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A COMPREHENSIVE REVIEW ON THE ARTIFICIAL INTELLIGENCE (AI) APPROACHES USED FOR EXAMINING THE MECHANICAL PROPERTIES OF CONCRETE INCORPORATING VARIOUS MATERIALS

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ABSTRACT

Remarkable growth in the use of AI in various fields of civil engineering is going on in the new era. The applications of Artificial Intelligence (AI) are widely considered for specifying the mechanical properties of concretes and noticeable results are reported. Hence, this systematic review aims to study different methods presented in various research in this regard. The gaps and shortcomings of the previous studies are presented, which can shed light on future studies by presenting new ideas. The major issues that the research seek to examine are accuracy and authenticity. The experimental costs and time spent specifying the concrete's mechanical properties will significantly reduce using AI techniques. It is recommended to employ AI methods more widely for composite materials. The suggestions presented here can be beneficial to those aiming to advance in this significant and offer more innovations.

Keywords: artificial intelligence; civil engineering; mechanical properties; concrete; composite materials.

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1. INTRODUCTION

Artificial Intelligence (AI) is a broad branch of computer science that creates intelligent machines based on imitating human behavior [1-5]. Such machines make decisions that typically require the human experience and help humans to anticipate potential problems and overcome them. Nowadays, many industries benefit from AI technology for producing novel

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materials and equipment [6-8]. The purpose of using AI techniques is met in the intelligence system, which refers to a branch of computer science that designs and studies the optimal calculation techniques for problem solving [9]. Accordingly, the present review focuses on the various methods employed for investigating the mechanical properties of the concrete in the literature.

Some different applications of AI are examined here, and they will be investigated more comprehensively in the following. For example, in 2016, Mashhad ban et al. [9] attempted to employ a particle swarm optimization (PSO) algorithm and artificial neural network (ANN) for predicting and modeling mechanical properties in fiber-reinforced Self-Compacting Concrete (SCC). SCC, known as a high-flowable homogenous concrete that improves the workability, stability, and durability of concrete matrixes, was proposed by Okamura in 1997 for the first time [10]. Using SCC along with its compaction under its weight, the problems of ordinary concretes, including permeability, segregation, bleeding are eliminated [11, 12]. In the study, the authors benefited from AI in reaching their aims. In a review in 2020 [13], the lack of accuracy of the experimental techniques for examining the concrete mechanical strength was revealed. The concrete structures represent different behavior under conditions such as cyclic loadings, severe thermo-mechanical loading in nuclear engineering, or any other types of loading. The nonlinear mechanical behavior of the materials occurs at high temperatures and severe loadings. The response of concrete is regulated through highly temperature-dependent and complicated properties [14]. The importance of using AI is highlighted in this condition where the properties are hardly specified, and the concrete structure undergoes severe loading.

A large number of studies in the broader literature have examined this topic in more detail [15-19]. To mention a few, Chou et al. [20] aimed to optimize the prediction accuracy of the compressive strength in high-performance concrete (HPC) by making comparisons between the data-mining techniques. The prospects of examining the concrete compressive strength through the additive materials instead of the water-to-cement ratio were examined in the research. It is entirely difficult to specify the concrete compressive strength as it is a highly nonlinear function of ingredients. In this case, the use of quantitative analyses with five various data-mining techniques, including ANN, support vector machines (SVM), multiple regression, multiple additive regression trees (MART), and bagging regression trees (BRT), was a good idea [21-23].

In another paper, the researchers used AI techniques whenever the mechanical properties of the concrete were hardly characterized. In 2013, Bingol et al. [24] used the ANN method for modeling the compressive strength of lightweight and semi-lightweight concretes with pumice aggregate under elevated temperatures. The target temperature, pumice aggregate ratio, and heating duration were considered the model inputs in the study. On the other hand, the compressive strength of pumice aggregate concrete was defined as the output [25]. The pumice aggregate concrete underwent high temperature and, after the date of its compressive strength, was collected based on presented empirical research. The agreement observed between the predicted values of the ANN and empirical ones emphasizes the authenticity of the adopted method. Actually, one of the best ways to prove the reliability and authenticity of the AI methods is by comparing the results obtained by AI and empirical methods [26, 27].

