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Machine Learning in the Modeling of 3D Printed Soil-Cement Materials: A Short Overview

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ABSTRACT

This paper addresses the challenges inherent in utilizing machine learning (ML) within 3D printing for soil-cement composites, focusing on issues such as material formulation, structural performance, and environmental sustainability. It reviews the application of various ML algorithms, including Artificial Neural Networks (ANN) and Support Vector Machines (SVM), for predicting material behavior and enhancing printability. The study also points out the need for standardized data protocols to combat data scarcity and improve model reliability. Potential pathways for future research include the development of hybrid models combining ML with physics-based simulations and the exploration of alternative, eco-friendly binding agents like geopolymers and biopolymers. The integration of ML with 3D printing technologies holds transformative potential for sustainable construction. By optimizing soil-cement composites, this approach not only enhances material properties but also significantly reduces carbon emissions and construction costs. Through a practical case study using excavated soil, we demonstrate how locally sourced materials can be effectively employed to create durable, environmentally responsible building components. This paper underscores the importance of ML in achieving these sustainability goals, offering insights into how these technologies can redefine modern construction practices.

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1. Introduction

The advent and proliferation of additive manufacturing technologies, commonly known as 3D printing, are transforming the construction sector. As these technologies evolve, their applications continue to expand, improving traditional construction practices and introducing novel, sustainable methods that were previously impractical. One of the most promising applications of 3D printing in construction is using soil-cement materials, which have gained attention for their ability to produce environmentally friendly and durable structures [1].

Machine learning approaches applied to optimize construction processes [2] can help to address the variability in soil properties and their interactions with cement, thereby enabling the prediction of the behavior of soil-cement composites. Goh et al. [3] reviewed the role of machine learning (ML) in 3D printing, highlighting its potential to optimize design, material selection, and process monitoring. The study emphasized that ML, particularly in situ monitoring and data sharing, can significantly enhance the reliability of 3D-printed parts, especially as data acquisition techniques improve. Advanced machine learning techniques have shown promise in predicting the elastic modulus of fiber-reinforced soil-cement mixtures. By including machine learning methods in 3D printing technologies, new opportunities for material property optimization and general construction practice efficiency enhancement have emerged.

3D printing is transforming industries by introducing innovative and sustainable methods. Figure 1 highlights its applications across fields such as medicine, construction, manufacturing, art, and space exploration. From custom prosthetics and aerospace prototypes to 3D-printed buildings and artistic designs, 3D printing enables efficiency and customization. In education and research, it enhances learning and experimental models, while in space, it facilitates the creation of habitats using local materials.

In soil science, 3D printing technology is also becoming a valuable tool since it allows precise soil structure models to be created, therefore improving research and teaching possibilities [4]. For example, Daher et al. created a new mix-design technique to enhance the printability and structural integrity of soil-based composites [5]. A significant technology for sustainable building methods, 3D printing in construction also provides significant thermal and environmental advantages like improved insulation and fewer carbon emissions [6]. Furthermore, the efforts of Bajpayee et al. [1]. The application of in situ resources for 3D printing highlights the financial and environmental benefits of employing locally accessible resources, hence lowering the demand for long-distance transportation of building supplies.

Moreover, as examined by Geng et al. [7], developments in ML approaches show great potential to enhance the predictive modeling and process optimization of 3D printed objects. For instance, Zhang et al. [8] investigated several ML techniques to improve the accuracy and efficiency of building operations, especially regarding the variation of soil conditions. Studies like those by Perrot et al. [9], which underline the relevance of rheological properties in guaranteeing the printability and structural integrity of 3D printed soil-cement structures, further support the potential of ML to transform material modeling and process control in 3D printing.

Apart from ML, the integration of sustainable materials—phase change materials and nano-silica aerogels—into 3D printing techniques has attracted a lot of interest because of their possible improvement of mechanical and thermal qualities. Investigating the use of earth-based concrete as a sustainable substitute for conventional building materials, researchers such as Tarhan et al. [10] have shown how likely it is to lower carbon emissions and resource use. Aumnate et al. [11] demonstrated that incorporating natural fibers, such as kenaf cellulose, into polylactic acid (PLA) can enhance the mechanical properties of 3D-printed biocomposites, offering increased strength and elongation while maintaining sustainability. This highlights the potential of natural fiber-reinforced biocomposites for applications requiring high mechanical performance and environmental sustainability. Additionally, the use of recycled resources such as waste tire textile fibers has been found to improve the mechanical characteristics of soil-fiber composites and support sustainability [12]. Similarly, Shariati et al. [13] conducted a comprehensive review on geotechnical reinforcement using end-of-life tires, emphasizing how incorporating scrap tires into soil mixtures can enhance mechanical properties, offer sustainable alternatives, and address environmental concerns associated with waste tire accumulation. These developments show how creatively technology could solve some of the most urgent problems facing the building sector, including sustainability, cost-effectiveness, and the necessity for innovative building ideas.

Fig. 1. Overview of 3D printing technologies and their applications across various fields. This diagram was created by the authors based on insights from multiple studies.

Probabilistic analyses paired with machine learning approaches can considerably improve the dependability of connections in structural applications, especially those involving slip-critical bolts and fillet welds, guaranteeing structural integrity under many circumstances [14]. Mainly through genetic algorithms and neural networks, artificial intelligence can maximize 3D printing operations, lower material waste, and enable the generation of intricate designs [15]. This study aims to provide a comprehensive review of the current state of 3D-printed soil-cement materials integrated with machine learning, highlighting the novel applications and advancements in this interdisciplinary field. The novelty of this work lies in its systematic synthesis of machine-learning techniques tailored explicitly for optimizing soil-cement 3D printing processes, which has not been extensively covered in previous literature. The scientific justification for this manuscript stems from the growing need for sustainable construction practices and the potential of machine learning to significantly enhance the efficiency, scalability, and environmental impact of 3D-printed soil-cement structures. Additionally, this review identifies gaps in current research and proposes future directions to bridge these gaps, thereby contributing to the advancement of both machine learning applications and sustainable construction technologies.

2. Overview of 3D printed soil-cement materials

2.1. Composition and characteristics

The properties and performance of 3D-printed soil-cement materials are significantly influenced by soil type, cement concentration, water ratio, and the optimization of cement mixtures for 3D printing applications. As demonstrated in studies involving soil-cement matrices in additive manufacturing [16], soil-cement has long been valued for its effectiveness in stabilizing soils and enhancing load-bearing capacity, making it a preferred choice in civil engineering, particularly in road construction. However, with advancements in 3D printing technology, soil-cement is being adopted in new fields, offering opportunities for innovative and environmentally friendly construction methods.

Research into optimizing cement mixtures for 3D printing has shown that key factors such as soil type, cement content, and water ratio play a critical role in determining the characteristics and performance of soil-cement composites, influencing their workability and durability [17]. Additionally, Xu et al. [18] investigated the incorporation of fly ash (FA) and ground granulated blast furnace slag (GGBFS) into cement-based 3D printing materials, finding that these additives significantly affect compressive strength, rheology, and printing properties. Their study revealed that optimizing FA content, particularly at 20%, enhances the fluidity and extrusion properties of the material, improving its printability without compromising structural integrity. This emphasizes the importance of selecting and proportioning additives to tailor soil-cement composites for 3D printing applications. Similarly, Mohan et al. [19] explored how aggregate content impacts the rheology and pumping behavior of 3D printing materials, noting that higher aggregate content increases plastic viscosity, which affects extrusion and printing processes. Their findings underscore the need to balance aggregate content to achieve optimal 3D printing performance.

The mechanical properties, mineral composition, and particle sizes of different soil types also affect the workability and strength of soil-cement mixtures, choosing soil a key factor in the design of 3D-printed constructions. Zhou et al. [20] examined the use of short fibers in 3D-printed cementitious composites, highlighting how fibers such as steel, polypropylene, and basalt significantly enhance compressive strength and interlayer adhesion. Their research stresses the importance of carefully selecting fiber type and content to improve printability and mechanical performance. Similarly, Suteja et al. [21] further demonstrated that natural fibers, like pineapple leaf fiber, can significantly improve the tensile strength of composite materials. Their research on pineapple leaf fiber-reinforced PLA composites indicates that natural fibers can be incorporated effectively into sustainable 3D printing materials without increasing dimensional error.

As illustrated in Figure 2, key factors influencing soil-cement composition include soil type, cement content, water content, and additives. Soil type impacts workability and strength, while cement content determines strength, cost, and emissions. Water content plays a role in hydration and printability; additives enhance mechanical properties and sustainability. Understanding these factors is crucial for optimizing the properties of 3D-printed soil-cement mixtures.

