
High Support Formwork Systems and AI in Construction: A Survey

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Abstract

This survey paper explores the multifaceted integration of advanced technologies, particularly Artificial Intelligence (AI), deep learning, and machine learning, within the construction industry. It systematically examines the transformative potential of these technologies across various domains, including high support formwork systems, structural health monitoring, construction safety, and predictive analytics. The survey outlines the challenges and opportunities presented by AI in optimizing construction processes, enhancing safety, and promoting sustainability. Key findings highlight the critical role of AI in decision-making, real-time monitoring, and predictive maintenance, underscoring the need for robust data management and ethical considerations. Despite the potential benefits, the paper identifies significant challenges related to data privacy, technological limitations, and regulatory compliance, which must be addressed to ensure the responsible deployment of AI. Future directions emphasize the development of standardized frameworks and methodologies to enhance AI's adaptability and resilience, particularly in dynamic construction environments. By advancing AI technologies and addressing ethical and regulatory challenges, the construction industry can achieve more efficient, safe, and sustainable outcomes, ultimately transforming traditional construction practices.

1 Introduction

1.1 Structure of the Survey

This survey provides a comprehensive examination of the integration of advanced technologies in the construction industry, specifically focusing on artificial intelligence (AI), deep learning, and machine learning. It highlights the transformative impacts of these technologies on project efficiency, safety, and productivity while addressing critical ethical considerations such as job security, data privacy, and decision-making transparency. The survey reviews existing literature, identifies key challenges, and outlines future research directions, underscoring the importance of responsible AI adoption in enhancing construction practices [1, 2, 3, 4, 5].

The paper begins with an introduction that contextualizes the transformative potential of these technologies in construction. Section 2, titled "Background and Definitions," provides foundational insights into core concepts, including high support formwork systems, AI, deep learning, and predictive analytics, establishing their relevance to the field.

Section 3, "High Support Formwork Systems," examines their significance and the challenges they present, detailing how AI and machine learning can optimize these systems for enhanced efficiency and safety. This section includes subsections on the importance of formwork systems, their design and implementation, and the role of AI in their optimization.

In Section 4, "Artificial Intelligence and Deep Learning in Construction," the roles of AI and deep learning in modern construction practices are explored, focusing on AI's decision-making capabilities, examples of deep learning applications, and the use of AI for real-time monitoring and task execution.

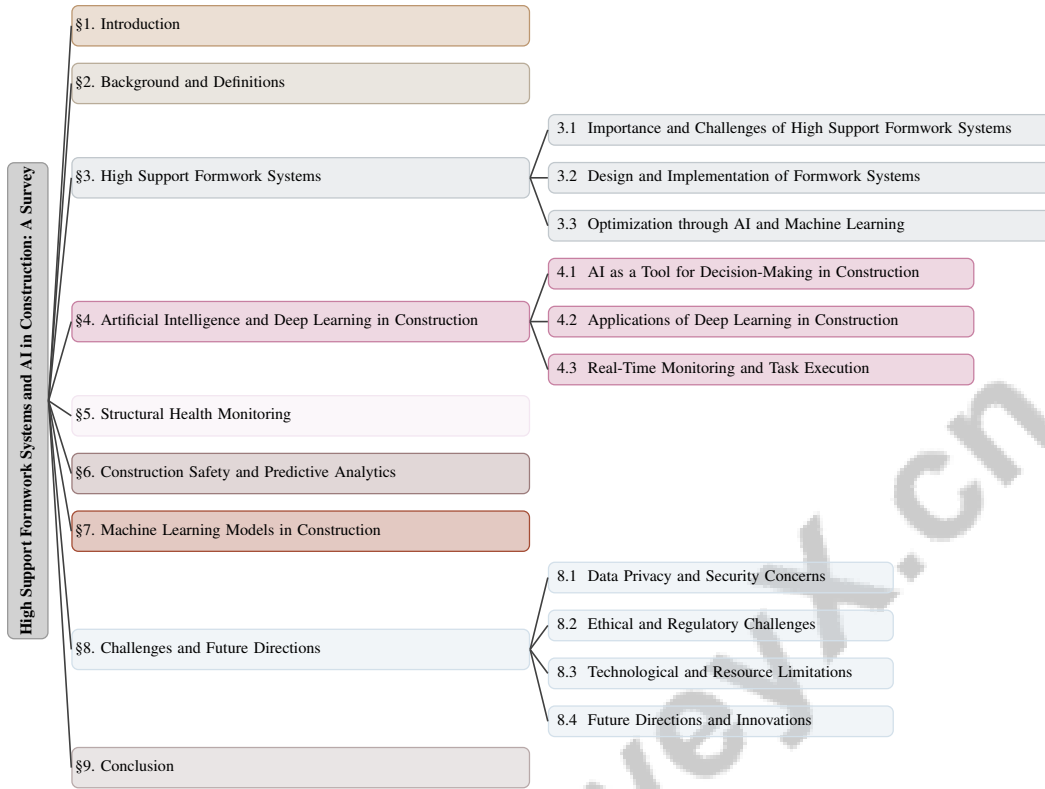


Figure 1: chapter structure

Section 5, "Structural Health Monitoring," investigates the application of AI and machine learning in continuously monitoring infrastructure integrity. It discusses intelligent high-formwork support monitoring systems that utilize advanced technologies for continuous data collection and analysis, enhancing safety and efficiency. The section also highlights the benefits of AI integration for predictive maintenance and fault detection, facilitating proactive identification of issues and significantly reducing downtime and maintenance costs across various industrial applications [6, 7, 8, 9, 10].