It is noteworthy that the special issue raised here is when AI techniques were found to be applicable in determining the mechanical properties of concrete or structures [25, 28, 29].

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According to the literature, what factors play a key role in reaching accurate results based on AI techniques? The superiority of the ANN methods over each other based on the algorithms and optimizers used for tuning and training needs to be discussed for making better decisions in practice. Accordingly, the present paper is conducted to answer such questions and even outline more issues. The previous studies, especially those published during the past four years, are targeted. The authors of this review do not generalize their findings to other domains, as the purpose here is solely helping an expert in the field of civil engineering to easily adopt the proper AI methods based on the considered concrete.

The rest of this paper is organized as follows: the method used for conducting the present review is outlined in the second section. Then, a short history of AI as well as its emergence in civil engineering is given in the second section. The fourth section illustrates the various AI techniques used in the related work and demonstrates their superiority over each other. The applications of AI in the other domains of civil engineering are presented in the fifth section. Finally, the findings and suggestions for future studies are presented in the sixth section.

2. METHODOLOGY

The review presented in this research is systematic and based on well-known resources, namely Elsevier and Springer journals [30-34]. In the beginning, many related studies regarding the role of AI applications in civil engineering and specifying the mechanical properties of the concerts were reviewed. Then, the techniques employed for reaching this purpose were investigated. Accordingly, 146 papers were selected, among which 94 were selected as the most suitable papers for this review. It was revealed that the selected studies significantly match the aim of this systematic review. The process conducted for reaching the conclusions is outlined in Fig. 1.

As depicted in Fig. 1, the selected papers are categorized based on the two concepts, including the AI applications and AI techniques used to specify the concrete's mechanical properties. The related papers were reviewed deeply to find more information regarding the novel techniques and applications. Then, the major limitations and gaps of the previous studies were presented to outline the significant suggestions for future studies [35-38].

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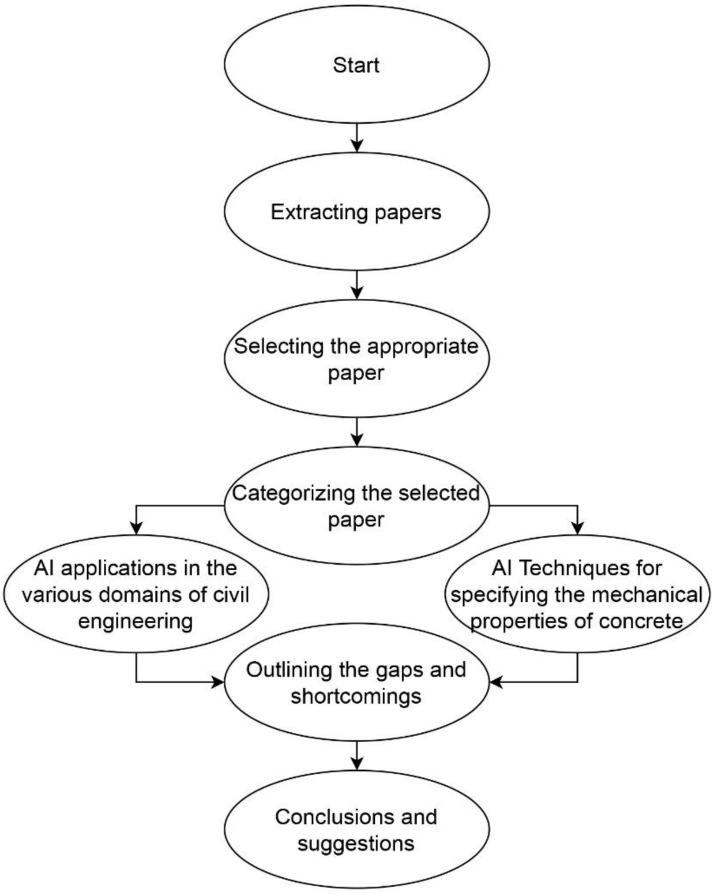