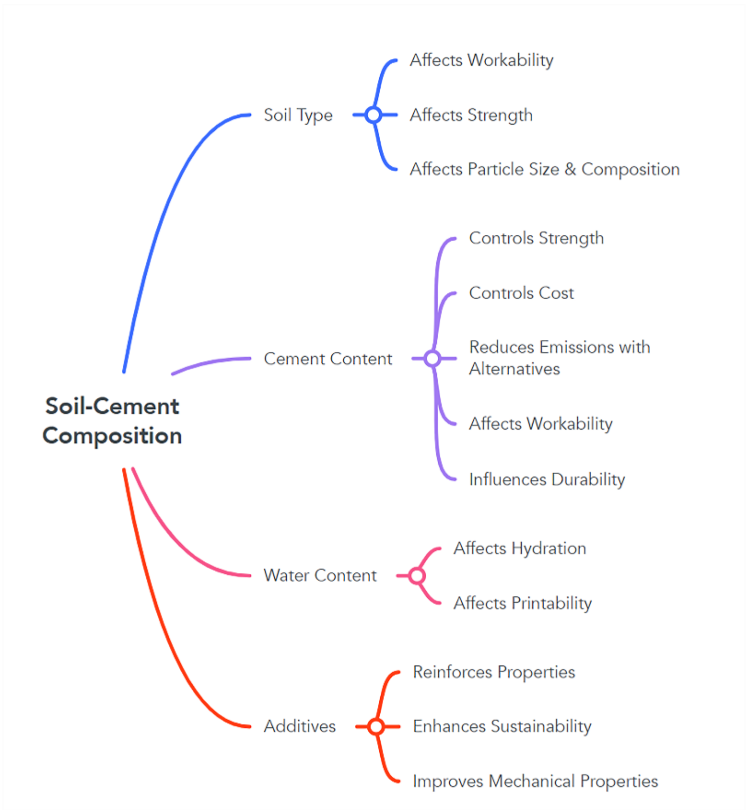

Fig. 2. Key factors affecting soil-cement composition, including soil type, cement content, water content, and additives, and their impact on strength, workability, and sustainability.

Recent research has introduced systematic methods for designing clay-based mixtures tailored for 3D printing, emphasizing the critical role of rheological properties. Asaf et al. [22] assessed various sand-clay mixtures and found that the grading and composition of clay particles significantly affect the rheological behavior and printing performance. Specifically, increasing kaolinite content enhances thixotropy, improving the material's ability to retain its shape after deposition, while coarser particles increase static yield stress, impacting stability during printing. They also developed an analytical model to predict the failure of 3D printed soil elements due to bottom layer plastic collapse, validated through printing tests. This study highlights the importance of considering both the fresh (green) and hardened states of clay mixtures to ensure optimal printability and structural integrity, providing essential guidelines for optimizing soil-based mixtures for sustainable 3D printing.

Moreover, a detailed understanding of these variations enables better customization of material mixtures, directly affecting the longevity and environmental sustainability of the structures produced. In a recent study by Eftekhar Afzali et al. [23], the compaction and compression behaviors of clayey sand stabilized with cement were evaluated using various waste materials and fibers, showing that palm fibers significantly enhanced the strength and compaction properties due to their uniform distribution and strong bonding capabilities. For instance, additives such as waste tire textile fibers have been shown to enhance the mechanical properties of soil-fiber composites, making them more suitable for load-bearing applications [12]. Perrot et al. [9], who emphasized the importance of rheological characteristics for ensuring printability and structural integrity, also explored the potential of earth-based materials for 3D printing.

The binding strength and overall hardness of the material depend on the ratio of cement to other components. While increasing cement content improves the stability of soil-cement mixtures, it also raises costs and environmental impacts, particularly concerning carbon emissions from cement production. A practical alternative for sustainable construction is the use of machine learning to optimize mix designs for

3D-printed geopolymers, which has shown notable improvements in both mechanical properties and printability [17]. Researchers such as Tarhan et al. [10] have investigated alternative materials, such as earth-based concrete, which provide a more sustainable solution by reducing reliance on cement.

Water content is another crucial factor affecting the hydration process, workability, and ultimate strength of the soil-cement composite. For optimal performance, the water-cement ratio must be precisely controlled. Silva et al. [24] emphasized the role of water content in achieving the desired attributes for 3D-printed soil-cement structures, noting its impact on printability and structural stability. Traditional empirical methods, which often require extensive physical testing, may not fully capture the subtleties of material behavior. For example, prediction models for compressive strength in concrete [25] show how soil structure affects pile response in geotechnical engineering, especially in overconsolidated clays.

Recent interest in developing soil-based mixtures specifically for 3D printing has led to new advancements. Daher et al. [5] created a mix-design method aimed at maximizing the structural integrity and printability of soil-based composites. Their research demonstrated that 3D printing can produce buildings with excellent mechanical strength and durability using soil-cement composites. Additionally, Wang et al. [26] found that incorporating coarse aggregates into 3D printed concrete (3DPC) improves mechanical properties, reduces cement usage, and lowers the carbon footprint. Adjusting the paste-aggregate ratio (P/A) optimizes printability and strength. At the same time, vibration and extrusion techniques help eliminate air bubbles and enhance interlayer bonding, resulting in denser and stronger 3DPC structures than traditional cast concrete.

Kaliyavaradhan et al. [27] reviewed testing methods for 3D printable concrete (3DPC), highlighting key factors such as flowability, extrudability, and interlayer bonding, which are critical for structural integrity. Their study emphasized the anisotropic nature of 3DPC and the need for standardized testing methods, especially for durability, as the technology progresses to larger-scale construction. Similarly, Ji et al. [28] proposed a systematic approach for selecting and designing earthen materials for 3D printing. By analyzing different soils—both natural and industrial—based on granularity, clay behavior, and linear shrinkage, they identified appropriate construction materials. They further evaluated the rheological properties, particularly yield stress, to select formulations that meet printability requirements such as pumpability, extrudability, and buildability. Their analytical model to predict plastic collapse during drying provides valuable insights for optimizing earthen materials for 3D printing.

Additionally, Ferretti et al. [29] explored the use of shredded rice husk as a biocomposite additive in earthen mixtures for 3D printing. Nodehi et al. [30] found that supplementary cementitious materials (SCMs), such as fly ash, improve printability and reduce the environmental impact of 3D printed concrete by lowering cement content. Their study emphasized optimizing mix designs to improve layer bonding and minimize shrinkage. Shredding rice husk, for example, enhances the long-term mechanical properties of hardened materials like compressive strength and stiffness, improving bonding between the rice husk and the soil matrix and contributing to better structural integrity. This method utilizes agricultural waste, supporting sustainability and improving the material's mechanical performance over time, making it more suitable for 3D printing applications.

Van Der Putten et al. [31] investigated the addition of polypropylene fibers in 3D printed cementitious materials, finding that shorter fibers (M3) reduced shrinkage while longer fibers (M6) significantly enhanced flexural strength. However, both fiber types increased porosity, which could impact durability. These findings illustrate the trade-offs when using fibers to balance shrinkage control and mechanical performance in 3D concrete printing. Zhang et al. [32] reviewed mixed design concepts for 3D printable concrete (3DPC), underscoring the need for tailored rheological properties to ensure pumpability and structural integrity. Their research stresses the importance of moving beyond trial-and-error approaches to develop scientific guidelines that account for both the fresh and hardened states of materials.

Finally, the potential of 3D printing extends beyond Earth. While its environmental benefits on Earth are well-documented, 3D printing is also being explored for constructing extraterrestrial habitats. By using local materials like Martian regolith, 3D printing can significantly reduce resource requirements. NASA's 3D-Printed Habitat Challenge demonstrated how local materials can be used to build sustainable habitats on Mars.

Figure 3 illustrates how 3D printing technology is revolutionizing extraterrestrial construction. Prototypes developed through NASA's 3D-Printed Habitat Challenge have shown how Martian regolith can be used to construct durable and sustainable habitats, showcasing the innovative use of local resources for space exploration.

Fig. 3. 3D-printed habitat prototypes for Martian exploration, demonstrating the use of local resources like Martian regolith [33].

Supporting the use of local materials in sustainable buildings, the mechanical characteristics of 3D-printed wall segments produced using earthen mixtures—such as compressive strength—are equivalent to those of conventional rammed earth [34].

Figure 4 highlights innovative examples of 3D-printed earth structures, such as Gaia House and Tecla Habitat. These designs integrate natural materials and fibers, showcasing the potential for 3D printing to create sustainable and structurally sound buildings using earth-based materials.

Fig. 4. Examples of sustainable earth-based 3D-printed structures, including Gaia House and Tecla Habitat [34].

2.2. Design flexibility

As shown by the use of parametric-integrated robotic 3D printing for complicated wall components [35], design flexibility lets architects and engineers investigate creative structural designs that satisfy particular project criteria.

As illustrated in Figure 5, the advantages of 3D printing in construction are multifaceted. The technology significantly enhances sustainability by utilizing locally available soil, reducing emissions. It also offers unmatched design flexibility, allowing for the creation of complex, customized designs that can adapt to challenging site conditions. Moreover, 3D printing delivers economic benefits by incorporating recycled materials and lowering transportation costs. Material use efficiency is another key advantage, as the process minimizes waste and optimizes resource utilization.

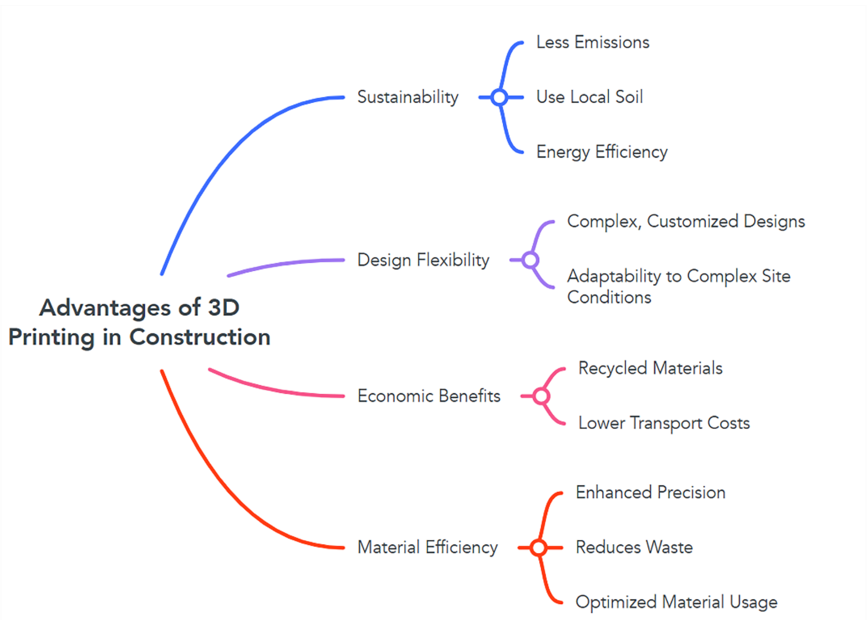

Fig. 5. Advantages of 3D printing in construction, highlighting sustainability, design flexibility, economic benefits, and material efficiency.