The survey progresses to Section 6, "Construction Safety and Predictive Analytics," analyzing how predictive analytics can enhance safety through hazard prediction and worker safety improvement, alongside advanced AI techniques aimed at operational efficiency.

Section 7, "Machine Learning Models in Construction," explores various machine learning models and their applications, emphasizing adaptive learning and forecasting capabilities. This discussion covers the application of machine learning models within software engineering, focusing on software quality assurance and maintenance, and underscores the role of Automated Machine Learning (AutoML) in optimizing model selection and algorithm development, enabling software engineers with limited AI expertise to create AI-driven systems [11, 12, 13].

The survey concludes with Section 8, "Challenges and Future Directions," identifying the challenges of integrating AI into construction and discussing future innovations to overcome these obstacles. This section addresses concerns related to data privacy and security, ethical and regulatory challenges, technological limitations, and potential future innovations.

The conclusion in Section 9 summarizes the survey's key findings, emphasizing AI's transformative potential in the construction industry. It highlights capabilities in enhancing productivity, optimizing energy consumption, and improving safety on construction sites. Additionally, it identifies critical ethical considerations related to AI adoption, such as job security and data privacy, while outlining areas for further research to address existing challenges and knowledge gaps, reinforcing the need for responsible and equitable implementation of AI technologies in construction [1, 14, 2, 15, 3]. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Artificial Intelligence (AI) and Machine Learning

AI and ML are pivotal in transforming the construction industry by enhancing efficiency, safety, and sustainability. AI replicates human cognitive functions, improving decision-making and mitigating errors in construction projects. ML, a key AI branch, develops algorithms for autonomous learning from large datasets, enhancing task performance without explicit programming. This is crucial in software engineering, where ML techniques like supervised, unsupervised, and deep learning enhance software quality assurance and maintenance. As ML evolves, it addresses software development challenges, including reliability and maintainability, fostering more intelligent systems [8, 11, 13, 16].

In construction, AI and ML are integral to predictive maintenance, where advanced techniques refine strategies by analyzing complex datasets. AI improves predictive models, enhancing construction forecasts and outcomes. Systems like CareFall use AI for safety, employing wearable technology and ML algorithms for accurate fall detection, significantly improving safety in high-risk environments like construction sites [3, 17].

AI integration in construction requires evaluating potential benefits and costs, particularly sustainability trade-offs. While AI enhances energy management and productivity, it also presents challenges like deployment issues and ethical concerns about job security and data privacy. Practitioners must navigate these complexities to ensure AI adoption aligns with sustainability goals [3, 18, 19, 1]. AI's role in advancing edge computing is crucial for processing extensive data on construction sites, enabling real-time decision-making.

However, challenges persist in realizing AI's full potential due to system brittleness, particularly with Out-Of-Distribution (OOD) inputs. Ensuring AI system reliability requires comprehensive research on AI model lifecycle management, including version control and holistic data management. A systematic mapping study highlights a research gap, with few publications addressing these aspects. Traditional quality management techniques may not suffice, necessitating new quality attributes like fairness and transparency to enhance AI trustworthiness in critical environments [8, 20].

As AI and ML advance, their construction applications will expand, offering innovation and efficiency opportunities. Understanding AI, Edge Computing, and the Industrial Metaverse is essential for successful integration. Ethical implications and practical challenges, including security and interoperability, must be considered alongside economic growth potential in sectors like healthcare and manufacturing. This holistic approach ensures technology benefits are maximized while managing associated risks [21, 22, 23, 5].

2.2 Deep Learning

Deep learning, a machine learning subset, uses multi-layer neural networks to model complex patterns in large datasets, crucial for high-dimensional function estimation [16]. In construction, deep learning processes vast data to enhance decision-making and operational efficiency, improving low-cost sensor performance by identifying patterns and correcting errors [24].

Challenges in deep learning include catastrophic forgetting in Deep Neural Networks (DNNs), where models lose learned information with new tasks. This necessitates continual learning strategies to retain knowledge. The environmental impact and opaque decision-making of deep learning systems highlight the need for sustainable, transparent alternatives [25].

Deep learning integration in construction raises concerns about model interpretability and quality metrics, crucial for reliability. Model brittleness can lead to performance degradation with unexpected inputs, necessitating robust engineering practices and systematic AI software development approaches.

Applications in construction include predictive maintenance, fault detection, real-time monitoring, and automation of complex tasks, enhancing efficiency, safety, and sustainability. As deep learning progresses, addressing challenges related to reliability and maintainability is essential to fully harness its potential, improving productivity and efficiency in project execution [3, 16, 4, 26].