Figure 1. The steps considered in the present review

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3. AI HISTORY

The invention of artificial intelligence is attributed to Alan Turing who had outlined the issue of "Machinery and Smart Calculations" and designed the Turing test which includes testing the ability of the machine to display smart-like behavior [39]. In computer science, artificial intelligence or machine intelligence refers to the intelligence obtained from any machine instead of humans. Any device capable of understanding the environment and activity with the maximum chance of success is examined in this research [36, 37, 40, 41]. The term artificial intelligence is used to describe machines or computers performing well-related cognitive activities among important cognitive activities, including "learning" and "problem-solving." Activities that fall into the category of smart machine activities change over time. In fact, due to the empowerment of cars, some activities are no longer intelligent. The theory of conscience in the definition of artificial intelligence says that any achievement that has not been made so far is called artificial intelligence [38, 42]. As a result, activities such as character recognition do not make one machine smart. In the modern world, more complex tasks such as recognizing human talk, competition in strategic games such as chess and chess, and automatic guidance of cars define real intelligence on computers [43].

Deep learning technologies have been used effectively in various industries, including civil engineering. In fact, with the emergence of complex buildings such as skyscrapers, machine-learning techniques have long been at the center of this section. Despite smart algorithms, macro data, and deep learning machines that change productivity performance, we see the use and development of artificial intelligence in the construction industry more than ever. AI has been used by civil engineers, contractors, and service providers to solve a wide range of challenges. For example, artificial intelligence in civil engineering has improved to some extent, and its performance directly affects construction processes. AI is employed in the early stages of many projects to improve design, risk management, and efficiency. It is essential to understand that construction organizations that use artificial intelligence processes are 50% more profitable. Notably, artificial intelligence generally offers a wide range of applications in civil engineering. In this century, robots can think instead of humans doing tasks, and engineers can make better decisions and provide their services more effectively [44].

Despite symbolic structures of any form and size in major cities worldwide, design and engineering standards have gone beyond their limitations. Accordingly, by using Artificial Intelligence in the 3D Modeling of Building Information (BIM), civil engineers can use BIM tools to facilitate the creation and design of 3D models prior to starting construction. Thanks to artificial intelligence design, many advanced buildings and structures have been constructed so far. Civil Engineering can produce designs and buildings and more by combining machine intelligence with the BIM process. They can also make the necessary changes to all high-precision design levels [2].

After several years, AI has received much attention in civil engineering due to its remarkable applications in this regard. Much progress has been made using Al in increasing the quality of personalized ads, virtual assistants, autonomous driving, and so on. Notably, using AI methodologies in civil and structural engineering [45] with impressive findings was very important [46]. According to Fig. 2, the studies conducted regarding AI applications in civil engineering, the expressions "artificial intelligence” or “AI” and “civil” or “structural” or "transportation" or "geotechnical" or "hydraulic" or "environmental" or "construction" or "structural health" were significantly used.

