

Review

Application Research Progress of Solid Waste Concrete Based on Machine Learning Technology

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Abstract

With accelerating urbanization, China generates large volumes of construction waste annually, much of which is landfilled, causing environmental damage and wasting recyclable resources. Traditional recycling technologies struggle with complex material compositions and performance degradation, limiting large-scale reuse. This highlights the need for intelligent, data-driven solutions to enhance solid waste recycling efficiency. Recent developments in machine learning (ML) have enabled more accurate performance prediction and optimization of waste concrete, offering new pathways for material regeneration. ML's nonlinear modeling and pattern recognition capabilities are particularly suited to capturing the complex behaviors of recycled materials. However, systematic reviews on ML applications across various waste concretes are still lacking, and future research directions remain unclear. This study conducts a scientometric analysis of 1762 publications (2011–2024) from the Web of Science Core Collection (WOSCC) and CNKI, aiming to map current trends and guide future research on ML applications in waste concrete recycling. The findings show a clear evolution: research has expanded from recycled concrete to a wider range of modified solid waste concretes. ML applications have advanced from compressive strength prediction to multi-objective optimization involving durability, cost, and mechanical performance. Algorithm development and model accuracy have improved steadily. Key challenges persist, including limited data quality and scale, which constrain complex model training. Research on specific properties such as salt-frost resistance is scarce due to high testing costs. Models often lack generalizability in coupled conditions (e.g., salt-frost-carbonation) and suffer from poor physical interpretability, hindering understanding of durability mechanisms. Nevertheless, unresolved issues remain, including the scarcity of standardized datasets, the limited integration of domain knowledge with ML methods, and the lack of comprehensive evaluations across multiple degradation mechanisms, all of which represent critical research gaps for future studies.

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1. Introduction

Construction waste is characterized by its large volume and high disposal difficulty. Conventional treatment methods often cause severe environmental pollution, whereas recycling and circular utilization can yield substantial environmental and economic benefits [1–5]. Previous studies have demonstrated that applying solid waste to construction

engineering is an effective disposal strategy. It is estimated that China consumes approximately 2.8 billion m³ of concrete annually, with about 75% of aggregates forming the skeleton of concrete. As natural resources are continuously depleted, recycled aggregates have been proven to be a promising alternative [6]. Meanwhile, with the rapid advancement of computational power, an increasing number of scholars have begun to apply machine learning (ML) and deep learning algorithms to concrete research, aiming to reduce costs, save resources, and shorten construction periods.

Artificial intelligence (AI), which emerged in the 1970s, has undergone half a century of development and has been gradually integrated into industries such as manufacturing and construction. As a core branch of AI, ML refers to algorithms that automatically learn patterns from data without relying on explicit physical formulations. Compared with traditional regression models that usually assume linear relationships, ML can capture non-linear, multivariate interactions, making it particularly suitable for modeling the complex behavior of waste-based concrete [6,7].

As illustrated in Figure 1, ML methods can be broadly categorized into supervised, semi-supervised, and unsupervised learning, each encompassing a variety of algorithms with distinct advantages and limitations. Supervised learning approaches—such as neural networks (NN), decision trees (DT), support vector machines (SVM), gradient boosting (GB), and regression analysis (RA)—are most commonly adopted in predicting concrete performance due to the availability of labeled experimental data. In contrast, unsupervised learning has been explored for clustering mix designs and anomaly detection. This classification framework provides a systematic foundation for understanding how different ML paradigms can be applied to waste-based concrete.

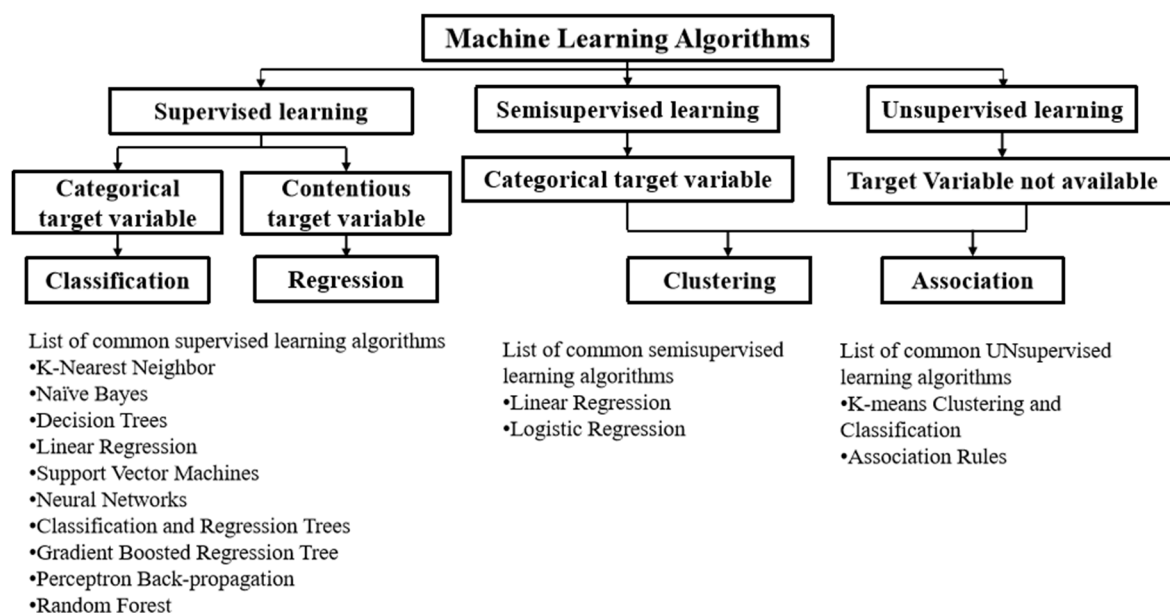


Figure 1. ML classification diagram.