3 High Support Formwork Systems

High support formwork systems are essential in construction, particularly for supporting concrete structures until they achieve the necessary strength. This section explores their significance and associated challenges, emphasizing the integration of advanced technologies like artificial intelligence to optimize performance and enhance safety and efficiency in construction. Figure 2 illustrates the hierarchical structure of high support formwork systems, highlighting the importance and challenges, as well as the design and implementation processes. The diagram categorizes the roles and challenges in construction, the design considerations and AI integration in implementation, and the efficiency, safety, and advanced AI approaches in optimization. This visual representation not only complements the discussion but also provides a clearer understanding of how these systems can be effectively managed and improved through technological advancements.

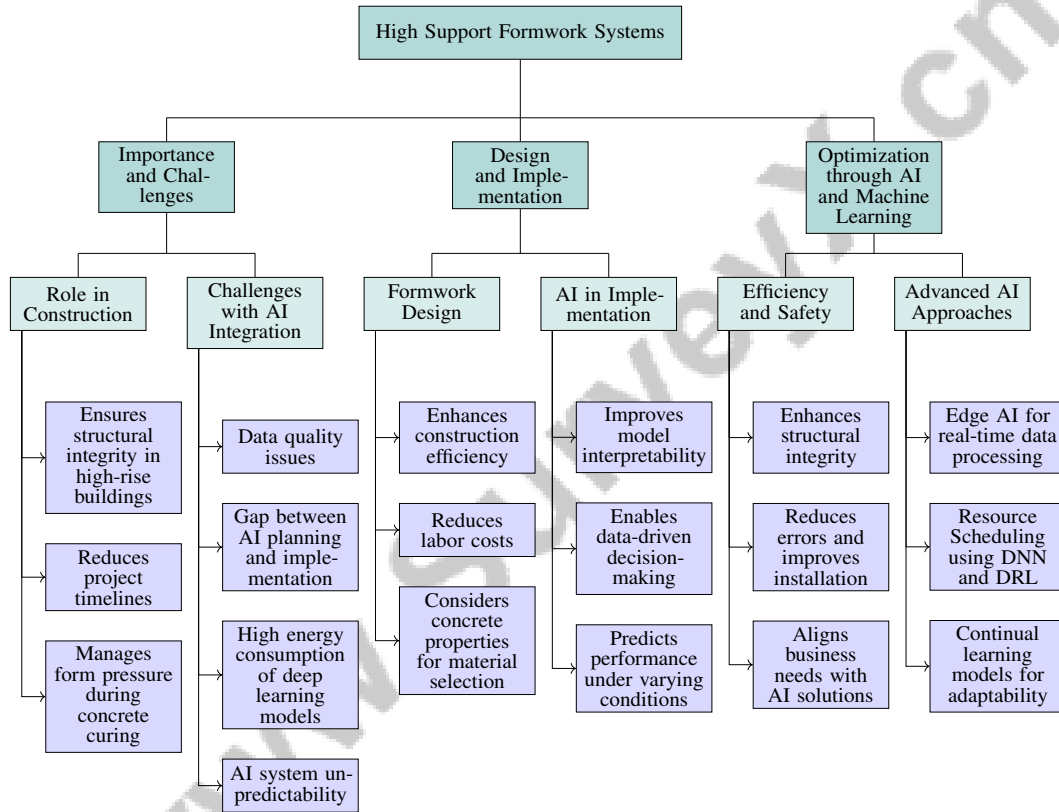


Figure 2: This figure illustrates the hierarchical structure of high support formwork systems, highlighting the importance and challenges, design and implementation, and optimization through AI and machine learning. The diagram categorizes the roles and challenges in construction, the design considerations and AI integration in implementation, and the efficiency, safety, and advanced AI approaches in optimization.

3.1 Importance and Challenges of High Support Formwork Systems

High support formwork systems play a critical role in modern construction, notably in high-rise buildings, by ensuring structural integrity and reducing project timelines [27]. They effectively manage form pressure during concrete curing, crucial for the longevity and safety of structures [27]. As illustrated in Figure 3, the hierarchical structure of these systems underscores their significance and the various challenges associated with their management, including the integration of AI technologies. This figure highlights key aspects such as structural integrity, project timelines, and form pressure management, alongside challenges like AI integration issues, data quality problems, and high energy consumption.

However, integrating AI technologies into these systems is challenging due to data quality issues and the gap between AI planning and implementation in the AEC industry, which can lead to misaligned expectations and suboptimal deployments [7, 14]. Traditional quality management practices fall short in addressing AI system reliability in formwork, necessitating robust methodologies to meet diverse project needs [8]. The high energy consumption of deep learning models further complicates scaling efforts [28]. Additionally, AI systems' unpredictability during real-world operations can lead to performance degradation [29].

Manual monitoring methods in traditional formwork systems often result in insufficient data and safety risks [9]. The uncertainty regarding AI's impact on labor dynamics adds complexity, requiring careful navigation of workforce and operational changes [30]. The lack of comprehensive studies on AI lifecycle management and a focus on algorithm development over lifecycle issues complicate AI integration [20].