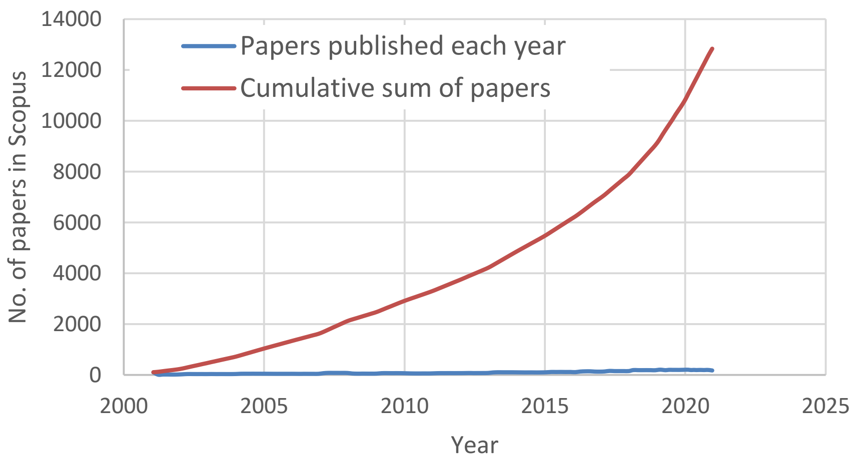

Figure 2. Presented studies regarding AI and civil engineering issues between 2000 to 2021 [47]

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AI's applications and recent advances in civil engineering issues promote cross-fertilization between such scientific fields. Accordingly, the combined studies and applications associated with structural engineering, civil engineering, and other fields have become very important.

It is also noteworthy to mention that due to the applications of AI, many studies in the broader literature have been presented in this regard [48-50]. An improved multi-strategy Particle Swarm Optimization (PSO) variant was used to solve constrained issues with the various methods [51]. Then, a number of enhancements were considered to the original algorithm, such as a novel local search operator based on the evolutionary strategy (ES). In another study, a technique based on the parallel updated particle swarm optimization (PUPSO) algorithm was employed for reducing the objective function of the cost of energy in the prestressed concrete–steel hybrid wind turbine towers [52]. The research was conducted from a life cycle perspective to show the direct examination, labor costs, and prices related to machinery and maintenance. The size and shape optimization of a guyed radio mast was examined by Cucuzza et al. [53] for radiocommunications employing the genetic algorithm (GA) and carrying out static and dynamic analyses according to the action of wind, ice, and seismic loads. Besides, GA was presented by Guo et al. for analyzing the correlation and two parametric techniques, namely floor plan generation, and component selection techniques [54]. Additionally, the performance of prefabricated buildings in terms of robustness and construction quality was examined. Employing the Taguchi method integrated hybrid harmony search algorithm, Uray et al. [55] obtained the efficient values of the control parameters of the harmony search algorithm statistically and specified their impact on the efficient solution. This research successfully applied a novel combined technique to various real-world engineering optimization issues [56]. The Gold Rush Optimization (GRO) algorithm was initially employed by Sarjamei et al. [57] to design real-scale symmetric structures subjected to frequency limitations efficiently. Then, the efficacy of cyclic symmetry was examined for reducing the required time with three examples, namely Disk, Silo, and Cooling Tower. In another research, the decision-making issue of pavement maintenance prioritization was examined according to quality and price. An efficient linear model was presented for increasing the quality with the restricted maintenance prices, and a multi-objective optimization model increased maintenance quality when reducing maintenance prices. Such models were presented to decide on real pavement maintenance considering sequential quadratic programming and GA [58-60].

As can be seen from Fig. 3, the growth of using AI techniques in civil engineering has been observed in the last two years, which has an unbalanced situation. This report has been presented by from the google trend. Then, the popularity of AI techniques increased significantly after 2022 to present more innovations in the field of civil engineering.

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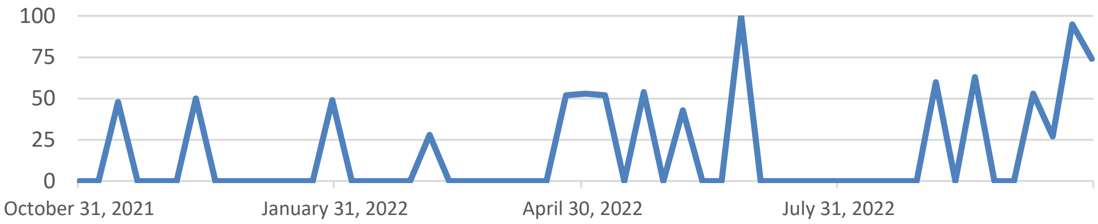