In its early stages, constrained by algorithm maturity and computational resources, research in this area produced fewer than ten studies annually. However, with breakthroughs in ML algorithms and the exponential growth of computational capacity, the past decade has witnessed an explosive increase in scholarly output, with an annual growth rate exceeding 300% [8–11]. Despite these advances, two major bottlenecks remain in practical applications: (1) existing studies are often fragmented and lack a systematic evaluation framework, and (2) insufficient model interpretability in engineering practice hinders technology transfer.

Therefore, this review aims to identify the thematic categories of research on waste-based concrete using ML, uncover the intrinsic connections among these categories, and bridge the interdisciplinary gap between green, low-carbon concrete and emerging AI techniques. Ultimately, this study seeks to provide valuable insights for researchers and practitioners interested in integrating ML methods into waste-based concrete research. To this end, this review employs Cite Space to systematically analyze the current state of ML applications in concrete research, summarize the strengths and limitations of existing algorithms, and propose potential future directions, thereby offering constructive guidance for the emerging field of intelligent civil engineering.

2. Methodology and Significance of the Study

2.1. Data Collection

The Web of Science Core Collection (WOSCC), maintained by the Institute for Scientific Information (ISI), was selected as the primary data source for this study (Bartol & Mackiewicz-Talarczyk). WOSCC is a comprehensive bibliographic database that supports advanced bibliometric analysis and provides access to extensive scholarly literature across disciplines including natural sciences, environmental sciences, and engineering technologies [12].

The following search strategy was employed: TS = (various types of waste concrete) AND (TS = ML OR TS = prediction OR TS = mix ratio optimization OR TS = algorithm).

The term “various types of waste concrete” includes recycled concrete, gangue concrete, rubber concrete, ceramic concrete, and waste glass concrete. The search period was set from 2011 to 2024, with 31 December 2024 as the final retrieval date. This timeframe was chosen due to the scarcity of relevant literature prior to 2011 and to account for the time lag in publication. A total of 1762 records were retrieved for analysis.

2.2. Research Methodology

Cite Space (version 6.3.R1) was used for bibliometric and visual analysis. As shown in Figure 2, this paper uses co-occurrence analysis and co-citation analysis to construct a knowledge network, supplemented by clustering and burst detection techniques to identify research trends and hotspots. In Cite Space visualizations, nodes represent entities such as references, institutions, or countries, while edges indicate cooperation, co-occurrence, or co-citation relationships. The thickness of the edges reflects the strength of the relationship. Color gradients are used to represent time, with cool colors (e.g., blue) indicating earlier publications and warm colors (e.g., orange, red) representing more recent ones [13].

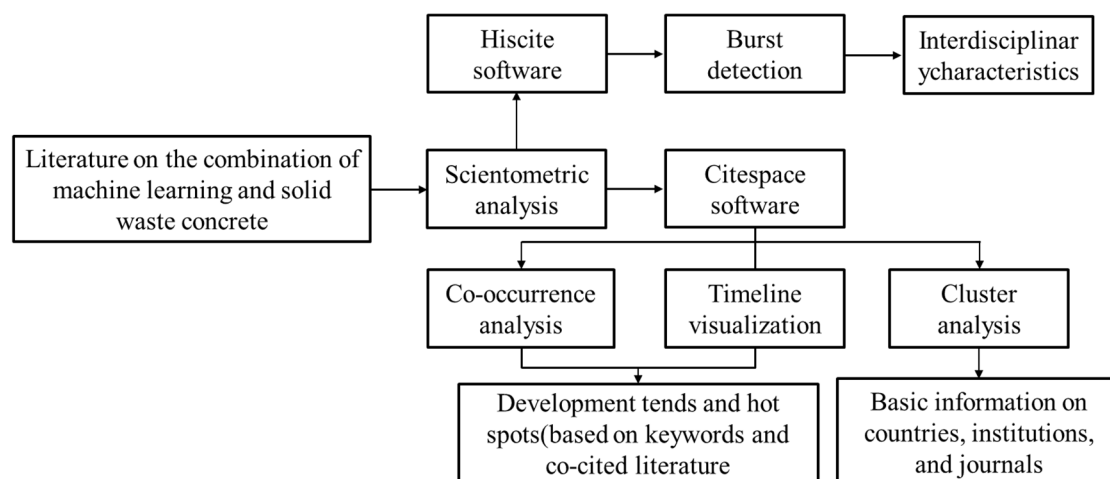


Figure 2. Design research outline.

Each node has a betweenness centrality (BC) value, which measures the importance of a node within the network. Nodes with $BC \geq 0.1$ are highlighted with a purple ring, indicating key transfer points or influential nodes in the domain. The BC value is calculated as follows [14]:

$$BC_i = \sum_{i \neq j \neq k} \frac{n_{st}^i}{g_{st}} \quad (1)$$

where g_{st} is the total number of shortest paths between nodes s and t , and n_{st}^i is the number of those paths that pass through node i .

Additionally, citation bursts—sudden increases in citations of specific articles—often signal emerging research frontiers. Clustering and burst detection help uncover evolving patterns and new application areas of ML in waste concrete research [15]. To assess clustering quality, modularity (Q) and silhouette score are used. A silhouette score >0.7 indicates high clustering reliability [16]. In Cite Space's keyword clustering map, each cluster is labeled using the Log Likelihood Ratio (LLR) algorithm and presented as # + cluster number + hashtag label. WOS also classifies articles into disciplinary categories. Analyzing the co-occurrence of subject categories helps identify core contributing fields and the interdisciplinary nature of ML applications in waste concrete [17]. Rapidly expanding categories—often highlighted via category burst detection—are used to indicate dynamic research directions. This study uses these techniques to map the knowledge landscape and reveal active themes and cross-disciplinary connections.

2.3. Research Significance

With the advancement of computational technologies, the application of ML in predicting the properties of concrete has grown rapidly. However, researchers still face challenges such as fragmented information, limited access to comprehensive insights, and difficulties in identifying emerging trends [18]. These limitations often hinder scholarly innovation and cross-disciplinary collaboration. To address these challenges, it is essential to employ scientometric techniques using specialized software tools to conduct systematic reviews. Such methods provide a structured, data-driven framework for mapping research developments, identifying influential publications, and uncovering knowledge gaps based on large-scale and trustworthy bibliographic data [19,20]. This study conducts a scientometric analysis of publications related to ML applications in waste concrete, based on records retrieved from the Web of Science (WOS) and China National Knowledge Infrastructure (CNKI) databases from 2011 to 2024. Scientometric methods enable the quantitative evaluation of extensive bibliographic datasets—an analytical capability that traditional narrative reviews often lack.