Material Efficiency: Working with soil-cement benefits especially from this efficiency since it allows precise control over the material mix and placement. 3D printing not only lowers expenses but also lessens the environmental impact of building projects by optimizing resource use [10]. Gomaa et al. [36] show how material efficiency can be attained while preserving structural integrity by incorporating ancient materials like cob into contemporary 3D printing techniques.

Sustainability: 3D printing reduces the carbon footprint of building projects by using locally accessible soil as the main component in soil cement, thereby reducing the requirement for material transportation over great distances. Furthermore, improving the sustainability of 3D printed constructions is possible by including recycled elements into the mix [1]. As investigated by Bajpayee et al. [1], the environmental advantages of using in situ soils for 3D printing demonstrate how this method can lower both costs and environmental effects, especially in resource-limited areas. Furthermore, as Reddi et al. [37] have stated, applying biomimetic ideas in stabilized earth architecture presents creative ways to improve the sustainability and lifetime of earth-based building materials.

Cost Reduction: Particularly when combining artificial intelligence and 3D printing to maximize cost efficiency and design, this economic benefit makes 3D printing an appealing alternative for significant building projects and affordable housing programs [38]. For instance, the use of waste tire textile fibers in soil has been demonstrated to improve mechanical qualities while lowering material costs, thereby providing a sensible alternative for reasonably priced buildings [10]. In terms of material efficiency and environmental benefits, Silva et al.'s (Silva et al. 2023) study on using soil-cement matrices in 3D printing further supports the potential cost reductions.

Particularly in the creation of anatomical models for surgical planning, machine learning algorithms have shown promise in increasing the accuracy and reducing the cost of 3D printing in the medical domain [39]. To effectively use this technology, however, the complex nature of soil-cement composites calls for sophisticated modeling methods.

The remarkable design flexibility of 3D printing has unlocked innovative possibilities in construction. However, to understand its broader implications, it is equally important to assess the economic feasibility of this technology. The following discussion explores the initial costs, operational challenges, and availability of 3D printing technology in construction.

2.3. Economic considerations of 3D printing technology in construction

While the advantages of 3D printing, such as material efficiency and sustainability, have been widely acknowledged, understanding its economic feasibility is crucial for broader adoption. Construction-grade 3D printers represent a significant capital investment, with costs ranging from $50,000 to $300,000, depending on the printer's capabilities and scale [40]. Advanced models, like those offered by companies such as Apis Cor, are tailored for specialized construction applications, but they also demand additional training and maintenance expenses.

Beyond the printer itself, launching a 3D printing-based construction project involves various ancillary costs. These include materials and supplies ($10,000–$50,000), site preparation, utility setup, design services, and insurance. The startup costs can range from $100,000 to $500,000, making the initial investment substantial for smaller firms or projects [40].

Despite these financial barriers, the adoption of 3D printing in construction is growing rapidly, driven by its potential to optimize resource use and reduce material waste. The construction 3D printing market is projected to expand significantly, making the technology more accessible over time. However, availability remains a challenge for smaller-scale operations, particularly in regions where specialized equipment and expertise are limited [41].

Addressing these economic challenges is essential to ensure that the benefits of 3D printing can be fully realized. Future advancements in cost-effective manufacturing processes, along with collaborative efforts to reduce equipment costs, could make 3D printing a more accessible and transformative tool in construction.

3. Case study: sustainable 3D printing with excavated soil–a practical application

3.1. Introduction

The growing focus on sustainability in construction has sparked interest in the use of excavated soil for 3D printing applications. Inspired by Daher et al. [5], this case study presents a detailed methodology and results for developing soil-based 3D-printable mixtures, emphasizing environmental benefits and practical feasibility. Leveraging excavated soil from the Grand Paris Express project, the study demonstrates how local materials can produce cost-effective and durable building components while minimizing environmental impacts.

3.2. Methodology

3.2.1. Materials and mix design

Raw excavated soil, sieved to 2 mm, was used as the primary material, ensuring compatibility with 3D printing equipment. Ordinary Portland Cement (OPC) acted as the hydraulic binder. Superplasticizers, including MasterGlenium ACE 456, were tested to enhance fluidity and printability.

Three mix designs (M1, M2, M3) were prepared with varying soil-to-cement ratios (2:1, 4:1, and 6:1). The water-to-fine ratio was fixed at 0.4, ensuring consistency in rheological properties. Table 1 summarizes the mix proportions and highlights the differences in soil-to-cement ratios across the mixtures.

Table 1
Mix Proportions for Soil-Based 3D-Printable Mixtures provides a detailed breakdown of M1, M2, and M3 compositions [5].

	Preliminary Mixtures		
	Mixture 1 (M1)	**Mixture 2 (M2)**	**Mixture 3 (M3)**
Cement mass (g)	300	300	300
Total soil mass (g)	700	1200	1700
Soil/cement ratio (~)	2	4	6
Soil mass <80 µm (g)	224	384	544
Fines = cement + soil <80 µm (g)	524	684	844
Water/fines ratio	0.40	0.40	0.40
% SP (wt.% fines) in dry content	To be determined	To be determined	To be determined

3.2.2. Printability testing

Printability testing involved evaluating both extrudability and buildability. The mixtures were tested using a manual gun and a laboratory gantry printer equipped with a 2 cm nozzle. Buildability was assessed using a modified mini-slump test, which measured the structural stability of the deposited layers.

Figure 6 shows the printability testing setup, including the laboratory gantry printer and manual extrusion gun, which were used to evaluate the performance of the mixtures under controlled conditions.

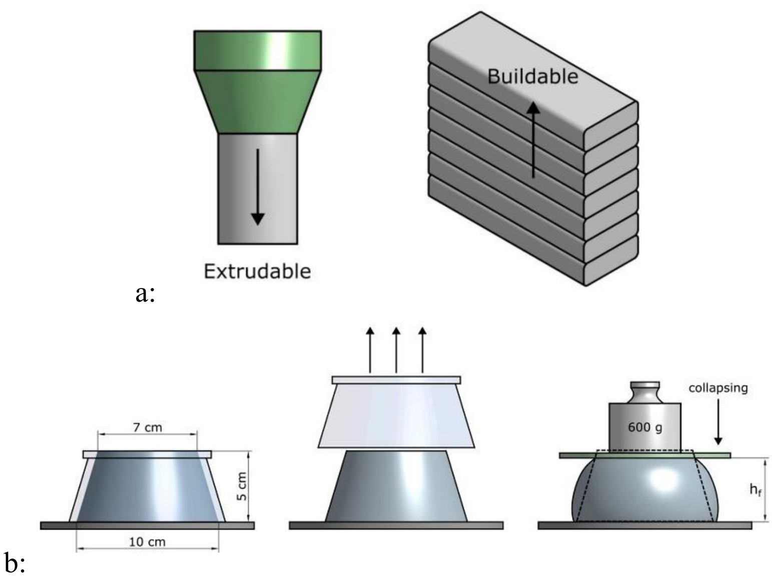

Fig. 6. a: Experimental Setup for Printability Testing visually represents the tools and methods used to test extrudability and buildability. b: Setup and procedure of the modified mini slump test for assessing the buildability of mortars [5].

3.2.3. Mechanical properties and durability

Compressive strength was tested following EN NF 196-1 standards at 1, 7, and 28 days. Samples included compacted, non-compacted, and 3D-printed specimens. Mercury Intrusion Porosimetry (MIP) was also used to analyze pore size distribution and interlayer bonding.

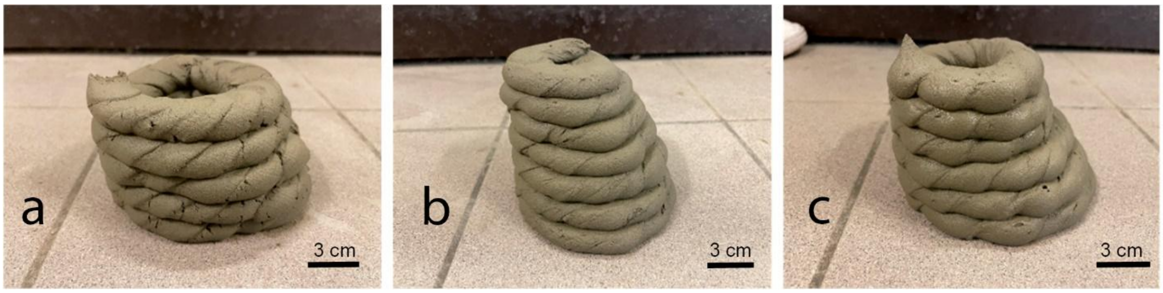

Fig. 7. Extrudability of M1 mixtures with a: 0.45%, b: 0.48%, and c: 0.51% SP content [5].