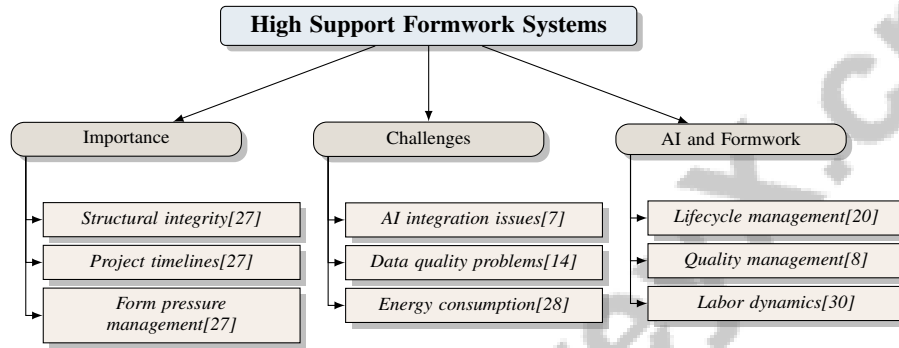


Figure 3: This figure illustrates the hierarchical structure of high support formwork systems, highlighting their importance, challenges, and the role of AI in their management. Key aspects include structural integrity, project timelines, and form pressure management, alongside challenges like AI integration issues, data quality problems, and high energy consumption. It also emphasizes AI's impact on lifecycle management, quality management, and labor dynamics within formwork systems.

3.2 Design and Implementation of Formwork Systems

The design and implementation of formwork systems are crucial for ensuring structural integrity and efficiency, particularly in high-rise buildings. Recent studies highlight that optimizing formwork design can significantly enhance construction efficiency and reduce labor costs [31]. The design process considers concrete properties, influencing material selection, such as timber, steel, aluminum, and plastic, each offering distinct advantages based on project requirements [27].

Strategic decisions in formwork implementation involve selecting appropriate types, planning assembly/disassembly processes, and integrating safety measures. AI approaches, including supervised and unsupervised learning, enhance these processes by improving model interpretability and enabling data-driven decision-making [32]. AI-driven models predict formwork performance under varying conditions, reducing structural failure risks and improving project outcomes [11, 20, 2]. As the construction industry embraces digital transformation, AI integration promises to revolutionize traditional practices, leading to more sustainable methodologies.

3.3 Optimization through AI and Machine Learning

AI and machine learning optimization of formwork systems represent a transformative advancement in construction, enhancing efficiency, safety, and resource management. AI technologies enable precise formwork setup, reducing errors and enhancing structural integrity, while advanced models streamline installation processes [33]. The LeanAI method effectively aligns business needs with AI problem statements, facilitating better decision-making and resource allocation in construction projects [14].

Edge AI technologies are particularly beneficial on construction sites, providing low-latency services essential for real-time data processing and decision-making [34]. AI-based frameworks like Resource Scheduling using DNN and DRL enhance operational efficiency by optimizing resource allocation

and task execution [35]. RIS-EMLO exemplifies AI's role in optimizing learning errors through beamforming and phase-shift adjustments [36].

Continual learning models, such as DCGMMs, improve adaptability and robustness in AI-driven formwork systems [37]. The multi-corrector method optimizes performance by enabling real-time error correction [38]. Adapting property-driven architectural patterns from aviation to construction can facilitate AI/ML integration, ensuring safer and more efficient systems [39]. The MUSIC architecture parallels formwork optimization, highlighting AI's cross-industry applicability [40].

Intelligent high-formwork support monitoring systems utilizing real-time data collection and analysis ensure safety and reliability throughout construction [9]. AI-driven methodologies align with sustainability goals, reducing carbon footprints and enhancing transparency [25]. Integrating AI and machine learning into formwork systems is crucial for improving construction practices, automating tasks, optimizing energy consumption, and enhancing safety by identifying potential hazards. As AI technologies evolve, they promise further enhancements, leading to more innovative construction methodologies [27, 3, 4].

4 Artificial Intelligence and Deep Learning in Construction

The integration of Artificial Intelligence (AI) in construction has revolutionized decision-making processes, offering tools to manage complex, data-driven projects efficiently. This section explores AI's multifaceted role in construction, particularly its ability to analyze large datasets, automate resource management, and enhance task performance, setting the stage for its transformative impact on project outcomes.

4.1 AI as a Tool for Decision-Making in Construction

AI enhances decision-making in construction by mimicking human cognitive functions, thereby improving project outcomes through the processing of large data volumes. This capability is crucial for navigating the complexities of modern construction projects, where swift and precise decisions are essential for optimizing outcomes, safety, and resource management [27, 33, 3, 4]. Advanced frameworks, such as zero-touch network systems integrating serverless and O-RAN architectures, automate resource allocation, enhancing AI applications' responsiveness in construction environments [41]. Additionally, edge site orchestration and wireless networking facilitate real-time decision-making by ensuring efficient data and service provisioning [21].

Explainable AI improves task performance during human-AI collaborations, particularly in visual inspection tasks, fostering trust and informed decision-making [42]. The triad framework—comprising data, domain context, and AI algorithms—ensures robust and contextually relevant AI-driven decisions [26]. Automated machine learning advancements, such as improved model selection and hyper-parameter tuning, optimize AI models for construction tasks, though resilience remains a concern [11, 29].