Through co-citation analysis, keyword co-occurrence mapping, and author productivity metrics, this study identifies key research contributors, highly cited articles, active geographic regions, and evolving research themes. The results offer a comprehensive overview of the field and serve as a valuable reference for scholars seeking to enhance collaboration, share innovative methodologies, and guide future research at the intersection of ML and sustainable concrete technologies.

3. Advances in mL for Waste Concrete

3.1. Mechanical Properties Study

To facilitate understanding, the advantages and disadvantages of commonly used algorithms are summarized in Table 1 [21–28]. In predicting the properties of solid waste concrete, different machine learning algorithms exhibit distinct strengths. Traditional approaches such as CART and KNN are valued for their simplicity and interpretability, but they show limited effectiveness when dealing with noisy data or high-dimensional

problems. Neural network-based methods (e.g., ANN, CNN, BPCNN, and RBF-CNN) are capable of modeling the complex nonlinear and multivariable interactions inherent in recycled concrete, thereby achieving higher predictive accuracy; however, they require large datasets and are prone to overfitting. Optimization and evolutionary algorithms (e.g., GA-BP, PSO, CSA, and GP) are frequently employed to improve model training, accelerate convergence, and avoid local minima, but often at the cost of higher computational demand. ELM offers a fast training alternative with good generalization ability, yet its reliance on random initialization leads to instability. Hybrid and adaptive approaches (e.g., AVM and FQ), as well as ensemble methods such as AdaBoost, integrate multiple techniques to balance accuracy, robustness, and interpretability. Overall, neural networks and ensemble learning methods (e.g., ANN, CNN, RF, and AdaBoost) dominate current applications, whereas optimization algorithms (e.g., GA, PSO, CSA) play a critical role in enhancing model reliability and performance under complex nonlinear conditions.

Table 1. Comparative Summary of Algorithms in Solid Waste Concrete Prediction.

Algorithm	Principle	Strengths	Limitations
CSA (Cuckoo Search Algorithm) [21]	A meta-heuristic optimization algorithm inspired by the brood parasitism behavior of cuckoos	Symbolic regression approach based on evolutionary computation	May converge slowly; relatively weak local search ability
ELM (Extreme Learning Machine) [21]	Randomly initializes hidden-layer parameters and solves output weights analytically	Extremely fast training; strong generalization ability	Performance depends on random initialization; stability issues
ANN (Artificial Neural Network) [22]	Multilayer perceptron that uses activation functions to model nonlinear relationships	Strong nonlinear modeling capability; widely applicable	Requires large datasets; prone to overfitting; limited interpretability
CART (Classification and Regression Tree) [22]	Decision tree algorithm based on recursive partitioning of the feature space	Simple and intuitive structure; high interpretability	Easily overfits; unstable with small datasets
GP (Genetic Programming) [22]	Symbolic regression approach based on evolutionary computation	Automatically generates mathematical expressions; provides interpretable results	High computational complexity; slow convergence
CNN (Convolutional Neural Network) [23]	A deep learning model that extracts spatial features through convolutional layers	Highly effective for image and structured data analysis; enables automatic feature extraction	Requires large datasets and significant computational resources; limited interpretability
GA-BP (Genetic Algorithm optimized BP Network) [23,24]	Uses a genetic algorithm to optimize the weights and structure of a BP neural network	Helps avoid local minima; improves predictive accuracy	Computationally expensive; requires extensive parameter tuning
RBF-CNN (Radial Basis Function Convolutional Neural Network) [25]	Hybrid model combining radial basis functions with convolutional layers	Improved fitting accuracy; better handling of nonlinear features	High model complexity; sensitive to parameter settings
BPCNN (Backpropagation Convolutional Neural Network) [26]	CNN trained with the backpropagation learning mechanism	Higher predictive accuracy; capable of capturing complex nonlinear patterns	Prone to local minima; computationally intensive training

Table 1. Cont.

Algorithm	Principle	Strengths	Limitations
PSO (Particle Swarm Optimization) [26,27]	Evolutionary optimization algorithm based on swarm intelligence and social sharing of information	Simple implementation; fast convergence	Susceptible to local optima; sensitive to parameter settings
KNN (K-Nearest Neighbors) [26]	Instance-based learning method relying on distance metrics	Simple and intuitive; no explicit training phase required	High computational cost; performance sensitive to data distribution
AVM (Adaptive Variable Method) [28]	Adaptive optimization approach that dynamically adjusts variable weights	High flexibility; suitable for complex problems	Theoretical foundation is underdeveloped; limited applications
AdaBoost [28]	Ensemble learning method that combines multiple weak classifiers into a strong classifier	Improves prediction accuracy; strong resistance to overfitting	Sensitive to noisy data; relatively high computational cost

In research on the mechanical properties of waste concrete, ML techniques are widely employed to predict and optimize key parameters such as compressive strength, elastic modulus, and workability [29]. These properties are critical for ensuring the structural safety and long-term performance of buildings and infrastructure. The table below summarizes representative studies that have applied ML algorithms to predict the mechanical behavior of various types of waste concrete. (In order to make the layout beautiful, the common parameters in the input variables of Tables 2 and 3 will be referred to as. W/C: Water-to-cement ratio; C: Cement, Fi: Fine aggregate, A: Age, CA: Carse Aggregate, Te: Temperature, FA: Fly ash; Ti: Time, WRA: water reducing admixture, RA: Recycled Coarse Aggregate, RC-1: Rubber Concrete, RC-2: Recycled Concrete, CGC: Coal gangue powder concrete, FAC: Fly ash Concrete, RAR: Recycled Coarse Aggregate Replacement Ratio, CS: Compressive strength, TS: Tensile strength, BS: Bending strength, FS: Flexural strength, CE: Carbon emissions, C: Cost, CD: Carbonation depth.)