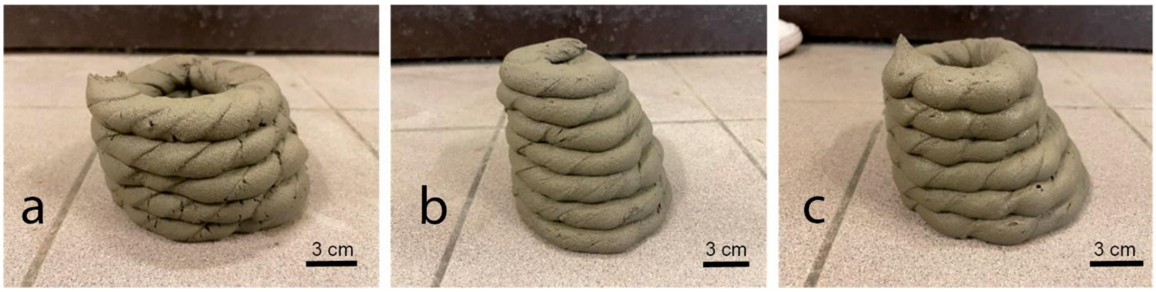

Fig. 8. Buildability of M1 mixtures with (a) 0.45%, (b) 0.48%, and (c) 0.51% SP content [5].

Figure 7 shows that the 0.45% SP mix for M1 was challenging to extrude and exhibited some cracking, whereas the 0.48% SP mix was easily extrudable. The 0.51% SP mix was also extrudable but very fluid, resulting in layer sagging. Additionally, Figure 8 indicates that both the 0.45% and 0.48% SP mixes were buildable (hf = 4.75 and 4.50 cm, respectively, exceeding the hf threshold of 4.50 cm, which corresponds to a commercially printable material), while the 0.51% SP mix was not buildable (hf = 2.70 cm, below the hf threshold). Since the 0.48% SP mix was the only one that met the printability requirements, it was selected for the development of the first printable mixture, M1, which is lower than the saturation amount of 1% determined for M1 using the mini cone test.

Figure 9 illustrates the compressive strength testing setup, showing the directions of applied forces (parallel and perpendicular) to evaluate the structural integrity of the printed specimens.

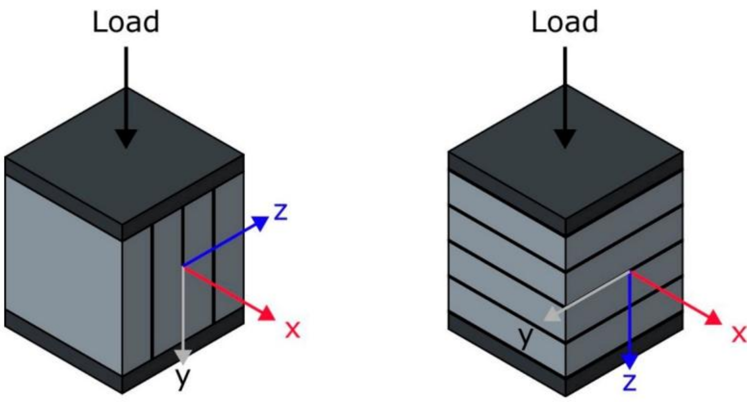

Fig. 9. *Compressive Strength Testing Setup* [5].

3.3. Results and discussion

3.3.1. Printability

All three mixtures demonstrated excellent extrudability and buildability in laboratory and field conditions. Mixture M3, with the highest soil content, displayed significant environmental advantages without compromising printability.

Table 2 compares the printability scores for the three mixtures, including the extrudability index, buildability ratings, and slump test results. This table highlights the specific strengths of each mix design.

Table 2
Printability Scores for Different Mix Designs summarizes the printability performance metrics for M1, M2, and M3 mixtures [5].

	Composition of M1 Mixture			Composition of M2 Mixture		Composition of M3 Mixture		
	SP=0.45%	SP=0.48%	SP=0.51%	SP=0.72%	SP=0.75%	SP=0.87%	SP=0.90%	SP=1.00%
Cement mass (g)		300		300			300	
Total soil mass (g)		700		1200			1700	
Soil/cement ratio (~)		2		4			6	
Soil mass <80 µm (g)		224		384			544	
Fines = cement + soil <80 µm		524		484			844	
Water/fines ratio		0.40		0.40			0.40	
% SP (wt. % fines)	0.45	0.48	0.51	0.72	0.75	0.87	0.90	1.00
	Extrudability and buildability of mixtures							
Extrudability	✗	✓	✓	✗	✓	✓	✓	✓
h_x (cm)	4.75	4.50	2.70	4.85	4.50	4.55	4.50	2.55
Buildability	✓	✓	✗	✓	✓	✓	✓	✗

3.3.2. Compressive strength

The compressive strengths of the mixtures ranged from 16 MPa to 34 MPa at 28 days, exceeding the minimum structural concrete requirements. Mixture M1 exhibited the highest strength, attributed to its lower soil content, while M3 demonstrated the potential for sustainability through reduced cement use.

Figure 10 outlines the compressive strength results at 1, 7, and 28 days, emphasizing the performance trends for the three mix designs. The table illustrates the balance between mechanical strength and sustainability considerations.

Using excavated soil reduced cement content by up to 60% compared to conventional 3D-printed concrete, significantly decreasing carbon emissions and material costs.

In conclusion, this case study highlights the potential of using excavated soil for sustainable 3D printing in construction. The results show that soil-based mixtures with varying soil-to-cement ratios can achieve a balance between printability, strength, and sustainability. Mixture M3, with the highest soil content, reduces cement use by up to 60%, lowering carbon emissions and costs. The printed components met structural strength requirements, demonstrating their feasibility for load-bearing applications. These findings support the use of excavated soil in 3D printing, offering both environmental and economic benefits, with further research needed on durability and large-scale implementation.

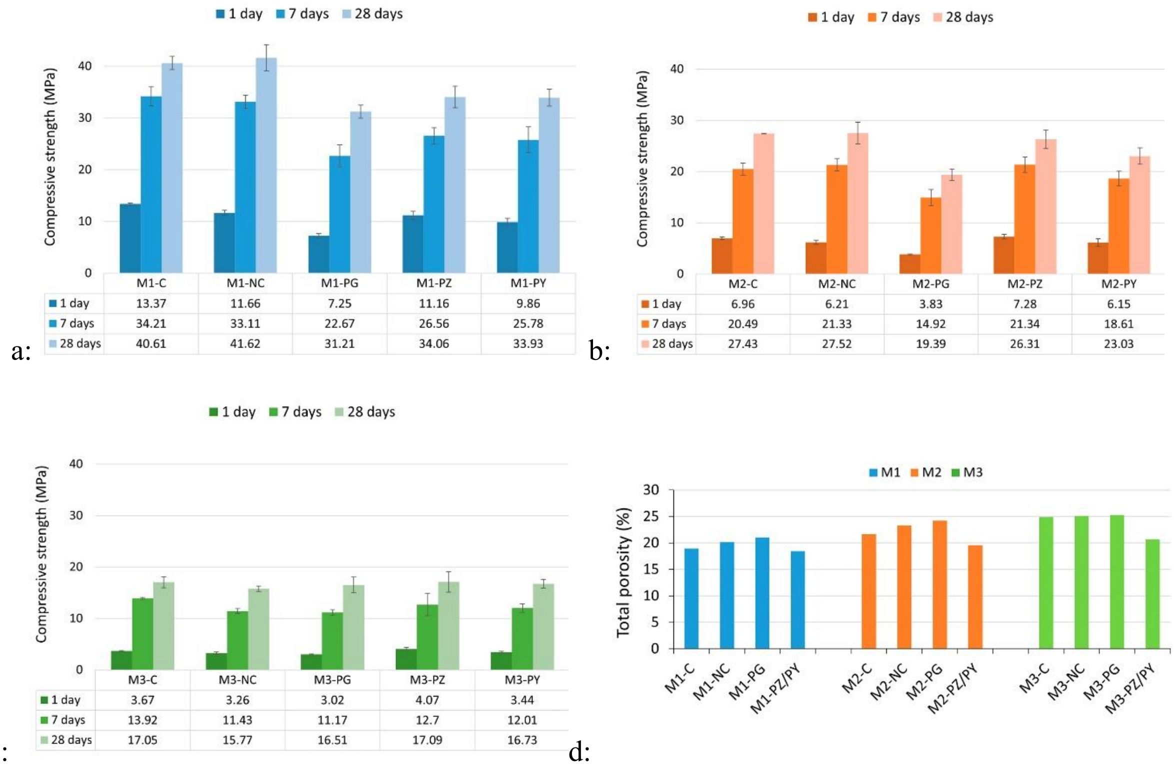

Fig. 10. Compressive strength at 1, 7, and 28 days of the different types of samples of the **a**: M1, **b**: M2, and **c**: M3 mixtures. d: Total porosity results for samples at 28 days (%) [5].

4. Methods of machine learning applied in material modeling

4.1. Learning under supervision

Machine learning encompasses a variety of techniques that enable computers to learn from data and make predictions or decisions without being explicitly programmed. The primary categories of machine learning include supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training a model on labeled data, where the correct output is provided, enabling the model to learn the mapping between inputs and outputs. Unsupervised learning, on the other hand, deals with unlabeled data, allowing the model to identify hidden patterns or intrinsic structures within the data. Reinforcement learning is a type of machine learning where an agent learns to make decisions by performing actions and receiving feedback in the form of rewards or penalties. These approaches provide a foundation for the various applications of machine learning in optimizing material modeling and 3D printing processes. When negotiating the complexity of soil-cement composites, machine learning provides more accurate forecasts and optimal material designs than conventional techniques.

