digital twin: a state-of-the-art review of its enabling technologies, applications and challenges. *J Intel Manufact Special Equipm*. 2021;2(1):1-34.

Huat CY, Armaghani DJ, Lai SH, Motaghedi H, Asteris PG, Fakharian P. Analyzing surface settlement factors in single and twin tunnels: a review study. *J Eng Res*. 2024.

Huat CY, Armaghani DJ, Momeni E, Lai SH. Empirical, statistical, and machine learning techniques for predicting surface settlement induced by tunnelling. In: Momeni E, Jahed Armaghani D, Azizi A, eds. *Artificial Intelligence in Mechatronics and Civil Engineering: Bridging the Gap*. Springer; 2023:39-77.

Jahed Armaghani D, Azizi A. An overview of field classifications to evaluate tunnel boring machine performance. *Applications of Artificial Intelligence in Tunnelling and Underground Space Technology. SpringerBriefs in Applied Sciences and Technology*. Springer; 2021a:1-16.

Jahed Armaghani D, Azizi A. A comparative study of artificial intelligence techniques to estimate TBM performance in various weathering zones. *Applications of Artificial Intelligence in Tunnelling and Underground Space Technology. SpringerBriefs in Applied Sciences and Technology*. Springer; 2021b:55-70.

Jahed Armaghani D, Ming YY, Salih Mohammed A, Momeni E, Maizir H. Effect of SVM kernel functions on bearing capacity assessment of deep foundations. *J Soft Comp Civil Eng*. 2023;7(3):111-128.

Jiang F, Ma L, Broyd T, Chen K. Digital twin and its implementations in the civil engineering sector. *Autom Construct*. 2021;130:103838.

Jiang X, Liu Z, Liu B, Liu J. Multi-sensor fusion for lateral vehicle localization in tunnels. *Appl Sci*. 2022;12(13):6634.

Koch C, Georgieva K, Kasireddy V, Akinci B, Fieguth P. A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure. *Adv Eng Inform*. 2015;29(2):196-210.

Kuang G, Li B, Mo S, Hu X, Li L. Review on machine learning-based defect detection of shield tunnel lining. *Period Polytech Civil Eng*. 2022;66(3):943-957.

Li S, Liu C, Zhou Z, Li L, Shi S, Yuan Y. Multi-sources information fusion analysis of water inrush disaster in tunnels based on improved theory of evidence. *Tunnel Undergr Space Technol*. 2021;113:103948.

Li T, Li X, Rui Y, Ling J, Zhao S, Zhu H. Digital twin for intelligent tunnel construction. *Automat Constr*. 2024;158:105210.

Li Z, Li J, Chen J, et al. Evolution law of pulsating seepage and thermal deformation by injecting high-temperature steam into coal for thermal coalbed methane recovery. *Deep Undergr Sci Eng*. 2024;4:119-131.

Lin S-S, Shen S-L, Zhou A, Xu Y-S. Risk assessment and management of excavation system based on fuzzy set theory and machine learning methods. *Automat Constr*. 2021;122:103490.

Liu L, Song Z, Li X. Artificial intelligence in tunnel construction: a comprehensive review of hotspots and frontier topics. *Geohazard Mech*. 2023;2(1):1-12.

Mahdevari S, Torabi SR, Monjezi M. Application of artificial intelligence algorithms in predicting tunnel convergence to avoid TBM jamming phenomenon. *Int J Rock Mech Min Sci.* 2012;55:33-44.

Mao M, Yang X, Liu C, Zhao T, Liu H. Deformation monitoring at shield tunnel joints: laboratory test and discrete element simulation. *Deep Undergr Sci Eng*. 2024;4(1):149-157.

Marcher T, Erharter G, Unterlass P. Capabilities and challenges using machine learning in tunnelling. In: Tusan H, eds. *Theory and Practice of Tunnel Engineering*. 2021.

Marcher T, Erharter GH, Winkler M. Machine learning in tunnelling–capabilities and challenges. *Geomech Tunnel*. 2020;13(2):191-198.

Mukhopadhyay SC, Tyagi SKS, Suryadevara NK, Piuri V, Scotti F, Zeadally S. Artificial intelligence-based sensors for next generation IoT applications: a review. *IEEE Sens J.* 2021;21(22):24920-24932.

Nandi A, Pal AKX. *Interpreting Machine Learning Models: Learn Model Interpretability and Explainability Methods*. Springer; 2021.

Omrany H, Al-Obaidi KM, Husain A, Ghaffarianhoseini A. Digital twins in the construction industry: a comprehensive review of current implementations, enabling technologies, and future directions. *Sustainability*. 2023;15(14):10908.

Pang Y, He T, Liu S, Zhu X, Lee C. Triboelectric nanogenerator-enabled digital twins in civil engineering infrastructure 4.0: a comprehensive review. *Adv Sci.* 2024;11:2306574.