Figure 3. The trend of using AI techniques in the civil engineering

4. THE VARIOUS AI TECHNIQUES

Among concrete tests, the compressive strength test as a mechanical characteristic and the chloride ion penetration test as a durability characteristic have received much attention, especially in structures exposed to Chloride ion invasion [58]. On the other hand, using pozzolans, such as fly ash, improves concrete's durability and mechanical properties. Replacing Portland cement with different percentages of fly ash may increase the compressive strength and durability of concrete against chloride ion penetration and reduces cement consumption, and contributes to sustainable development. Besides, ANNs and support vector machines (SVMs) are two examples of AI algorithms that can be employed to predict concrete's mechanical properties and durability [61, 62]. Notably, both methods can be used to predict new concrete properties through training based on available data. The algorithms selected for reaching this purpose vary based on the different mechanical properties of the concretes. Several studies have been conducted in this regard between the years 2018 and 2022 which are presented in Table 1.

Table 1: Significant algorithms used for predicting the concrete's mechanical properties

No.	Year	Aims	Tests	Method / Algorithm
1	2019 [6]	Estimating the elastic modulus, compressive strength, and tensile strength of the ultra-high concrete under severe loadings	Experimenting with the rate-sensitive behavior of ultra-high-performance concrete (UHPC)	Case-based reasoning (CBR)
2	2020 [63]	Estimating the mechanical properties of concrete made with waste foundry sand (CMWFS).	Considering a dataset consisting of 234 compressive strength, 163 split tensile strength, and 85 elastic modulus	Gene expression programming (GEP)
3	2019 [64]	Specifying the various properties of the concrete, filler ability and passing ability of fresh mixtures, and compressive, split-tensile, and flexural strength of hardened concrete.	The empirical results of strength properties	Genetic programming (GEP) and artificial neural networks (ANN)
4	2021 [65]	Anticipating the ITZ properties and the computed stress–displacement curve along with the optimized ITZ fracture parameters	The RILEM test	An inverse method and AI technique

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5	2019 [66]	Anticipating the RAC's mechanical properties.	The empirical results of the incorporation of recycled concrete aggregates (RCAs) in a concrete mix	Multiple nonlinear regression (MNR) and artificial neural networks (ANN)
6	2021 [67]	Predicting the mechanical properties of concrete containing waste foundry sand (WFS)	The dataset of compressive strength, splitting tensile strength, modulus of elasticity, and flexural strength of concrete containing WFS	An artificial neural network (ANN) assisted by a multi-objective multi-verse optimizer (MOMVO) algorithm
7	2020 [68]	Prediction of chloride diffusivity in concrete	653 distinctive diffusion coefficient experimental results	An artificial neural network (ANN) technique
8	2021 [69]	Predicting the compressive strength of fly-ash-based geopolymer concrete (GPC) with bottom ash as a replacement of fine aggregates	In-house lab scale testing of GPC	A machine learning-based ANN
9	2021 [70]	Predicting the mechanical properties of concrete containing recycled coarse aggregate (RCA)	The empirical data of RCA	Supervised machine learning (ML) algorithms, gene expression programming (GEP), ANN, and the k-fold cross-validation method
10	2020 [71]	Predicting the mechanical properties of Jute Fiber Reinforced Concrete Composites (JFRCC)	Comparison between the empirical results and SVR ones	Response Surface Methodology (RSM), Artificial Neural Networks (ANN), Support Vector Regression (SVR)
11	2019 [72]	Examining the residual properties of rubberized concrete under elevated temperature	The experimental results obtained for the considered material	Sensitivity analysis and ANN
12	2021 [73]	Anticipating the recycled aggregate concrete compressive strength	1030 datasets collected from related studies	Levenberg-Marquardt (LM) algorithm and ANN
13	2011 [42]	Offering a novel technique for examining the seismic vulnerability of the current concrete structures with moment resisting frames (MRF).	Examining a number of 2-D structural models with the various number of bays and stories	Iranian seismic design code, Standard 2800 (First Edition) Artificial Neural Network
14	2008 [38]	Eradicating the requirement for time-intensive matrix inversion	Holistic framework and optimization method	Neural network
15	2001 [35]	Anticipating the moment-rotation specific for saddle-like connections	138 connections and M-diagrams	Finite element models FEM and BP neural networks