Linear Regression: Though its limitations in complex material behavior modeling can be resolved by more advanced AI techniques in construction, linear regression is a fundamental statistical method used for predicting the relationship between a dependent variable and one or more independent variables [2]. Though it offers a simple process, its application in complicated material modeling, such as 3D printing, is limited because of its linear assumptions, which demand more complex models for reliable predictions. By significantly lowering the requirement for rigorous physical testing, using linear regression in predicting soil-cement characteristics will hasten the creation of ideal mix designs.

Decision Trees: These non-linear models divide data into subsets depending on feature values, resulting in a tree-like structure. These easily interpretable models are beneficial for capturing complex relationships between variables. According to Zhang et al. [42], machine-learning approaches have successfully simulated complex soil parameters used in geotechnical design, offering significant advantages over traditional methods. These techniques allow for more accurate predictions of soil behavior, making them particularly useful in optimizing soil-cement mixtures for 3D printing. Similarly, Alatoom and Al-Hamdan [43] conducted a comparative study of various machine learning algorithms—including ANN, Random Forest, Decision Trees, SVM, and others—for estimating vehicular delay at signalized intersections, emphasizing the importance of selecting the most suitable algorithm to achieve optimal prediction accuracy in civil engineering applications. Furthermore, Lim et al. [44] evaluated several machine learning classifiers using geophysical data for modeling soil parameters, with Decision Trees achieving high accuracy. Decision Trees are particularly well-suited for simulating the intricate interactions between soil particles and cement in 3D-printed structures, as they effectively handle non-linear relationships.

Support Vector Machines (SVM): Powerful methods for both classification and regression problems; Support Vector Machines (SVM) discover the ideal hyperplane separating many classes or predicting continuous values. By means of kernel functions, these models can manage non-linear relations and are wildly successful in high-dimensional environments. Puri et al. [45] highlighted their possible use in civil engineering by using SVMs to accurately forecast geotechnical characteristics. Emphasizing SVM's resilience and accuracy in predicting soil behavior, Owusu-Ansah et al. [46] investigated the use of SVM in modeling soil properties. SVMs are a valuable tool in the modeling of 3D-printed soil-cement materials since their adaptability in handling challenging datasets guarantees reliable predictions.

Neural Networks: Designed to learn complicated, non-linear correlations between inputs and outputs, neural networks have layers of linked nodes (neurons). These models are perfect for use in 3D printing since they are especially helpful for huge datasets with many attributes. Achieving great predictive accuracy, Alyami et al. [2] predicted the compressive strength of 3D-printed fiber-reinforced concrete using neural networks. Further proving the adaptability of neural networks in construction uses, as investigated by Khandel et al. [47], the combination of fiber optic sensors with ANN has also shown promise in evaluating the performance of structural components like prestressed concrete bridge girders. These illustrations show how well neural networks might improve 3D printed material predictive modeling and process optimization. Furthermore, Naderpour et al. [48] optimized the seismic performance of tuned mass dampers in reinforced concrete buildings using machine learning techniques, showcasing how ML can effectively enhance structural resilience by optimizing vibration mitigation strategies.

4.2. Unsupervised learning

Data without specified labels can have patterns found using unsupervised learning methods. Examining the fundamental structure of the data and finding fresh ideas that might not be immediately obvious benefits these approaches especially.

Clustering: Techniques—such as hierarchical clustering and k-means—group data points depending on their similarity. Clustering allows one to classify samples based on their characteristics within the framework of 3D-printed soil-cement materials, thereby exposing underlying structures and data homogeneity. Lim et al. [44] highlighted their possibilities in classifying soil-cement composites based on their mechanical and physical features as they showed the efficiency of clustering methods in modeling soil properties. Clustering applied in material modeling can enable researchers to find ideal mix designs and enhance the general 3D printed structural performance.

Dimensionality Reduction: Principal Component Analysis (PCA) and other dimensionality reduction methods help simplify the data by converting it into a lower-dimensional space while preserving important information. Visualizing high-dimensional data and spotting salient aspects that support material performance depends especially on dimensionality reduction. Using PCA to investigate elements influencing the strength development in cement-treated clayey soils, Abdallah et al. [49] showed its application in material modeling and the optimization of cementitious composites.

4.3. Reinforcement learning

Reinforcement learning (RL) is a machine learning method whereby an agent learns to make decisions through interactions with an environment and feedback in the form of penalties or rewards. The agent aims to pick a policy that, over time, optimizes the overall payoff. Within the framework of 3D printed soil-cement composites, RL can be applied to maximize printing process parameters like nozzle speed, layer height, and curing time, thereby obtaining desired material characteristics and structural performance.

Machine learning offers various techniques to improve the modeling of soil-cement materials. These methods include supervised, unsupervised, and hybrid approaches, each contributing uniquely to optimizing 3D printing processes. As shown in Figure 11, the application of machine learning techniques in 3D printing includes methods such as linear regression, clustering, reinforcement learning, and more, each tailored to solve specific challenges in material modeling and process control.

Applications in Predictive Maintenance: Latifi et al. [50] created a deep reinforcement learning framework combining life cycle cost analysis (LCCA) and life cycle assessment (LCA) to maximize predictive maintenance of road assets. This framework can be modified to maximize the performance and maintenance of 3D-printed soil-cement constructions, thereby guaranteeing their long-term dependability and resilience. As Khandel and Soliman show, the use of RL in infrastructure resilience planning further illustrates its potential to improve the dependability of building techniques.

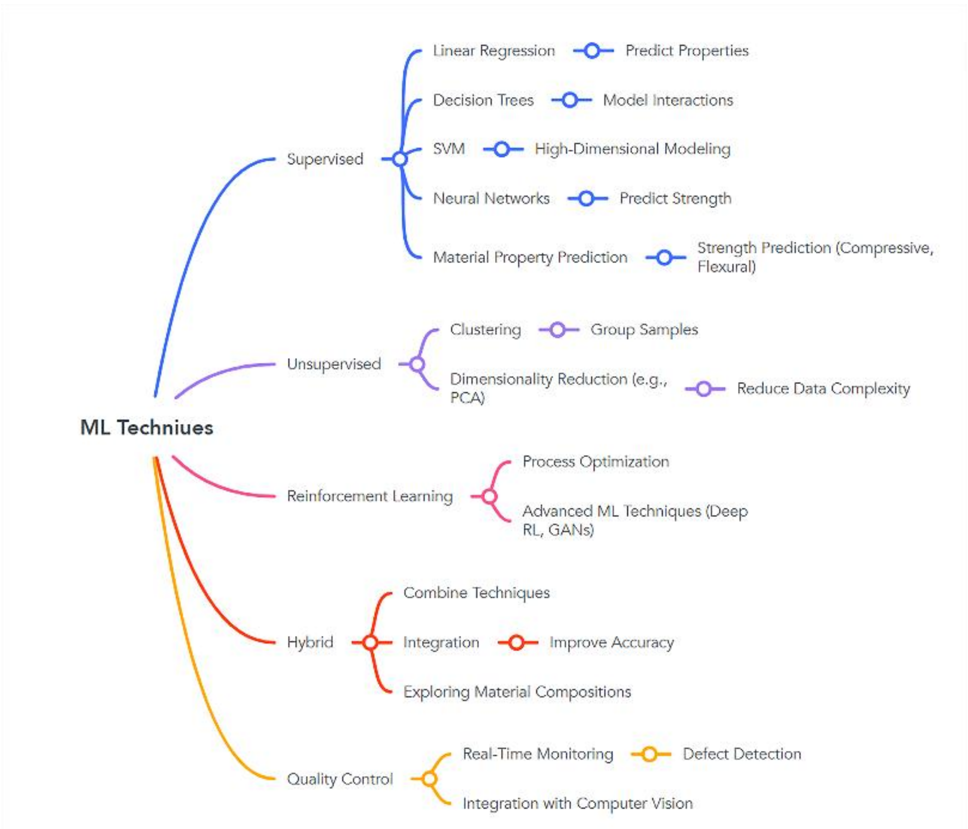

Fig. 11. Overview of machine learning techniques applied in 3D printed soil-cement materials, including supervised, unsupervised, and reinforcement learning.

Process Optimization: 3D printing allows reinforcement learning to be used for process optimization as well. To maximize aerosol jet printing (AJP) process parameters, Zhang et al. [8], for example, presented a hybrid machine learning method combining RL with other methodologies, thereby producing improved print quality and reducing experimental trials. Particularly considering the heterogeneity of soil-cement materials, the combination of RL with conventional machine-learning techniques provides a strong tool for improving the intricate operations involved in 3D printing.

4.4. Hybrid machine learning methods

Combining multiple algorithms or strategies in hybrid machine learning allows one to use their advantages and raise overall performance. These techniques are especially helpful in sophisticated uses like 3D printing, where several considerations must be considered concurrently.

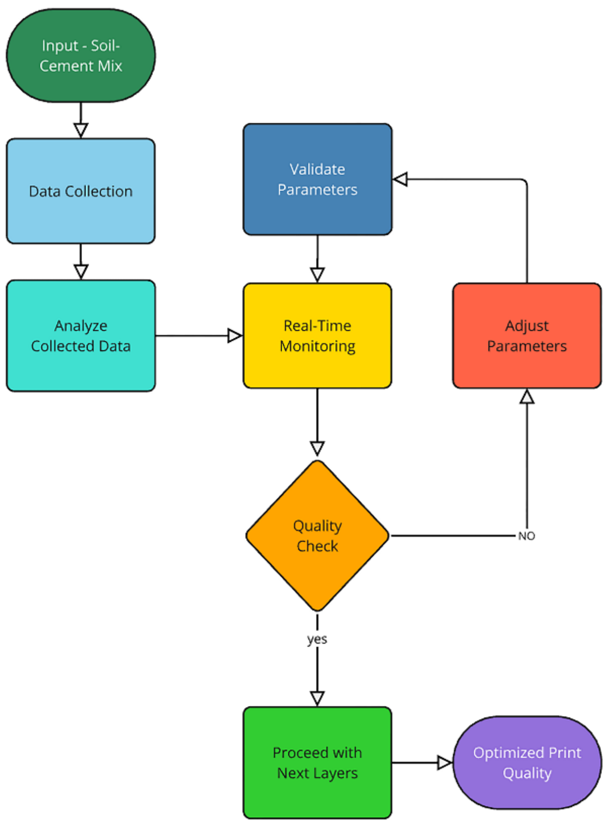

Fig. 12. Real-time monitoring and quality control process for optimizing 3D-printed soil-cement materials.