AI's evolution promises to further advance construction practices by automating repetitive tasks, optimizing energy consumption, and improving site safety through real-time sensor and camera data analysis. Machine learning models streamline cost document classification, enabling better project comparisons and performance analysis. This transformative approach modernizes decision-making processes, addressing challenges like carbon emission reduction and ethical AI usage, fostering a more responsible construction environment [3, 1, 4, 14].

4.2 Applications of Deep Learning in Construction

Deep learning is a transformative technology in construction, optimizing processes by handling complex nonlinear data relationships [16]. Applications, such as the ConvoWaste system for waste segregation, demonstrate deep learning's potential in automating resource management [43]. Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) in condition monitoring enhance predictive maintenance of machinery and infrastructure [6], though challenges like data quality persist.

Deep learning improves low-cost sensor array accuracy, applicable to construction scenarios requiring reliable structural integrity and safety monitoring [24]. Continual learning ensures deep learning

models adapt to evolving project requirements without forgetting past knowledge, maintaining effectiveness throughout construction projects [37]. Explainable AI in deep learning enhances human-AI collaboration by providing transparency and improving task performance, essential in construction for informed decision-making [42].

Analog deep learning methods offer opportunities for reducing power consumption and increasing processing speed in construction applications, where energy efficiency and rapid decision-making are crucial [28]. As deep learning technologies evolve, their construction applications are expected to expand, offering innovative solutions for enhancing project outcomes and sustainability.

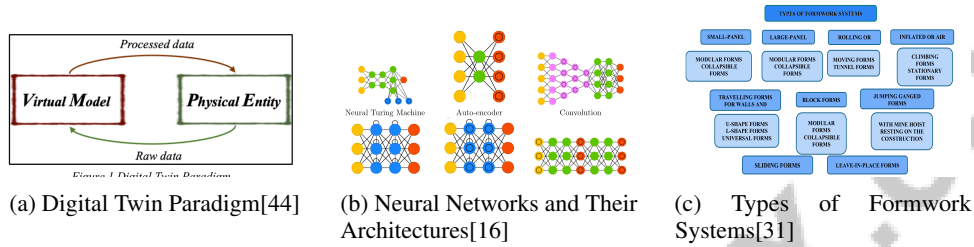


Figure 4: Examples of Applications of Deep Learning in Construction

Figure 4 illustrates three distinct deep learning applications in construction. The "Digital Twin Paradigm" facilitates real-time data exchange between virtual models and physical entities, optimizing construction operations. "Neural Networks and Their Architectures" process complex construction data for advanced analysis and predictive modeling. "Types of Formwork Systems" categorize different designs, emphasizing the selection of appropriate systems for specific tasks. These applications underscore deep learning's transformative potential in revolutionizing construction practices [44, 16, 31].

4.3 Real-Time Monitoring and Task Execution

AI's integration for real-time monitoring and task execution in construction enhances efficiency, accuracy, and safety. AI processes extensive datasets in real-time, improving proactive decision-making across industries like healthcare, finance, and manufacturing. This capability mitigates risks, optimizes resource allocation, and fosters innovation, while also presenting challenges like ethical concerns [19, 5].

AI provides personalized explanations aligning with users' mental models, enhancing compliance and task performance [45]. Automation of routine monitoring tasks frees human resources for strategic activities, crucial in environments where real-time data maintains structural integrity and efficiency. AI enhances operational efficiency through continuous monitoring, predictive maintenance, and energy optimization, transforming infrastructure maintenance and operation [18, 3, 26, 10].

AI technologies integrate real-time data from sensors and drones, offering a comprehensive overview of construction site activities. This integration streamlines project management and enhances safety by identifying potential hazards for timely interventions, supporting dynamic scheduling and resource management. AI's adaptability to changing conditions further enhances its utility in real-time monitoring, adjusting processes based on the latest data [3, 1, 5].

As AI advances, its applications in real-time monitoring and task execution are expected to expand, enhancing productivity and efficiency by automating routine tasks, optimizing energy consumption, and improving safety measures. AI analyzes building designs for potential issues, recommends solutions, and monitors site conditions to prevent accidents, contributing to a safer and more sustainable construction industry [3, 2, 5]. The ongoing development of AI technologies will likely lead to more sophisticated systems, transforming the industry and setting new standards for project management and execution.

5 Structural Health Monitoring

5.1 Intelligent High-Formwork Support Monitoring Systems

Intelligent high-formwork support monitoring systems are critical for ensuring the safety and stability of temporary structures in construction. These systems leverage real-time data collection and advanced AI technologies to monitor formwork integrity, preventing accidents and ensuring structural safety during construction [9]. By offering continuous monitoring and immediate feedback, these systems enable timely interventions upon detecting potential weaknesses.

The development of these systems necessitates a multidisciplinary approach, involving collaboration among data scientists, legal experts, and economists to ensure technical soundness, regulatory compliance, and economic viability [46]. Such collaboration is essential for crafting robust monitoring solutions that adapt to the dynamic environments of construction sites.

Analogous to systems like CareFall, which utilize AI algorithms for anomaly detection and preventive alerts in elder care [17], AI-driven monitoring in construction enhances formwork reliability by providing precise, actionable insights from real-time data.