With regards to Table 1, different AI techniques have been presented for specifying the mechanical properties of the various concretes. The methods and algorithms employed in the related studies are various and lead to accurate results [5, 61, 74]. However, the issue of accuracy has been ignored in the literature. In 2018, Tanyildizi [75] employed ANN and SVM to approximate carbon fiber-reinforced lightweight concrete's compressive strength and flexural strength with silica fume subjected to elevated temperature. After that, the specimens were examined considering the strength experiments. The output variables included the compressive and flexural strengths of the lightweight concrete specified in the study. The obtained findings emphasize the use of the ANN model that gave an accuracy of 99.02% and 96.8%. In 2021, Song et al. [76] used Gene expression programming (GEP), ANN, and Decision tree (DT) algorithms for anticipating the compressive concrete (CS) and obtained remarkable results. In advance of 2021, Kandiri et al. [77] predicted the compressive strength of concrete in which recycled aggregate was considered using modified ANN with the various optimizers, namely GA, salp swarm algorithm (SSA), and grasshopper optimization algorithm (GOA) combined with ANN. Overall, the issue of accuracy is very important in the related studies. Hence, Table 2 outlines the accuracy of the algorithms used to predict the concretes' mechanical properties.

Table 2: The accuracy of the used method for specifying the mechanical properties of the concretes

No	Year	Aim	Method / Algorithm	Accuracy
1	2021 / [78]	Predicting the compressive strength of concrete at high temperature	A comparative study using SML	R^2 of 0.82 and 0.83
2	2020 / [79]	Modeling these concretes' compressive strength, modulus of elasticity, flexural strength, and splitting tensile strength.	M5P algorithm	83.76% to 98%
3	2020 / [80]	Anticipating the mechanical properties of manufactured-sand concrete	Three-based models	uniaxial compressive strength (R = 0.9887) and splitting tensile strength (R = 0.9666)
4	2021 / [81]	Anticipating the compressive strength of concrete	Whale optimization algorithm (WOA), dragonfly algorithm (DA), and ant colony optimization (ACO)	Errors of 2.0746, 2.5138, and 2.8843
5	2020 / [82]	Anticipating the mechanical properties of hydraulic concrete	A linear regression model (Bayesian Ridge), an advanced predictive model (Gaussian Processes), a regression tree model (Decision Trees), and an ensemble learning regression model (Gradient Boosting)	Acceptable performance
6	2021 / [83]	Specifying the mechanical properties of cement mortar	The multilayer perceptron (MLP) neural network, radial basis function (RBF) network, and general regression neural network (GRNN)	R^2 values of 0.997 and 0.9987 for flexural strength and compressive strength

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7	2022 / [84]	Specifying the thermo-mechanical properties of rubber-modified recycled aggregate concrete	The hyperparameters of machine learning (ML) models tuned by the beetle antennae search (BAS) algorithm	Acceptable performance
8	2021 / [85]	Specifying mechanical properties of foundry sand-based concrete	Multi-expression programming based on AI	Acceptable performance
9	2021 / [86]	Specifying the compressive strength of concrete containing metakaolin	ANN models	R values of 0.9813 for the 7-day state and 0.9821 for the 28-day state
10	2021 / [87]	Specifying compressive strength of fly ash-based concrete	Individual and ensemble algorithm	R^2 values of 0.911

According to the values of accuracy obtained for the various purposes shown in Table 2, many factors play a significant role in achieving such values. However, the use of mentioned algorithms and their accuracy can be validated through the empirical results. Besides, similar studies can confirm the obtained findings. The studies being conducted compete with each other in terms of accuracy, speed, and authenticity. These three factors are the determinant features that specify the efficiency of the proposed methods and algorithms. Accordingly, future studies seek to propose more accurate methods and attempt to be the best in this competition.