Combining ML Techniques for Optimal Performance: Zhang et al. [8] introduced a hybrid machine learning method combining experimental sampling, data clustering, classification, and transfer learning to maximize the operating process window in aerosol jet printing (AJP). This method effectively lowered experimental trials and enhanced print quality, thereby proving the possibilities of hybrid approaches in maximizing 3D printing techniques. As recommended by Zhang et al. [8], the combination of hybrid ML techniques with conventional material modeling approaches can result in more accurate and robust predictions in the modeling of 3D-printed soil-cement systems.

Integration with Traditional Methods: As shown by the successful mix of artificial intelligence with 3D printing for structural engineering applications [51], integrating machine learning techniques with conventional material modeling methodologies can lead to more robust and accurate forecasts. 3D-printed soil-cement buildings can achieve much-improved accuracy and efficiency by means of an integrated machine-learning framework covering design, quality control, and process optimization [50]. In additive manufacturing, for instance, the combination of data-driven optimization with real-time monitoring can greatly improve decision-making, especially in balancing considerations including cost, quality, and throughput. The advancement of laser-based production techniques depends on such systems [51]. These methods demonstrate the advantages of merging modern ML techniques with conventional procedures. Similarly, Long et al. [52] employed stacking ensemble techniques combined with Bayesian optimization to enhance the prediction of soil liquefaction, demonstrating the effectiveness of hybrid machine learning methods in geotechnical engineering applications.

Figure 12 outlines the key steps involved in real-time monitoring, parameter validation, and quality control to further illustrate how machine learning optimizes the 3D printing process for soil-cement materials. This process ensures that every aspect of the print is continuously adjusted for optimal quality and consistency.

Enhancing Predictive Accuracy: Hybrid approaches also greatly enhance the prediction accuracy of machine learning models. Using interpretable ML methods, including SHAP analysis, Uddin et al. [53] projected the mechanical characteristics of 3D-printed fiber-reinforced concrete, thereby determining important variables such as fiber type and curing time. Combining several ML approaches can produce more accurate and dependable predictions, as shown by the work of Tran et al. [54] on applying Bayesian Regularization and Evolution Algorithms for predicting workability properties in 3D printing.

4.5. Machine learning for process optimization and quality control

Process Optimization: Dabbagh et al. [55] show that extrusion-based 3D printing systems may be optimized using machine learning techniques, guaranteeing constant material properties and high-quality prints by lowering material waste and enhancing print quality. With ANN models demonstrating the best prediction accuracy, Tamir et al. [56] used SVM, Random Forest, and ANN algorithms to predict and optimize print quality based on parameters like print speed and temperature. As illustrated in Figure 13, the optimized toolpath for robotic 3D clay printing uses a hexagonal infill pattern. This approach reduces material consumption while maintaining the structure's strength and stability, demonstrating how 3D printing can enhance material efficiency and structural integrity.

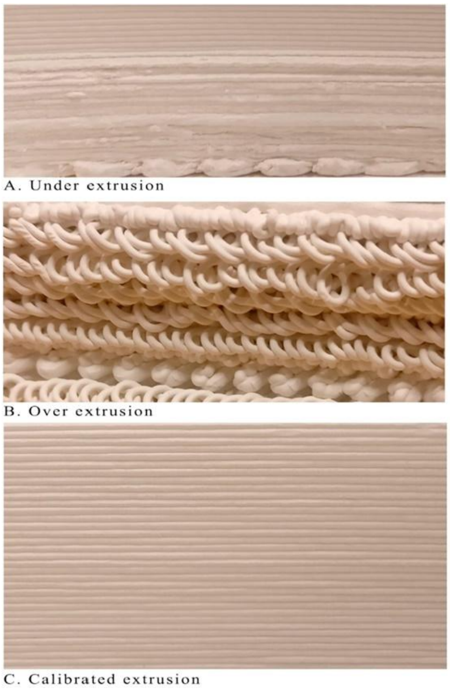

Fig. 13. Optimized toolpath for robotic 3D clay printing to reduce material usage while maintaining structural integrity [35].

Real-Time Process Monitoring: Delli and Chang investigated using supervised machine learning for real-time process monitoring in 3D printing using Support Vector Machines, Decision Trees, and Random Forests to identify flaws during production [57]. With over 90% accuracy, Random Forests outperformed other models, highlighting the possibility of integrating machine learning into 3D printing processes to improve quality control and reduce faults.

Optimization of Print Parameters: Zhang et al. [8] introduced a hybrid ML method combining RL with other methods to optimize aerosol jet printing (AJP) process parameters, thereby improving print quality and reducing experimental trials. As Zhang et al. [8] argued, integrating ML with conventional material modeling techniques can produce more robust and accurate predictions in modeling 3D-printed soil-cement systems.

5. Future directions in machine learning applications

According to Thu et al. [58], the integration of machine learning in 3D-printed concrete has achieved notable progress; hence, further improvements in this field will be vital to maximize material qualities and improve construction efficiency. Some possible future approaches include:

5.1. Development of hybrid models

Combining physics-based simulations with data-driven machine learning models can result in more accurate and robust predictions—hybrid models. This method can take advantage of the strengths of both techniques to capture the intricate behavior of soil-cement composites [59].

5.2. Exploration of alternative binding agents

Investigating substitute binding agents—including biopolymers and geopolymers—opens an opportunity to reduce the carbon footprint of building materials. Using machine learning to improve the mix design of these materials can help increase their structural and environmental performance even further [60].

5.3. Advancements in automation and robotics

The 3D printing process's efficiency and accuracy could be significantly enhanced through real-time multi-resolution scanning with machine learning for conformal robotic 3D printing in architecture [61]. Incorporating machine learning into these systems could help further control process parameters, improving operational efficiency and print quality [62].

Building upon the suggestion to explore robotics and hybrid modeling, a promising avenue for future research is the development of experimental frameworks that integrate cable-driven parallel robots (CDPRs) for enhanced 3D printing of soil-cement materials. For instance, CDPRs offer a highly adaptable and scalable approach to robotic 3D printing, as demonstrated in the work of Qian et al.[63], where the modeling and experimental validation of a CDPR showcased its ability to achieve precise motion control and flexible workspace utilization. By leveraging such robotic systems, optimizing the deposition patterns and interlayer bonding of soil-cement composites becomes feasible, thereby improving structural integrity and reducing material waste. Additionally, hybrid modeling frameworks that combine machine learning algorithms with physics-based simulations can enable real-time optimization of robotic parameters, such as cable tension and end-effector velocity, during printing. Future experimental studies could focus on integrating CDPRs with machine learning-driven feedback systems to dynamically adjust printing parameters based on in situ monitoring of material properties. This approach not only enhances the scalability and accuracy of the 3D printing process but also paves the way for automated construction practices that are both efficient and environmentally sustainable.

5.4. Multi-material printing

The development of multi-material 3D printing technologies, particularly when optimized using advanced machine learning frameworks, enables the fabrication of composite structures with tailored properties, greatly increasing the versatility and application range of 3D-printed constructions [64]. Further extending these capacities might involve machine learning to maximize material combinations and deposition techniques.

6. Applications of machine learning in 3d printed soil-cement modeling

6.1. Predictive modeling of mechanical properties

Among the primary uses of machine learning in 3D-printed soil-cement materials is predictive modeling of mechanical parameters like compressive strength, tensile strength, and elasticity. Training models using experimental data helps researchers maximize the mix design for particular uses and forecast the performance of future soil-cement mixtures. This predictive capability enhances efficiency and reduces material waste, contributing significantly to more sustainable construction methods.

Compressive Strength Prediction: Compressive strength is a key factor in determining the load-bearing capacity of 3D-printed soil-cement materials. Alyami et al. [2] employed XGBoost, a robust gradient boosting algorithm, to predict the compressive strength of 3D-printed fiber-reinforced concrete, achieving a remarkable accuracy with an R-squared value of 0.98. Similarly, El Khessaimi et al. [65] used ML methods to forecast limestone calcined clay cement' (LC3) compressive strength using XGBoost as the most accurate among the tested algorithms. As shown in Izadgoshasb et al. [66], precisely forecasting compressive strength using ML models allows researchers to maximize mix designs and improve material performance without resorting to extensive physical testing.

Tensile and Flexural Strength Prediction: Apart from compressive strength, tensile and flexural strength prediction is a crucial mechanical feature influencing 3D printed soil-cement material resilience and durability. Ali et al. [67] created a machine-learning model using Random Forest to estimate the tensile and flexural strength of 3D-printed concrete with great accuracy in forecasts. More robust and durable 3D printed constructions can be developed using ML models' prediction of these features. Similarly, Raeisi et al. [68] employed neural networks and the group method of data handling (GMDH) technique to predict the flexural capacity of reinforced concrete beams strengthened with near-surface mounted FRP, demonstrating the effectiveness of soft computing methods in accurately forecasting structural performance enhancements.