As the construction industry embraces digital transformation, integrating intelligent monitoring systems becomes increasingly vital. These systems enhance safety and efficiency while promoting sustainability by minimizing accidents and material waste. The ongoing evolution of AI technologies is poised to bolster the capabilities of high-formwork support monitoring systems, crucial for maintaining the structural integrity of newly poured concrete. By harnessing big data and advanced analytics, these systems enable real-time monitoring and automatic data transmission, thus improving construction safety and efficiency. This AI integration overcomes the limitations of traditional manual monitoring, fostering resilient and adaptive construction practices that prioritize safety and sustainability [27, 9, 3, 4].

5.2 Predictive Maintenance and Fault Detection

AI significantly enhances predictive maintenance and fault detection in construction, improving reliability and efficiency. AI technologies revolutionize the monitoring and maintenance of construction equipment and infrastructure, ensuring optimal performance and reducing the risk of unexpected failures [3].

Traditional predictive maintenance often relies on outdated techniques, which do not fully leverage modern machine learning capabilities, resulting in less effective failure predictions [10]. In contrast, AI-driven systems employ sophisticated algorithms to analyze extensive datasets, enabling more accurate and timely predictions. This proactive approach minimizes downtime and extends the lifespan of construction assets.

Empirical methods underpin AI applications in predictive maintenance, offering objective evaluations of formwork systems that impact project success in terms of time, cost, and quality [33]. These methods support a data-driven maintenance approach, allowing for early identification of potential issues before they escalate.

AI's continuous and real-time monitoring capabilities are particularly advantageous in construction, where timely detection of structural issues is critical [9]. By providing immediate feedback on equipment and infrastructure conditions, AI technologies facilitate timely interventions that prevent costly repairs and ensure project safety and integrity.

As the construction industry evolves, the adoption of AI-driven predictive maintenance and fault detection systems is expected to increase. These systems enhance operational efficiency and contribute to sustainable practices by optimizing resource utilization and reducing waste. The advancement of AI technologies will further refine construction maintenance strategies, automating routine tasks, optimizing energy consumption, and improving site safety. By analyzing energy usage patterns, AI can identify cost-saving opportunities and propose actionable improvements, thereby reducing expenses and carbon emissions. Moreover, AI's capability to process data from sensors and cameras aids in detecting potential hazards on construction sites, enhancing worker safety and minimizing accident risks. As these capabilities evolve, they will unlock new avenues for innovation and efficiency within the construction industry [3, 15].

6 Construction Safety and Predictive Analytics

6.1 Applications of Predictive Analytics in Construction Safety

Predictive analytics in construction safety utilizes data-driven methodologies to anticipate and mitigate hazards, enhancing safety and efficiency. By employing sophisticated statistical models and machine learning algorithms, patterns indicative of safety risks are identified, allowing for proactive preventive measures. Techniques such as Support Vector Machines, Random Forests, and Long Short-Term Memory networks improve prediction accuracy across various sectors [6, 47, 48, 10].

Models are trained on historical data, including incident reports, environmental conditions, and worker behavior, to uncover correlations and causal relationships. However, their limited generalizability beyond training data poses risks in critical scenarios [48]. Developing robust models that adapt to dynamic construction environments is essential.

The rise of machine learning techniques, like supervised learning and anomaly detection, has enhanced predictive analytics across domains, including software engineering and predictive maintenance, by leveraging large datasets to improve accuracy and efficiency [8, 16, 10, 13]. Continuous site monitoring provides real-time safety insights, enabling managers to identify anomalies and intervene promptly.

Integrating predictive analytics with IoT devices improves data collection's granularity and timeliness, enhancing safety risk predictions. IoT sensors monitor parameters like structural integrity and environmental conditions, offering a comprehensive site overview. AI analyzes this data to optimize energy consumption and identify hazards, leading to cost savings and reduced emissions [3, 1]. Real-time data enhances predictive models, allowing precise safety management.

Predictive analytics not only anticipates and prevents accidents but also fosters safety awareness and improvement. By leveraging data-driven insights, construction firms can implement targeted interventions, optimize resources, and mitigate costly incidents. As technologies evolve, their integration into safety management promises significant enhancements through AI-driven real-time analysis, transforming safety practices and fostering a safer work environment [47, 3, 1, 10].

6.2 Advanced AI Techniques for Safety and Efficiency

Advanced AI techniques are pivotal in enhancing safety and efficiency in construction by addressing complex challenges with innovative models and algorithms. The Deep Convolutional Gaussian Mixture Model exemplifies a novel approach that integrates new knowledge while minimizing catastrophic forgetting, ensuring consistent performance in dynamic environments [37].

In predictive maintenance, Long Short-Term Memory networks outperform other models in forecasting and anomaly detection, as demonstrated in the aviation industry. Their potential to transform construction maintenance is significant, where accurate predictions are crucial for minimizing downtime and optimizing resources [10].

Integrating these advanced techniques facilitates real-time monitoring and adaptive learning. By analyzing sensor and camera data, companies can proactively enhance safety measures, identify hazards, and reduce accident risks. AI also streamlines workflows by automating tasks and optimizing energy use, improving productivity while achieving cost savings and lower emissions. As AI technologies evolve, their applications in construction safety and efficiency are expected to expand, offering new opportunities for innovation and improvement, while necessitating consideration of ethical implications like job security and data privacy [3, 1].