Table 2. Research on mechanical properties.

Author	Year	Concrete Type	Algorithm	Input Variable	Output Variable	Evaluation Index
Zhang D [30]	2017	Gangue Base Polymer Concrete	CSA	SiO ₂ , Al ₂ O ₃ , Fe ₂ O ₃ , CaO	CS	MAE
Zou P [31]	2018	CGC	CNN	W/C, C, Fi, CA, A, Coal gangue powder		MAPE
Zhou S [32]	2023	Activated CGC		W/C, C, Fi, CA, A, Coal gangue powder		MSE
Li G [33]	2021	CGC	BPCNN	Yield strength, Compressive strength, Stell ratio, Outside diameter of steel pipe	Ultimate bearing capacity	MSE

Table 2. Cont.

Author	Year	Concrete Type	Algorithm	Input Variable	Output Variable	Evaluation Index
Khoa [34]	2020	FAC	ANN	FA, Fi, CA, W, Glass-water solution, NaOH solution content and concentration, Ti, Te	CS	R MAE MSE RMSE
Ayaz [35]	2021		CART, AdaBoost regression	FA, CA, Fi, (NaOH, Na ₂ Si ₃ , SiO ₂ , Na ₂ O And NaOH molar concentration), Ti		R MAE MSE RMSE
Yang D [36]	2024		PSO	C, FA, WRA, CA, Fi, W		MSE
Mahdi [37]	2021		ELM, ANN	WRA, CA, Fi, W/C, C, FA		R MAE
Wang Q [38]	2009		BPNN	FA, Tensile strength Equivalent diameter of steel bars	Ultimate bond stress	MAE MRE
Zhou R [39]	2001		RBF-CNN	FA, W/C, Binding material	CS	MAE MRE
Han M [40]	2001		BPNN	C, FA, W, WRA, Fi, CA, A		MRE
Xu J [41]	2020	RC-1	BPNN	W/C, Rubber content, freeze–thaw cycles	Relative dynamic elastic modulus	MRE
Zhang L [42]	2018	RC-1	BPNN	Rubber content, Rubber particle size, Freeze–thaw cycles C, W/C	Relative dynamic elastic modulus TS CS	MAE MSE
Huang W [43]	2021	RC-2	PSO-BP, GA-BP	W/C, C, Replacement rate of broken ceramic tiles and brick, Natural aggregate replacement rate	CS	RMSE R
Zhu W [44]	2014		GA-SVM	W, C, Fi, CA, FA, WRA, RCA		MRE
Tian X [45]	2013		BPNN	W/C, Fi, C, RCAR		MSE MAE
Ceng X [46]	2023	Ceramisite concrete	GA-BP	W/C, Nanometer SiO ₂ Ceramic, A		RMSE R ²
Sakshi [47]	2021	FA C	ANN	WRA, Fi, CA, FA, NaSi ₃ , NaOH, Solid powder and liquid ratio, Ti		MSE R
Peng Y [48]	2021		BPNN, SVM, ELM	W, C, Fi, CA, FA, Alkaline activators, Chemical admixtures		MAE RMSE R ²

Table 2. Cont.

Author	Year	Concrete Type	Algorithm	Input Variable	Output Variable	Evaluation Index
Shah [49]	2023	FA-slag concrete	ANN, CART	Slag, W, C, Fi, CA, FA, A	CS	MAE RMSE MAPE R ²
Dilshad [50]	2023	FAC	FQ, NLR, MLR, ANN	W, C, Fi, CA, FA		MAE RMSE MAPE R ²
Zhang [51]	2020	RC-1	ELM, BPNN, AVM	Rubber content, Rubber particle size, Polypropylene fiber content, C, W/C, Concrete strength	TS BS	R ² RSD MRE
Mostafa [52]	2020		NMVR, GP, ANN, ANFIS, AVM	Rubber content Rubber particle size W/C, C, Fi, Co	CS	MAE RMSE MAPE R ²
Huang [53]	2021		ANN	Rubber substitution percentage, Rubber particle size, W, C, Fi, Co, WRA, W/C, Particle size	CS BS TS Elastic modulus	R ² RMSE
Thuy [54]	2021		ANN	W/C, C, Fi, CA, WRA, Rubber content Rubber particle size		R ² RMSE
Li [55]	2022		GEP	NaOH concentration Ti, W/C, C, Fi, CA	CS	MAE RMSE MAPE R ²
Mahdi [56]	2023		MLP-ANN, RT, SVR, GPR	W/C, C, Fi, CA, FA, Rubber content, Rubber particle size, WRA, Slag		MAE MAPE R ²
Nudrat [57]	2024		AdaBoost, CART, RF	W, C, Fi, CA, WRA, Rubber, Silica fume, Steel fiber, A	CS TS	MAE R ²
Reza [58]	2021		AVM, ANN, MLR	W, C, Fi, CA, WRA, RCA, Regenerated fiber		R MSE
Biswal [59]	2022		XGBoost, KNN, ANN, AVM, LR, CART, RF	RCA, C, FA, Slag Metakaolinite	CS	MAE RMSE MAPE R ²
Wang [60]	2023		FA-AVM, CART, MLR	Recycled aggregate size, C, W/C, RCA, Recycled aggregate cement water absorption	BS	RMSE R
Abed [61]	2024		LR-AVM-ANN	Ti, C, Te, W/C, RCAR, Fine-to-coarse aggregate ratio	CS TS BS Elastic modulus	RMSE R ²

Table 3. Durability-related research.