Dynamic Yield Stress Prediction: Another important quality affecting the flowability and printability of the material is the dynamic yield stress (DYS) of 3D-printed concrete. Using ANN models, Geng et al. [69] projected the dynamic yield stress of 3D-printed concrete, thereby improving the dependability and efficiency of the 3DPC operations. Accurate DYS prediction made possible by ML models allows researchers to maximize the printing process and guarantee consistent material qualities.

6.2. Quality control and defect detection

Quality control is a key component of 3D printing, especially in building uses where the structural integrity of printed components is crucial. Machine learning methods, especially computer vision and image recognition, can be used to monitor the 3D printing process in real time. These technologies guarantee the integrity of the finished product by identifying flaws in the printed constructions, including cracks, voids, and layer misalignments, thereby allowing quick corrective action.

Figure 14 shows the experimental setup for real-time monitoring of 3D printing processes. Using machine learning algorithms such as Support Vector Machines, this system continuously detects defects, allowing for immediate corrections, which ensures higher print quality and reduces material waste.

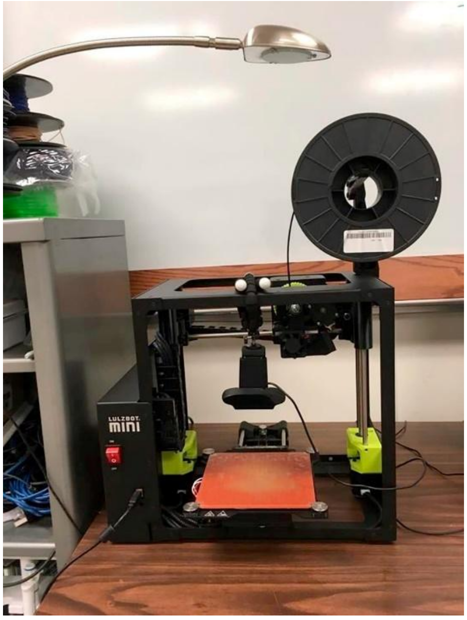

Fig. 14. Real-time monitoring system for 3D printing processes, using machine learning algorithms to detect defects and ensure print quality [57].

Real-Time Defect Detection: Delli and Chang's [57] study on automated process monitoring in 3D printing showed the promise of supervised machine learning methods, including Support Vector Machines and Random Forests, in identifying flaws throughout the printing process. Manufacturers may find and fix flaws in real time by integrating these algorithms into the 3D printing process, thereby lowering the possibility of structural breakdowns and raising the overall quality of produced components.

Integration with Computer Vision: Further opportunities to improve quality control in 3D printing arise from the intersection of machine learning with computer vision methods. For conformal robotic 3D printing in architecture, Nicholas et al. [61], for instance, demonstrated a system combining real-time multi-resolution scanning with machine learning. This method overcomes traditional limitations and allows for sophisticated, high-quality printed structures, improving accuracy and adaptability in large-scale manufacturing. Machine learning and computer vision enable constant monitoring of the printing process, ensuring that flaws are detected and corrected before they threaten the structural integrity of the final product.

7. Machine learning in geotechnical applications

Machine learning methods have also benefited geotechnical uses, including soil property and behavior prediction. Reviewing machine learning approaches for modeling soil parameters in geotechnical design, Zhang et al. [59] highlighted the superiority of ML models over conventional statistical methods. Emphasizing ensemble techniques like Random Forest for their accuracy and resilience in forecasting soil changes, the study focused on how ML can enhance predictive capabilities in geotechnical engineering.

7.1. Soil classification and prediction

Aydın et al. [70] used a Gayrettepe–Istanbul Airport metro project dataset to apply machine learning methods to increase soil classification accuracy. Missing data and class imbalance were handled using preprocessing methods, including KNN imputation and SMOTE; gradient-boosting systems, including XGBoost, LightGBM, and Catboost, obtained great accuracy rates. This study underscores the potential of ML to simplify geotechnical engineering procedures and raise soil classification accuracy.

7.2. Enhancing predictive modeling in geotechnics

Puri et al. [45] investigated how machine learning methods might be used to forecast geotechnical parameters necessary for civil engineering projects. Using a dataset of soil characteristics, the study ran SVM, Random Forest, and ANN models; ANN models showed great predictive accuracy. This study implies that ML can replace conventional empirical approaches with more excellent reliability by significantly improving the accuracy and efficiency of geotechnical studies.

8. Sustainable construction and environmental impact

By optimizing material use, lowering waste, and improving construction process efficiency, machine learning can significantly help promote sustainable building techniques. For example, Bajpayee et al. [1] investigated the possibilities of 3D-printed construction materials derived from in situ soils to support environmentally friendly building methods. The study showed notable increases in compressive strength and durability through mechanical and chemical treatments meant to improve soil conditions for additive manufacturing. Sahana et al. [71] similarly created stabilized earth materials for 3D printing, examining how carbon sequestration affected their engineering qualities.

8.1. Optimizing material usage

Given 3D printed soil-cement materials, the application of machine learning in material use optimization is especially pertinent. Using ML techniques allows researchers to find the ideal blend designs that maximize performance while minimizing material use. For 3D printed geopolymers, Bagheri and Cremona investigated the use of machine learning to optimize mix designs, thereby obtaining notable mechanical characteristics and printability [8]. By displaying improved mechanical qualities and printability, the optimized designs helped to save process times and material waste.

8.2. Reducing environmental impact

3D-printed soil-cement products have significant environmental advantages. Furthermore, the precise control provided by 3D printing technology reduces material waste and optimizes resource use, thereby supporting more environmentally friendly building methods. Further underlining the environmental advantages of using industrial by-products for soil stabilization is research on using cement clinker and fly ash in stabilizing dispersive soils [72]. Recent advances in the characterization of carbonation behavior in slag-based concrete have been made using nanotomography, as demonstrated by Mehdizadeh et al. [73]where full-field X-ray imaging provides detailed insights into the 3D structural changes and pore structure dynamics, which are crucial for assessing the durability and carbonation impact on concrete.

8.3. Innovations in sustainable construction

Studies like those by Tarhan et al. [10], who investigated the use of earth-based concrete as a sustainable alternative to conventional building materials, help to further assist innovations in sustainable construction by combining machine learning with sustainable building methods. Similarly, Son and Khoi [74] applied an adaptive selection slime mold algorithm to optimize construction projects' time-cost-quality-environment trade-offs, highlighting the potential of advanced AI algorithms to enhance sustainability and efficiency in construction management by simultaneously optimizing multiple objectives. Due to its versatility, low cost, and low environmental impact, the study emphasizes how suitable the material is for

3D printing—especially in construction. As Minke investigates, using earth as a sustainable building material coupled with biomimetic ideas in stabilized earth construction covered by Reddi et al. [37] presents creative ways to improve the longevity and sustainability of earth-based building materials. While the integration of 3D printing and soil cement has demonstrated its potential for sustainability, machine learning offers additional capabilities to quantitatively optimize key aspects such as energy consumption, material efficiency, and carbon emissions. The following section delves into specific examples of how ML frameworks have been applied to achieve measurable improvements in these areas.

8.4. Machine learning optimizations for lowering energy use, waste, and carbon emissions

Integrating machine learning (ML) into 3D printing processes for soil-cement materials provides unprecedented opportunities for enhancing sustainability through energy optimization, waste reduction, and carbon emission mitigation. ML frameworks have demonstrated measurable improvements in construction efficiency and environmental impact by leveraging predictive modeling, process optimization, and real-time monitoring.

Energy Optimization

ML algorithms dynamically optimize printing parameters such as nozzle speed, layer height, and material deposition rates, significantly reducing energy consumption. For instance, reinforcement learning (RL) models can adaptively adjust operational settings, achieving up to 25% energy savings compared to conventional approaches. Additionally, nozzle path optimization reduces non-productive movements, while advanced algorithms like XGBoost determine ideal curing times and layer thickness, further minimizing energy demands.

Reduction in Material Waste

Material efficiency is another critical benefit of ML-driven optimizations. Predictive models utilizing neural networks estimate the precise material quantities required for structures, preventing overuse and minimizing excess. This precision reduces material waste by **15-20%**. Furthermore, clustering algorithms can classify soil compositions and exclude non-usable components during the mix-design phase, ensuring better resource utilization.

Carbon Emission Reduction

The application of ML in mix design optimization enables a reduction in carbon-intensive materials like cement by incorporating supplementary cementitious materials (SCMs) such as fly ash and ground granulated blast furnace slag (GGBFS). This approach has been shown to lower carbon emissions by **20-30%** per cubic meter of printed material. Lifecycle assessments, powered by ML models, evaluate environmental footprints and recommend process adjustments, contributing to substantial carbon savings[75]

Quantitative Case Study

In a case study by Xu et al. [18], a hybrid ML model combining RL and decision trees optimized the production of a 3D-printed building prototype. The model achieved:

- **22% reduction** in energy consumption through dynamic parameter tuning.
- **19% reduction** in material waste by optimizing deposition precision.
- **27% decrease** in carbon emissions by reducing cement use and optimizing curing processes.

These quantitative advancements underscore the transformative potential of machine learning in sustainable construction practices. However, fully realizing these benefits requires overcoming significant challenges, including data scarcity, computational demands, and standardization issues, as discussed in the following section.

9. Challenges and future directions

9.1. Data availability and quality

Gathering comprehensive datasets across a broad spectrum of factors and scenarios is challenging in the realm of 3D-printed soil-cement materials. Standardizing data collection techniques and building shared databases should be top priorities in efforts to facilitate research and development.