7 Machine Learning Models in Construction

7.1 Application of Various Machine Learning Models

Machine learning models are integral to modern construction, offering solutions that enhance efficiency, safety, and sustainability. These models facilitate the classification of cost documents per the International Construction Measurement Standard (ICMS), enabling precise benchmarking across projects. Automation through machine learning optimizes energy use in buildings and enhances site safety via real-time hazard detection, reducing costs and carbon emissions [3, 13, 2, 4]. Applications

span predictive maintenance, resource optimization, safety management, and quality control, each utilizing specific algorithms to address industry challenges.

Predictive maintenance is a key application, employing Long Short-Term Memory (LSTM) networks and Deep Neural Networks (DNNs) to forecast equipment failures and optimize maintenance schedules [10]. These models use historical and real-time data to predict issues, enabling timely interventions that minimize downtime and extend asset lifespan.

In resource scheduling and optimization, machine learning enhances the allocation of materials, labor, and equipment. Advanced algorithms like Deep Reinforcement Learning (DRL) enable dynamic resource management by learning from past data and adapting to site conditions [35]. This adaptability is crucial for optimizing workflows and reducing costs.

For safety management, anomaly detection algorithms identify potential hazards and prevent accidents by analyzing sensor data patterns, allowing for preemptive corrective actions. This proactive approach enhances worker safety and fosters continuous improvement, addressing ethical and sustainability considerations [1, 19].

In quality control, machine learning models monitor construction quality and compliance with standards. Advanced techniques analyze large datasets to identify patterns and assess quality attributes like fairness and robustness. Convolutional Neural Networks (CNNs) are effective in analyzing visual data, identifying defects, and ensuring specifications are met [8, 4, 13].

As the industry embraces digital transformation, machine learning's role is expected to expand, fostering innovation and efficiency. Research in formwork engineering and AI integration into construction methodologies aims to improve sustainability and effectiveness. Addressing challenges like form pressure and adopting alternative binders will lead to innovative materials and systems that enhance efficiency and safety, while AI technologies optimize resource management and productivity, presenting new regulatory and ethical considerations [27, 49, 19].

7.2 AutoML in Construction

Automated Machine Learning (AutoML) revolutionizes construction by automating model selection and tuning. Frameworks like Model-Driven Software Engineering (MDSE) and Model-Driven Architecture Engineering (MDAE) use Bayesian Optimization to streamline model and hyper-parameter selection for AI-intensive domains [11]. This reduces manual intervention, allowing professionals to focus on strategic decisions.

AutoML integration enhances machine learning applications across project phases, improving cost analysis and performance benchmarking through automated document classification and optimizing resource consumption and safety protocols [3, 13, 2, 4]. By optimizing model selection, AutoML ensures suitable algorithms are used for specific tasks, enhancing predictive analytics, resource allocation, and safety management.

AutoML democratizes machine learning in construction, enabling those without extensive technical expertise to effectively use sophisticated AI technologies. This empowers both software engineers and non-experts to select optimal models, facilitating AI-intensive system development and enhancing productivity across applications [16, 2, 11, 12, 13]. This accessibility allows managers and engineers to harness machine learning's full potential, driving innovation and efficiency.

As digital technologies are increasingly adopted, AutoML's role will expand, improving project outcomes and operational excellence. Task automation, such as cost document classification and building energy optimization, will enhance decision-making, streamline project comparisons using ICMS, and improve safety by identifying hazards. AutoML integration is set to transform construction management and engineering, driving efficiency and innovation [44, 7, 2, 3, 4]. Ongoing AutoML framework development will further streamline applications, paving the way for more adaptive and intelligent methodologies.

8 Challenges and Future Directions

8.1 Data Privacy and Security Concerns

Integrating AI in construction introduces critical challenges regarding data privacy and security, essential for maintaining AI systems' integrity and trust. Risks include data breaches and unauthorized access to sensitive information, threatening project security and stakeholder privacy [3]. The complexity of integrating AI with existing systems demands robust security protocols to mitigate vulnerabilities [3]. The dependency on high-quality training data raises privacy issues; poor data quality can result in inaccurate predictions, potentially undermining safety and efficiency [24]. Ensuring data quality requires comprehensive management practices throughout the AI lifecycle, a gap often inadequately addressed in current research [26]. Ethical concerns and biases further complicate these challenges, necessitating inclusive practices to mitigate biases [15]. The lack of transparency in AI decision-making exacerbates trust issues, as benchmarks frequently overlook real-world application complexities [42]. Additionally, deploying AI in resource-constrained edge environments introduces overlooked security challenges [21]. The absence of methods for evaluating AI under Out-Of-Distribution (OOD) conditions limits assurance of reliability and safety [29]. A structured approach to quantifying trust in AI systems is essential for fostering user engagement and product enhancement [50]. Prioritizing data privacy and security will improve AI technologies' reliability and acceptance, paving the way for more secure and efficient practices in construction.