5. THE APPLICATIONS OF AI

The applications of AI introduced in the previous section were primarily related to predicting the mechanical properties of concretes [6, 60, 61, 80]; the other applications need to be considered in this section [76, 85, 88]. Since about 7% of the world's workforce is employed in the construction industry, construction is a major part of the world's economy. Other active sectors in the economy have used artificial intelligence and other technologies to improve their performance and increase their productivity, yet the construction sector has not made much progress in using artificial intelligence technology [89]. The global growth of the construction industry over the past few decades has been only 1% per year, which is a very small figure for the construction sector compared to the growth rate of 3.6% in the manufacturing sector and 2.8% for the entire world economy. Productivity or total economic output per worker in construction has not improved much over the years. In contrast, productivity has grown by 1,500 percent since 1945 in the retail, manufacturing, and agricultural sectors. One of the reasons for this is that construction is one of the least digitized industries and has been slower to adopt new technologies than other industries. Using new and advanced technologies can be daunting and risky for construction project teams, while machine learning and artificial intelligence can help them increase efficiency in work sites and save money. Artificial intelligence-based solutions with a positive impact in other industries are related to their impact on the construction industry. The potential applications of machine learning and artificial intelligence in civil engineering are widely

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employed. The industry's demand for information, unforeseen issues, and change orders are commonplace. Machine learning is like an intelligent method used for massive data. The project managers need to be aware of the sensitive items of their concern. Several applications of AI techniques in the field of civil engineering are mentioned in Table 3.

Table 3: The application of AI techniques in the civil engineering

No	Reference / Year	Method	Applications `
1	[90] / 2020	Metaheuristic optimization algorithms based on AI	Predicting soil temperature
2	[91] / 2021	Explainable artificial intelligence (XAI)	Smart city
3	[92] / 2021	Genetic programming (GP)	Civil engineering and construction
4	[93] / 2019	Artificial Intelligence Models and C-W-based Explicit Equations	Estimation of Colebrook friction factor
5	[94] / 2019	AI-based models and metaheuristic algorithms	Modeling evaporation
6	[95] / 2022	AI methods	Civil engineering
7	[96] / 2019	Independent and unsupervised learning	Extracting temperature-dependent material models
8	[97] / 2022	AI with non-destructive testing (NDT)	Non-Destructive Testing in Civil Engineering
9	[98] / 2019	A particle swarm optimization (PSO)-based adaptive network-based fuzzy inference system	Construction of civil engineering structures
10	[99] / 2020	GA, NN, fuzzy logic, fuzzy sets, and machine learning	Engineering and Construction

The applications of AI techniques include but are not limited to the above methods, while future research can continue to present more innovations and accuracy for prediction tasks [100, 101].

6. CONCLUSION

In summary, this study reviewed the studies conducted on predicting the mechanical properties of concretes using AI and novel algorithms. The conducted review is systematic and based on various methods used to specify the concretes' mechanical properties. The major applications of AI are attributed to the reduction of the experiments' costs and time. However, the accuracy and authenticity of the used AI techniques need to be verified by some database or comparison between the empirical and simulation results. The investigations necessary for mechanical behaviors can be made using these technologies. The other applications of AI in civil engineering have also been reviewed, and obtained findings were presented. Numerical mechanical properties of concrete can be determined more accurate when using neural network methodologies. The major suggestions for future studies are as follows:

- Using AI for long-term experiments with higher durability, such as chloride and sulfate attacks.

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- Using different optimizers for the algorithms presented in the previous studies and making statistical comparisons between them to offer the most accurate one.
- Using AI techniques when the dataset is missing, or it is not possible to measure the primary specimen.

Using ML or ANN to suggest the mechanical properties of the concretes when real data is not available.

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