Putra I. State-of-the-art of artificial intelligence methods in structural health monitoring. In: Kristiawan SA, Gan BS, Shahin M, Sharma A, eds. *International Conference on Rehabilitation and Maintenance in Civil Engineering*. Springer; 2021:325-338.

Qi C, Wang M, Kocharyan G, Kunitskikh A, Wang Z. Dynamically triggered seismicity on a tectonic scale: a review. *Deep Undergr Sci Eng*. 2023;3(1):1-24.

Ramirez RA, Lee GJ, Choi SK, et al. Monitoring of construction-induced urban ground deformations using sentinel-1 PS-InSAR: the case study of tunneling in Dangjin, Korea. *Int J Appl Earth Obs Geoinform*. 2022;108:102721.

Rathore MM, Shah SA, Shukla D, Bentafat E, Bakiras S. The role of AI, machine learning, and big data in digital twinning: a systematic literature review, challenges, and opportunities. *IEEE Access*. 2021;9:32030-32052.

Sakr M, Sadhu A. Recent progress and future outlook of digital twins in structural health monitoring of civil infrastructure. *Smart Mater Struct* 2024;33:033001.

Shaffiee Haghshenas S, Shaffiee Haghshenas S, Abduelrhman MA, Zare S, Mikaeil R. Identifying and ranking of mechanized tunneling project's risks by using a fuzzy multi-criteria decision making technique. *J Soft Comp Civil Eng*. 2022;6(1):29-45.

Shahrour I, Bian H, Xie X, Zhang Z. Smart technology applications for the optimal management of underground facilities. *Undergr Space*. 2021;6(5):551-559.

Shahzad M, Shafiq MT, Douglas D, Kassem M. Digital twins in built environments: an investigation of the characteristics, applications, and challenges. *Buildings*. 2022;12(2):120.

Sharma VB, Tewari S, Biswas S, et al. Recent advancements in AI-enabled smart electronics packaging for structural health monitoring. *Metals*. 2021;11(10):1537.

Sjölander A, Belloni V, Ansell A, Nordström E. Towards automated inspections of tunnels: a review of optical inspections and autonomous assessment of concrete tunnel linings. *Sensors*. 2023;23(6):3189.

Sofi A, Jane Regita J, Rane B, Lau HH. Structural health monitoring using wireless smart sensor network–an overview. *Mech Syst Sig Process*. 2022;163:108113.

Tan X, Chen W, Wang L, Ye W. Development of an optimization model for a monitoring point in tunnel stress deduction using a machine learning algorithm. *Deep Undergr Sci Eng*. 2025;4(1):35-45.

Tuama A, Comby F, Chaumont M. Camera model identification with the use of deep convolutional neural networks. In: *2016 IEEE International Workshop on Information Forensics and Security (WIFS)*. IEEE; 2016:1-6.

Vishwarupe V, Joshi PM, Mathias N, Maheshwari S, Mhaisalkar S, Pawar V. Explainable AI and interpretable machine learning: a case study in perspective. *Proc Comp Sci*. 2022;204:869-876.

Wang X, Hosseini S, Jahed Armaghani D, Tonnizam Mohamad E. Data-driven optimized artificial neural network technique for prediction of flyrock induced by boulder blasting. *Mathematics*. 2023;11(10):2358.

Wu H, Liu S, Cheng C, Cao S, Cui Y, Zhang D. Multiscale variational autoencoder aided convolutional neural network for pose estimation of tunneling machine using a single monocular image. *IEEE Trans Indust Inform*. 2021;18(8):5161-5170.

Wu Z, Chang Y, Li Q, Cai R. A novel method for tunnel digital twin construction and virtual-real fusion application. *Electronics*. 2022; 11(9):1413.

Xu H, Zhou J, G. Asteris P, Jahed Armaghani D, Tahir MM. Supervised machine learning techniques to the prediction of tunnel boring machine penetration rate. *Appl Sci*. 2019;9(18):3715.

Xu X, Yang H. Vision measurement of tunnel structures with robust modelling and deep learning algorithms. *Sensors*. 2020;20(17):4945.

Yang H, Xu X. Structure monitoring and deformation analysis of tunnel structure. *Compos Struct*. 2021;276:114565.

Ye Z, Ye Y, Zhang C, et al. A digital twin approach for tunnel construction safety early warning and management. *Comp Indus*. 2023;144:103783.

Yu G, Lin D, Wang Y, Hu M, Sugumaran V, Chen J. Digital twin-enabled and knowledge-driven decision support for tunnel electromechanical equipment maintenance. *Tunnel Undergr Space Technol*. 2023;140:105318.

Yu G, Wang Y, Mao Z, Hu M, Sugumaran V, Wang YK. A digital twin-based decision analysis framework for operation and maintenance of tunnels. *Tunnel Undergr Space Technol*. 2021;116:104125.

Zeng L, Zhou B, Xie X, et al. A novel real-time monitoring system for the measurement of the annular grout thickness during simultaneous backfill grouting. *Tunnel Undergr Space Technol*. 2020;105:103567.