Data Scarcity and Variability: Zhang et al. [59] highlighted in their assessment of machine learning applications in soil constitutive modeling the importance of large, high-quality datasets in addressing data scarcity and variability. By measuring the physical properties of materials, such as the sphericity of tiny particles, using techniques like those proposed by Kaviani-Hamedani et al. [76], data scarcity and variability—which otherwise impede the creation of accurate and reliable ML models—may be addressed. Utilizing common databases and standardizing data collection can overcome these obstacles and improve the efficacy of ML models in this domain.

Ensuring Data Integrity: Ensuring the accuracy and dependability of the predictions depends on the data used to train ML models being intact. Researchers must guarantee that any anomalies or outliers are appropriately addressed and that the data is gathered consistently. This is crucial in the context of 3D-printed soil-cement systems, where the variation in soil parameters might provide uneven outcomes.

Additionally, benchmarking and consistent data-gathering procedures are paramount in machine learning applications for 3D-printed materials. Benchmarking allows for evaluating and comparing different machine learning models and techniques to determine the most effective approach for a given application. Consistent data gathering ensures that the data used for training and testing models is reliable, representative, and free from biases, which is critical for achieving accurate and generalizable predictions. Establishing standardized data collection protocols and benchmarking datasets can significantly enhance the robustness and reproducibility of machine learning models in this field.

9.2. Model interpretability

Understanding material behavior and ensuring the reliability of predictions depend on knowing the decision-making process of complex models, such as deep neural networks. Wider acceptance of machine learning in this discipline depends on developing methods to improve model interpretability.

Enhancing Model Transparency: Uddin et al. [53] sought to forecast the mechanical characteristics of 3D-printed fiber-reinforced concrete. This method offers important new perspectives on the decision-making process of ML models by identifying important variables such as fiber type and curing time, thereby improving their dependability and transparency.

Balancing Accuracy and Interpretability: Although sophisticated ML models—like deep neural networks—can achieve high predictive accuracy, they often function as "black boxes" with poor interpretability. Researchers must find a balance between interpretability and model accuracy so that the models provide insightful analysis of the variables affecting material behavior.

9.3. Computational demands

In particular, deep learning algorithms and machine learning models demand ample computational resources for training and inference. Effectively applying ML to the modeling of 3D-printed soil-cement systems depends on ensuring access to suitable computational resources.

Addressing Computational Challenges: Geng et al. [59] examined the integration of machine learning with construction 3D printing, noting computational needs as a main difficulty. They promoted future developments in ML models and multidisciplinary cooperation to fully utilize ML in the 3D printing of buildings. Wider acceptance of ML in this discipline depends on addressing these computational challenges.

Optimizing Computational Efficiency: Researchers must investigate techniques to maximize the computational efficiency of ML models, especially in the framework of large-scale building projects. This can call for the creation of more effective algorithms, the application of resources housed on cloud-based computers, and the merging of parallel processing methods.

9.4. Environmental impact

Developing 3D-printed soil cement still revolves mostly around sustainability since these materials seek to reduce the environmental impact of building activities. Although the use of recycled materials and locally accessible soils can help lower the carbon footprint of building projects, the entire lifecycle environmental impact of these resources must be carefully assessed.

Promoting Sustainability: Studies such as those by Tarhan et al. [10] and Sahana et al. [71] have shown how well earth-based, stabilized earth materials might lower carbon emissions and resource usage. These results highlight the urgent need for the building sector to support sustainability.

Lifecycle Assessment: From raw material extraction to end-of-life disposal, combining artificial intelligence, remote sensing, and 3D printing technologies transforms civil infrastructure sustainability by optimizing resource use and enabling real-time monitoring [60]. This strategy ensures that the environmental advantages of these materials are fully exploited and helps identify areas needing improvement

9.5. Standardization and regulation

Using 3D-printed soil-cement materials in buildings requires creating uniform procedures and regulatory systems. Widespread usage of these materials in building projects depends on their meeting industry criteria for performance, durability, and safety.

Developing Industry Standards: Buswell et al. [64] offered a comprehensive roadmap for developing 3D concrete printing technology, highlighting essential research areas, including structural performance, material formulation, and process control. The evolution of industry standards and regulatory systems depends on ensuring the reliability and safety of 3D-printed soil-cement buildings.

Ensuring Compliance with Regulations: Researchers and industry stakeholders must collaborate to develop standardized standards for the testing and certification of 3D-printed soil-cement materials. The broader acceptance of these materials in the building sector depends on assurances of compliance with current regulations and on creating new standards if necessary.

9.6. Future research directions

As the field of 3D-printed soil-cement materials evolves, several potential study options can be found. These include investigating novel material compositions, developing advanced ML methods, and incorporating emerging technologies such as robotics and automation.

As shown in Figure 15, future directions for machine learning in 3D-printed soil cement include addressing current data challenges, developing sustainable binders, and advancing automation and robotics. Integrating machine learning into these areas promises to enhance scalability, sustainability, and material performance in construction. As the field evolves, the convergence of these technologies will drive innovation in building materials and construction techniques.

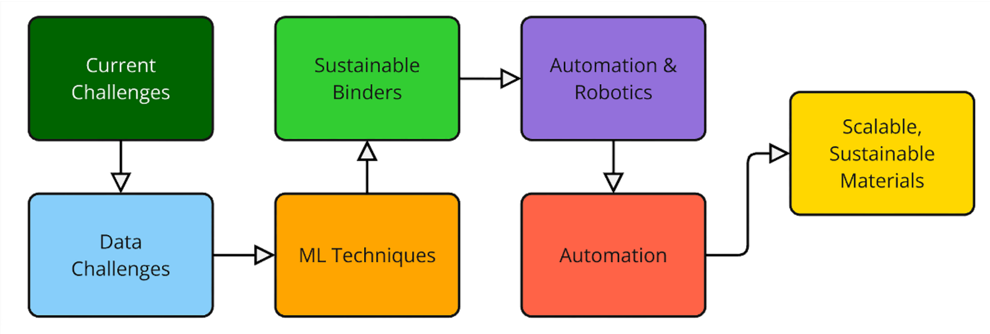

Fig. 15. Future directions in the application of machine learning for 3D printed soil-cement, focusing on automation, sustainable materials, and process optimization.

Exploring New Material Compositions: The performance and sustainability of 3D printed soil-cement composites can be improved through newly developed materials, including geopolymers and biopolymers. Investigating other binding agents and additives that might enhance the mechanical qualities and environmental impact of these materials should be ongoing for researchers.

Advancing Machine Learning Techniques: Future studies should develop more advanced machine learning techniques, such as deep reinforcement learning and generative adversarial networks (GANs), to further enhance the predictive modeling and process optimization of 3D printed soil-cement materials. Similarly, Asteris et al. [77] introduced DERGA, a novel data ensemble refinement greedy algorithm, to identify crucial parameters associated with cardiovascular disease, achieving high prediction accuracy. This demonstrates the potential of advanced ensemble methods in enhancing predictive modeling in complex systems, suggesting that such algorithms could be adapted to improve the modeling and optimization of 3D-printed soil-cement materials.

Integrating Robotics and Automation: Combining robotics and automation technology into the 3D printing process will help increase scalability, accuracy, and efficiency. Further studies should investigate the prospects of these technologies to transform the building sector and open new avenues for 3D-printed soil-cement materials.

10. Conclusion

Integrating machine learning (ML) with 3D printing technologies offers a transformative approach to sustainable construction, mainly by developing optimized soil-cement composites. This study highlights the potential of advanced ML algorithms, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and hybrid modeling techniques, in addressing key challenges in material formulation, structural performance, and environmental sustainability. ML-driven optimizations reduce reliance on traditional empirical methods, enabling efficient material designs that improve printability, mechanical properties, and ecological impacts. Leveraging 3D printing for soil-cement materials demonstrates tangible benefits, including significant reductions in material waste, carbon emissions, and construction costs, while utilizing locally available resources.

To further advance this field, researchers should prioritize developing standardized protocols for data collection, storage, and sharing to address data scarcity and improve the reliability of ML models. Collaborative databases for 3D-printed soil-cement applications can enhance global research efforts. Additionally, integrating ML with physics-based simulations is recommended to capture the intricate behavior of soil-cement composites under varying environmental and structural conditions. Researchers should also explore alternative binding agents, such as geopolymers and biopolymers, to further reduce the carbon footprint of construction materials. Long-term field studies and predictive modeling are critical for advancing the durability and reliability of 3D-printed structures.

Practitioners are encouraged to adopt ML-enabled real-time monitoring systems to ensure consistent quality control and detect flaws during printing, reducing costs and enhancing reliability. Lifecycle assessment tools should be utilized to quantify and minimize environmental impacts, including energy use and material waste. Adopting advanced robotic 3D printing systems can enhance efficiency, scalability, and precision in construction projects, particularly for complex geometries or challenging site conditions. Furthermore, training programs for practitioners on ML algorithms and 3D printing technology are necessary to bridge the gap between research advancements and practical implementation.

Efforts to improve scalability, economic feasibility, and regulatory frameworks are crucial for advancing this interdisciplinary field. Researchers and practitioners should collaborate to standardize practices, develop cost-effective manufacturing processes, and ensure safety and performance standards compliance. Such efforts will not only revolutionize material science but also contribute to resilient, cost-effective, and environmentally responsible construction practices, shaping the future of the built environment.

CRediT authorship contribution statement

Mehran Fareghian: Led the initial draft preparation, writing—editing

Mohammad Afrazi: Conceptualization of the review structure, writing—critical review and editing

Danial Jahed Armaghani: Supervision, final manuscript review, and approval

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