Author	Year	Concrete Type	Algorithm	Input Variable	Output Variable	Evaluation Index
Zhuo J [62]	2012	FAC	BPNN	W/C, C, Fi, CA, FA	Chloride diffusion coefficient	MAE
Zou J [63]	2024	RC-2	MPS-GMM	7 stress levels (0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85)	Fatigue life	MSE
Dong T [64]	2023		ANN RF AVM GA PSO	W/C, C, Fi, CA, FA, RCAR, Coarse aggregate of water absorption	Chloride diffusion coefficient	MAE RMSE MAPE R ²
V. Tran [65]	2022		XGB-RRHC GB-RRHC RF-RRHC SVM-RRHC	Ti, W/C, W, Fi, FA, Concentration, CoCO ₂ , Relative humidity, cement, Te	CD	MAE RMSE MAPE R ²
Huang [66]	2023	RC-1	WOA-ELM, WOA-RF WOA-ANN	W/C, C, Fi, CA, Rubber size, WRA, Rubber content	Chlorine ion permeability coefficient	RMS MAE MAPE R ²
Amiri [67]	2022	RC-2	ANN	A, W/C, C, CA, Slag, RCA	Chloride diffusion coefficient Compressive strength loss rate	MAPE
Liu [68]	2021		BPNN	W, C, RCA, FA, WRA, Water absorption of RCA	Damage coefficient	RMSE R ² MAPE
Liu [69]	2021		BPNN PSOANN WOANN	W, C, RCAR, Water absorption of RCA, Te, Ti, Relative humidity, CO ₂ concentration	CD	RMSE MAPE SI R ² OBJ
Jin [70]	2022		BPNN	W, C, RCAR, W/C, Water absorption of RCA, Fi, CA	Resistance to chloride permeability	RMSE MAPE SI R ²
Liu [71]	2022		ANN	W, C, RCAR, W/C, Water absorption of RCA, Compressive strength, Solution concentration, Wet maturity, Dry maturity, Number of cycles, Durability coefficient	Sulfate permeability coefficient	RMSE MAPE OBJ R ²
Liu [72]	2022			W, C, Fi, RCA, Mineral admixture, CA, RCA apparent density and water absorption	Resistance to chloride permeability	RMSE MAPE SI R ² OBJ
Cemalgil [73]		Silica fume-steel fiber concrete	GRELM-PSO GRELM-GWO	C, FA, Co, Steel fiber, WRA, A, Number of cycles	Wear loss rate Freeze–thaw loss rate	RMSE R

Table 3. Cont.

Author	Year	Concrete Type	Algorithm	Input Variable	Output Variable	Evaluation Index
Huang [74]	2024	RC-1	ANN SVR ELM MSSA	W, C, W/C, Co, Fi, Rubber particle size [0, 1], [1, 3], [3, 10], Admixtures Freeze–thaw cycle	Relative dynamic elastic modulus	RMSE MAPE R ²
Fu [75]			ANN	C, RCAR, W/C, Fi, Sand ratio, Rubber content, Freeze–thaw cycles	Relative dynamic elastic modulus	RMSE MAPE R ²
Xu [76]		Basalt Fiber Reinforced Concrete	BAS-BPNN GA-BPNN PSO-BPNN PSO-LSTM BAS-LSTM	Fiber content, Salt Solution Type, Freeze–Thaw Cycles	Relative Dynamic Elastic Modulus, CS	RMSE MAPE SI R ²

As shown in Table 2, numerous researchers have applied ML algorithms to predict the mechanical properties of concrete, with a primary focus on various types of waste materials such as FA, RA, and rubber waste. Among these properties, compressive strength is the most frequently predicted, while other mechanical indicators—such as elastic modulus and splitting tensile strength—have received comparatively less attention. Each algorithm listed in Table 1 has its own advantages and limitations; thus, no single model can be considered optimal in all aspects. The choice of algorithm should be based on specific criteria and problem requirements. ANN and RF have become the most widely used ML techniques in the prediction of solid waste concrete properties due to their complementary advantages. ANNs dominate because of their strong ability to model highly nonlinear and multivariable relationships, which are inherent in concrete mixes incorporating heterogeneous waste materials. They can capture complex interactions among mix proportions, curing conditions, and waste composition, thereby achieving superior predictive accuracy for properties such as compressive strength. In contrast, RFs are frequently adopted for their robustness, stability, and ease of implementation. They handle noisy and limited datasets effectively, avoid severe overfitting through ensemble learning, and provide variable importance measures, which allow researchers to identify the most influential mix parameters. Compared with other algorithms, the balance of high predictive performance (ANNs) and interpretability with robustness (RFs) explains why these two methods dominate current research. On the other hand, if higher accuracy and model optimization are priorities, meta-heuristic algorithms can be employed to enhance base models. When model interpretability is required, decision tree-based methods such as Classification and Regression Trees (CARTs) or evolutionary algorithms are preferred, as they can generate explicit mathematical expressions and provide a clearer understanding of input–output interactions. Moreover, although hybrid models show great promise for real-world engineering applications, the increasing volume and complexity of data present challenges. Simple models often struggle with convergence under complex nonlinear relationships, while more powerful models—though capable of reducing generalization error—are prone to overfitting. Striking a balance between model complexity and generalization remains a major challenge. Therefore, the development of new hybrid algorithmic frameworks has become both a growing trend and a significant research challenge in this field.

3.2. Durability Prediction Study

Traditional methods for predicting concrete durability are mainly based on mechanism-driven models, which have certain limitations. For example, when the material composition

changes, the existing model will no longer be applicable and a new model needs to be built. In addition, as the number of influencing factor indicators considered increases, the physical equations constructed by the traditional method are difficult to effectively assess the importance of the indicators and their interactions. In contrast, the prediction of concrete durability using ML techniques not only ensures the accuracy of the prediction, but also reveals the mechanism of the input variables on the durability indexes through the feature importance analysis. Currently, As shown in Table 3, the concrete durability assessed by ML modeling includes chloride resistance, carbonation resistance, sulfate resistance, and frost resistance.