8.2 Ethical and Regulatory Challenges

AI implementation in construction presents ethical and regulatory challenges that must be addressed for responsible deployment. Defining the problems AI should solve is complex, complicating ethical and regulatory considerations in the AEC sector [14]. This ambiguity risks misaligning AI applications with industry requirements and ethical standards. A framework identifying nine key ethical issues highlights concerns like job displacement, data privacy, security, and liability [1]. These issues underscore AI's socio-economic impacts, including worker displacement and the need for robust data protection. Variability in individual mental models complicates personalization, requiring AI systems to navigate diverse user expectations [45]. Biases in AI systems can perpetuate inequalities, necessitating inclusive practices that promote fairness [51]. Integrating ethical guidelines into quality management frameworks ensures AI engineering adheres to ethical standards [8]. Regulatory challenges are compounded by the lack of comprehensive standards for evaluating AI systems, particularly regarding accountability and liability. The opacity of AI models, especially deep learning-based ones, hinders clear explanations of decision-making processes, essential for trust and accountability in safety-critical applications. A multidisciplinary approach integrating technical, legal, and economic aspects of AI explainability is necessary to establish effective guidelines addressing AI integration's ethical implications across various sectors [46, 52, 5]. Collaboration among industry stakeholders, policymakers, and researchers is required to develop guidelines promoting responsible AI use and addressing critical issues like job security and data privacy. By synthesizing insights from various AI risk assessment frameworks and implementing structured planning methods like LeanAI, stakeholders can ensure ethical AI deployment, enhancing project efficiency while safeguarding societal interests [3, 1, 52, 14].

8.3 Technological and Resource Limitations

AI integration in construction faces technological and resource limitations hindering seamless adoption and effectiveness. A primary concern is the trial-and-error nature of existing machine learning methods, leading to inefficiencies in model selection and tuning, complicating AI deployment [11]. This complexity is exacerbated by substantial initial investments required for advanced formwork systems, often prohibitive for many projects. Deploying AI technologies necessitates extensive computational and communication resources, causing network congestion and inefficiencies, particularly in edge AI applications. The increased communication overhead, as seen in the MUSIC architecture, reflects technological and resource limitations in AI integration within construction [40]. These constraints pose data management and privacy challenges, as significant data transmission is required for traditional learning paradigms. The absence of standardized methodologies and insufficient data availability impede AI models' reproducibility and validation, limiting scalability and effectiveness. Accurate uncertainty estimations in AI model placement are vital for optimizing performance in

next-generation 6G networks, yet challenges arise due to unpredictable factors introduced by AI models, including variations in resource consumption and fluctuating performance [46, 50, 53, 12, 29]. This variability limits AI integration in resource-constrained environments. The interconnectedness of resources in AI applications introduces cybersecurity risks, such as information leakage or unauthorized access, necessitating measures to ensure security and reliability. Addressing technological and resource limitations requires innovative solutions, including advancements in resource management strategies, improved data quality and availability, and standardized methodologies for AI deployment. Overcoming these challenges will enable the construction industry to enhance efficiency, improve safety, and promote sustainability through optimized energy consumption and reduced carbon emissions, contributing to broader sustainable development goals [1, 18, 49, 15, 3].

8.4 Future Directions and Innovations

AI's future in construction is poised for transformative advancements, particularly in developing standardized frameworks for responsible and effective deployment. Future research should focus on creating standardized curricula for teaching machine learning across engineering disciplines, facilitating AI integration into construction practices while addressing ethical implications [54]. Emerging trends, such as integrating predictive maintenance with IoT and digital twins, offer promising avenues for enhancing efficiency and sustainability. Research should aim to improve LSTM models' interpretability and data quality to support these technologies [10]. Developing standardized benchmarks and improving model validation techniques will ensure AI systems' reliability and adaptability in dynamic environments [26]. Addressing Out-Of-Distribution (OOD) input challenges remains a priority, necessitating standardized metrics for OOD performance and methodologies enhancing AI resilience [29]. Expanding data collection to encompass diverse environments and improving decision-making algorithms will enhance intelligent monitoring systems' predictive capabilities [9]. Developing interconnected AI risk assessment frameworks is essential for addressing gaps and adapting to specific contexts and stakeholder needs, ensuring AI applications are effective and safe [52]. Focusing on these future directions and innovations will enable the construction industry to harness AI technologies' full potential, driving efficiency, safety, and sustainability while addressing ethical and practical deployment challenges.

9 Conclusion

Artificial Intelligence (AI) is transforming the construction industry by enhancing efficiency, safety, and sustainability. The integration of AI technologies facilitates optimized construction processes, such as predictive maintenance, resource management, and real-time monitoring. This survey highlights AI's role in promoting sustainable development while addressing the challenges that accompany its implementation.

The findings underscore the importance of addressing ethical and regulatory challenges to ensure responsible AI deployment within the Architecture, Engineering, and Construction (AEC) sector. Establishing ethical guidelines is crucial for fostering trust and accountability in AI applications. Additionally, advancing AI technologies to enhance performance across various sectors, particularly through model adaptation and optimization for edge environments, is essential.

Future research should focus on developing comprehensive solutions to address AI deployment challenges, especially in model adaptation and optimization for specific environments. As AI adoption grows among manufacturers and its economic impacts become more pronounced, fostering innovation and addressing integration challenges within construction practices are imperative. By tackling these issues and exploring future research directions, the construction industry can harness AI technologies to advance toward more efficient, safe, and sustainable methodologies.

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