Zhang L, Chao W, Liu Z, Cong Y, Wang Z. Crack propagation characteristics during progressive failure of circular tunnels and the early warning thereof based on multi-sensor data fusion. *Geomech Geophys Geo-Energy Geo-Res*. 2022;8(5):172.

Zhang W, Gu X, Hong L, Han L, Wang L. Comprehensive review of machine learning in geotechnical reliability analysis: algorithms, applications and further challenges. *Appl Soft Comp*. 2023;136:110066.

Zhang Y, Zheng L, He L, Jiao Y, Peng H, Gamage RP. Bibliometric analysis of research challenges and trends in urban underground space. *Deep Undergr Sci Eng*. 2024;3(2):207-215.

Zhou J, Huang S, Zhou T, Armaghani DJ, Qiu Y. Employing a genetic algorithm and grey wolf optimizer for optimizing RF models to evaluate soil liquefaction potential. *Artif Intel Rev*. 2022;55(7): 5673-5705.

Zhou J, Li E, Wei H, Li C, Qiao Q, Armaghani DJ. Random forests and cubist algorithms for predicting shear strengths of rockfill materials. *Appl Sci*. 2019;9(8):1621.

Zinno R, Haghshenas SS, Guido G, VItale A. Artificial intelligence and structural health monitoring of bridges: a review of the state-of-the-art. *IEEE Access*. 2022;10:88058-88078.

AUTHOR BIOGRAPHIES

Mr. Mohammad Afrazi received his BS degree in Civil Engineering from Shiraz University in 2014 and his MS degree in Civil Engineering from Tarbiat Modares University in 2018. He worked as a researcher at the School of Civil and Environmental Engineering at Tarbiat Modares University for four years. Currently, he is pursuing his second MS degree in Mechanical Engineering with a specialization in Robotics and Mechatronics Systems at New Mexico Tech, Socorro, NM, USA. He is passionate about solving real-world problems by applying robotics, optimization, Artificial Intelligence, and control theory.

Danial Jahed Armaghani is a prominent researcher in the field of civil and geotechnical engineering. His work has made significant contributions to the understanding and mitigation of geotechnical and geological hazards, earning him a reputation as an excellent researcher in his field. Dr. Danial's research focuses on a wide range of topics, including slope stability analysis, rock mechanics, tunnel construction, surface and deep excavations, and applying machine learning models and optimization algorithms to solve various geotechnical problems. Dr. Danial is currently working as a Research Fellow at the School of Civil and Environmental Engineering, University of Technology Sydney, Australia. He has published more than 350 articles in well-established ISI and Scopus journals and at national and international conferences. His published works have received more than 25 000 citations, which indicate the significant impact and influence of his research in the academic and scientific community. He was among the top 2% of scientists for four consecutive years from 2019 to 2024, according to Stanford University. He was also among the highly ranked scholars worldwide according to ScholarGPS in Civil and Environmental Engineering.

Mr. Hossein Afrazi received his BS degree in civil engineering from Birjand University in 2022. Currently, he is pursuing his MS degree in Civil Engineering with a specialization in Geotechnical Engineering at Shahid Bahonar University of Kerman, Kerman, Iran. His research interests include sustainable construction materials, soil stabilization techniques, and material recycling and reuse.

Dr. Hadi Fattahi is an associate professor in the Faculty of Earth Sciences and Engineering at Arak University of Technology, Arak, Iran. He holds a PhD in Rock Mechanics Engineering. Dr. Fattahi has published over 110 ISI-indexed papers in prestigious journals, solidifying his position as a leading researcher in his field. His research interests include computational intelligence applications, tunneling, and geomechanics reliability analysis. He has also served as a reviewer for several high-impact international journals. In addition to his academic achievements, Dr. Fattahi has contributed to major geotechnical projects, including tunneling design and rock mass modulus determination. His expertise spans computational intelligence techniques and advanced numerical modeling tools, making him a recognized authority in geotechnical engineering and rock mechanics.

Dr. Pijush Samui is a professor in the department of Civil Engineering at NIT Patna, India. He received his PhD in Geotechnical Engineering from the Indian Institute of Science, Bangalore, India, in 2008. His research interests include geohazards, earthquake engineering, concrete technology, pile foundation, slope stability, and the application of AI for solving different problems in civil engineering. Dr. Samui is not only a repeat Elsevier editor but also a prolific contributor to journal papers, book chapters, and peer-reviewed conference proceedings. Dr. Samui has received several awards for excellence in research and teaching, including the IIT Roorkee Shamsher Prakash Research Award, IGS—Sardar Resham Singh Memorial Award, and IACMAG Excellent Regional Contributions Award. He is a fellow of the Indian Society of Earthquake Technology (ISET). He is a guest professor at the University of Science and Technology, Beijing. He also holds the Title of Docent at Tampere University. He was an Adjunct Professor at Ton Duc Thang University (Vietnam) (2018–2021).

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