As shown in Table 3, a considerable number of studies have employed ANN or their optimized variants. This prevalence is largely due to the heterogeneous nature of waste concrete, which often incorporates multiple industrial by-products such as FA, slag, and recycled aggregates. These materials exhibit significant variability in physicochemical properties and interact in complex, nonlinear ways. For general machine learning models, when the coupled environment exceeds the boundary of statistical extrapolation, a critical threshold of material failure may occur. For example, when the replacement rate of recycled aggregate increases to 80%, the prediction error of compressive strength surges to 22–35% [77]. ANN provide a scientific, cost-effective, and highly accurate solution for assessing durability, owing to their strong capabilities in nonlinear modeling, multi-factor coupling analysis, and efficient predictive performance.

Despite recent advancements in ML-based durability assessment of waste concrete, several core challenges remain [78]:

- (1) Insufficient data quality and scale: Experimental data are often fragmented, small in sample size, and noisy—factors that limit the development of robust and generalizable models. For example, data on salt-freezing resistance are scarce due to the high cost of extreme environmental testing.
- (2) Limited model generalization: Most models are designed for single durability indicators (e.g., compressive strength or chloride diffusion coefficient) and perform poorly under multi-objective coupling scenarios, such as the combined effects of salt-freezing and carbonation.
- (3) Lack of physical interpretability: Although many black-box models achieve high predictive accuracy, they often lack integration with material science principles, making it difficult to uncover the fundamental mechanisms of durability degradation.

3.3. Multi-Objective Optimization

The core of multi-objective optimization in solid waste concrete lies in balancing mechanical performance, workability, durability, environmental benefits (e.g., reduced carbon emissions), and cost. Machine learning techniques, particularly multi-objective optimization algorithms, provide effective tools to address these complex and often conflicting objectives. As summarized in Table 4, recent studies have applied such methods. Researchers frequently adopt genetic algorithms such as NSGA-II and NSGA-III to obtain Pareto-optimal solutions, which represent trade-offs among competing goals—for example, achieving higher strength and lower carbon emissions under cost constraints. This approach enables decision-makers to select mix designs based on practical requirements.

Table 4. Summary of Optimization Algorithms Applied in Concrete Research.

Author	Year	Concrete Type	Optimization Algorithm	Input Variables	Optimization Objectives
Hu X [79]	2025	Waste Glass Concrete	NSGA-II	Hollow glass microspheres; glass fiber content	CS; Sound absorption coefficient
Jin L [80]	2024	RC-2	LSTM-MOPSO	Wr (water content in RAC), RCA, Co, Fi, C, RCAR, W/C, WRA	CS; C
Wang P [81]	2022	Hybrid Fiber Recycled Concrete	NSGA-II	Dosage of steel fiber (SF) and macro polypropylene fiber (MPPF)	FS, CS, Abrasion resistance
Tang [82]	2023	RC-1	SVM	RP, RCA, T	Peak strain; CS
Amin [83]	2023	RC-1	BPNN-AGE-MOEA	W/C, CR, rubber content	C, Fracture parameters, CS
Fan [84]	2024	RC-2	NSGA-II	NCA, RCA, RFA, NFA, FA, S, SF, C, W, SP, CS	C, CE, CS
Cen [85]	2024	RC-2	BO-GPR	Volume fraction (Vf), W/C, WA, RACR	CS, C
Onyelowe [86]	2022	FAC	ANN-BP; ANN-GRG; ANN-GA; EPR; GP	W/C, Fi, Co, RCA, FA	CS, LCA
Sun [87]	2022	Waste Glass Powder Concrete	FA-RF	WGP size; WGP dosage; sodium sulfate; Fi; alkali; T	UCS and C; ASR and C
Hashmi [88]	2019	FAC	NSGA-II	FA contents (0–60%)	CS; C
Sharma [89]	2025	Rubber–Glass Fiber Concrete	NSGA-III	Styrene–butadiene rubber (SBR), silica fume, and fibers (glass, polypropylene)	Permeability coefficient, CS; C
Liu [90]	2022	RC-2	CMOPSO	Age; Cement content; RCA replacement ratio	CS, C, CE, Energy consumption

Recent research trends indicate that optimization objectives are no longer limited to compressive strength; environmental impact and cost are now considered equally important alongside mechanical and durability properties. This shift reflects the growing acceptance of sustainable, low-carbon design principles. Moreover, scholars are increasingly investigating synergistic effects and optimal combinations of multiple industrial solid wastes to maximize both utilization and performance. Nevertheless, most current studies still focus on short-term indicators, such as 28-day compressive strength, while long-term durability remains underexplored due to limited data availability. Looking ahead, with technological advances and strengthened interdisciplinary collaboration, further progress toward a resource-efficient and low-carbon concrete industry is anticipated.

4. Cite Space Based Research Trend Analysis

4.1. Research Areas and Article Types

This assessment was conducted using Scopus Analyzer and Cite Space to identify the most relevant research domains. As shown in Figure 3, the top three disciplines contributing to the literature are engineering (38%), computer science (16%), and materials science (12%), together accounting for 66% of all retrieved documents. In addition, the types of publications in the Scopus database were analyzed (see Figure 4). Among the

retrieved records, journal articles constituted the majority (67%), followed by conference papers (25%), conference reviews (6%), and journal reviews (2%). The analysis timeframe was set from 2011 to 2024. Around 2014, research on the application of ML in concrete began to take shape, coinciding with the maturation of foundational ML algorithms. At that stage, most publications focused on basic algorithmic models, which laid the groundwork for integrating ML into concrete research. Between 2016 and 2024, the number of publications increased steadily, reflecting growing interest in interdisciplinary approaches. During this period, a surge of studies emerged, featuring not only enhanced ML models but also a broader variety of waste materials. The field has since advanced both in algorithmic development and in the diversification of material types under study.

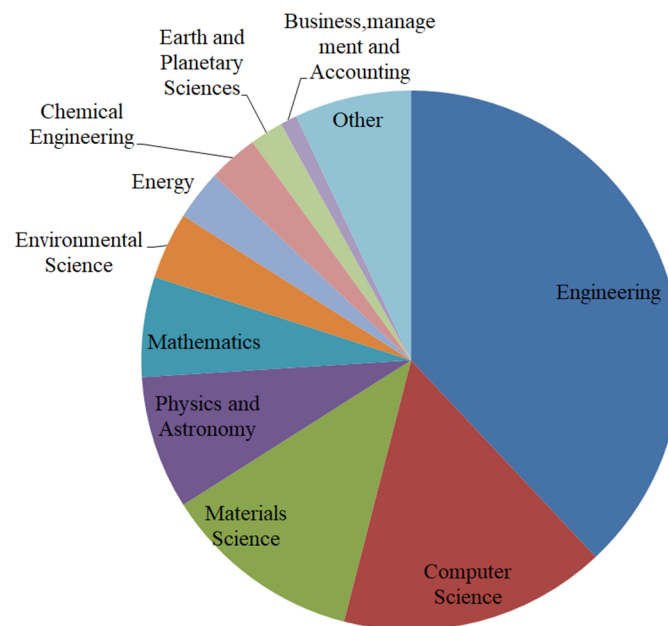


Figure 3. The related topic areas of the article.

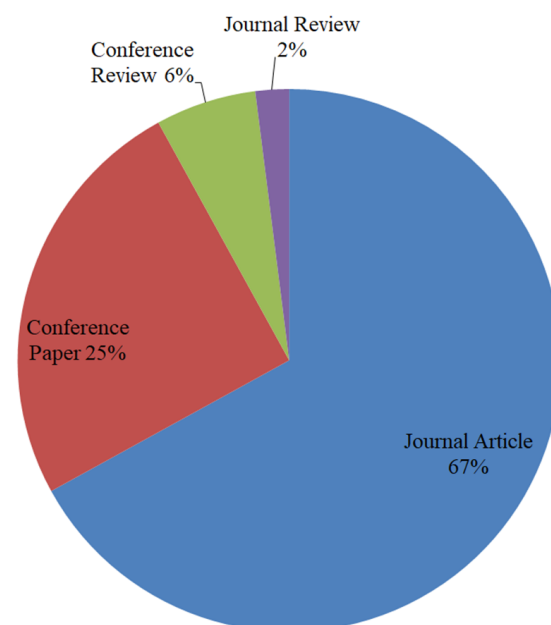


Figure 4. Article type.

4.2. Analysis of National and Institutional Research Activity

The research activity of a country is often evaluated based on the number of publications that it produces. From 2001 to 2023, a total of 68 countries or regions published studies related to the application of machine learning in waste concrete. To further explore the roles of different countries, we constructed an international collaboration network using Cite Space (Figure 5). In the graphical representation, the size of each node corresponds to the number of publications from a given country or region. Nodes highlighted with purple circles indicate higher centrality, typically reflecting stronger collaborative links with other countries in the network. Moreover, the thickness of the connecting lines between two nodes represents the frequency of collaboration among the respective countries or regions. As shown in the figure, the key countries in this field include China, India, Saudi Arabia, and Vietnam. These countries are represented by larger nodes surrounded by purple circles.

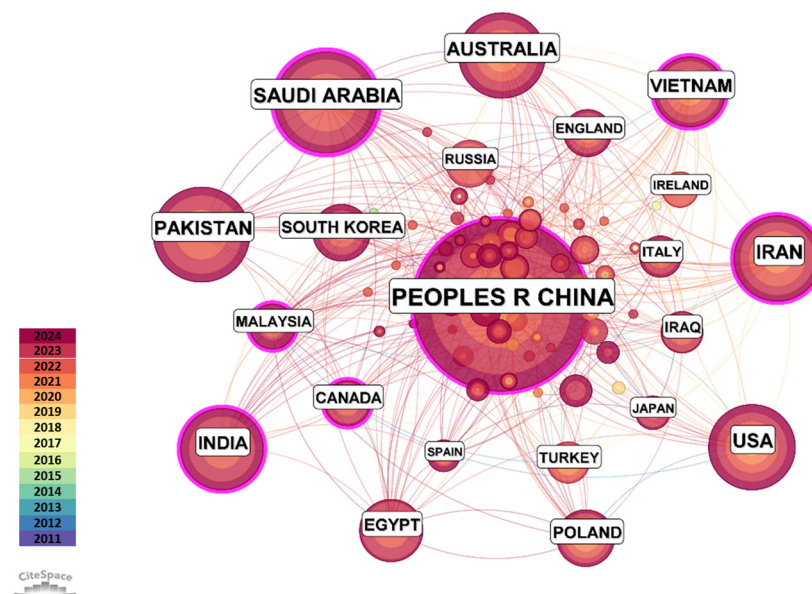


Figure 5. Country co-occurrence map.

Based on author affiliations, a total of 184 institutions have made significant contributions to the research combining waste concrete and ML. The distribution of these institutions, visualized using Cite Space, is shown in Figure 6. In this network map, each node represents an institution, and node size is proportional to the number of publications produced by that institution. The majority of research institutions are concentrated in countries such as China, the United States, and India. For instance, Chinese institutions such as Southeast University [72] and the Chinese Academy of Sciences [73] have produced notable research in areas involving coal gangue powder concrete and vitrified concrete. In contrast, institutions in the United States [74,75] have placed greater emphasis on the optimization and application of ML algorithms. This geographical distribution reflects the differing national priorities in this interdisciplinary research area. As the field continues to evolve, an increasing number of institutions are integrating ML with disciplines such as materials science and environmental engineering. For example, some institutions [64] have significantly improved predictive performance by introducing deep learning algorithms to optimize concrete mix design. Despite these advancements, the overall institutional collaboration network remains fragmented. Most institutions operate in isolation, with limited cross-institutional or cross-disciplinary partnerships, which hinders the broader dissemination and practical application of research outcomes. Therefore, establishing a collaborative platform that promotes inter-institutional and interdisciplinary coopera-

tion is essential for accelerating future developments in the integration of ML and waste concrete research.

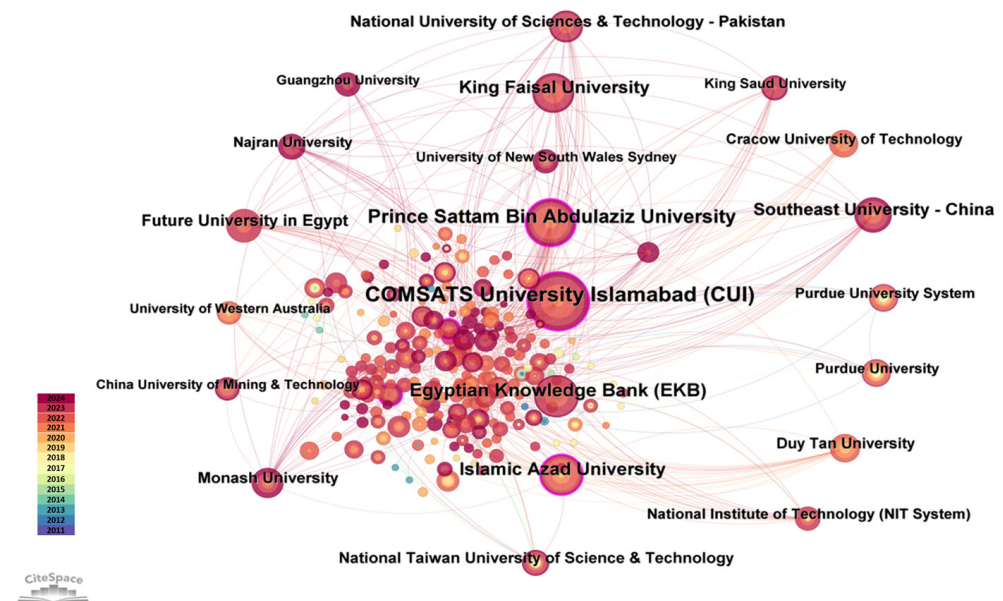


Figure 6. Institution co-occurrence diagram.

4.3. Disciplinary Category Co-Occurrence Analysis

A disciplinary co-occurrence network was generated using Cite Space to analyze the thematic distribution of publications from 2011 to 2023 (see Figure 7). In total, 59 unique subject categories were identified across all retrieved records. Based on frequency and betweenness centrality metrics, Table 5 lists the top 20 most prominent categories in the network. The co-occurrence analysis revealed that categories such as Environmental Science, Civil Engineering, and Multidisciplinary Computer Science exhibit significantly larger nodes, indicating higher occurrence frequencies and stronger interdisciplinary connections. In this visualization, node size reflects the frequency of a subject category, while the number and density of connecting lines represent the extent of its linkage with other fields [77]. In addition to the core categories, disciplines such as Artificial Intelligence Engineering, Architecture and Building Materials, and Computer Science and Technology also play indispensable roles in this research domain. These findings highlight the strongly interdisciplinary nature of studies combining ML and waste concrete. For instance, the integration of Materials Science and Computer Science has driven the development of intelligent mix design for high-performance concrete, while the overlap between Environmental Science and Civil Engineering supports the advancement of sustainable construction practices. The prominent positions occupied by Environmental Science and Green and Sustainable Science and Technology in the network further reflect the growing demand for environmentally responsible and resource-efficient materials. However, as interdisciplinary collaboration deepens, new challenges have emerged. Notably, there is a significant lack of standardized datasets and harmonized experimental protocols across disciplines. This discrepancy increases research costs and reduces the comparability and reproducibility of results. Establishing unified standards and data-sharing mechanisms is therefore essential to support more coherent and impactful interdisciplinary research in this field.

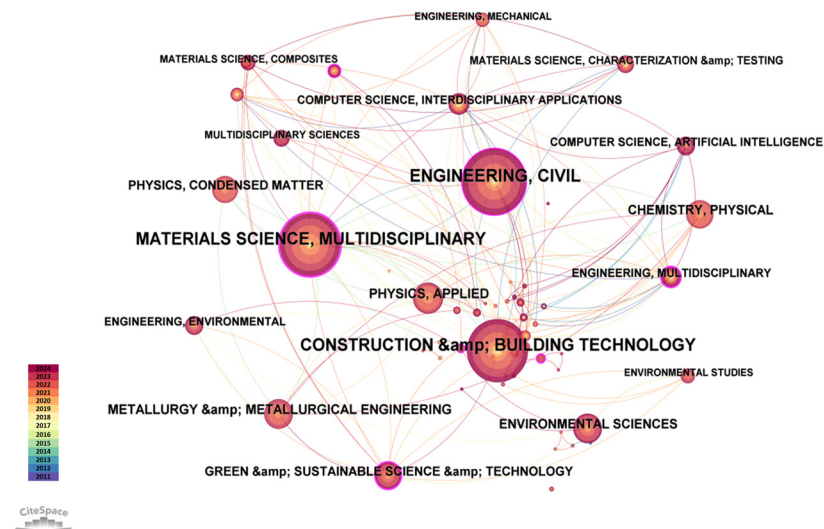


Figure 7. Co-occurrence graph of subject categories.

Table 5. Subject category information table.

Number	Subject Categories	Centrality	Quantity
1	Engineering, Civil	0.18	431
2	Construction, Building Technology	0.02	389
3	Materials Science, Multidisciplinary	0.48	388
4	Physics, Applied	0.04	196
5	Metallurgy, Metallurgical engineering	0.08	174
6	Environmental sciences	0.07	155
7	Chemistry, Physical	0.09	102
8	Physics, Condensed matter	0	98
9	Green, Sustainable Science, Technology	0.33	86
10	Computer Science, Interdisciplinary Applications	0.07	54
11	Engineering, Multidisciplinary	0.24	50
12	Computer Science, Artificial Intelligence	0.06	49
13	Engineering, Environmental	0	46
14	Materials Science, Characterization, Testing	0	39
15	Materials Science, Composites	0.06	31
16	Multidisciplinary Sciences	0	31
17	Engineering, Mechanical	0.02	28
18	Environmental Studies	0.03	28
19	Mechanics	0.09	20
20	Chemistry, Multidisciplinary	0.12	18

In response to the above issues, this paper proposes a general cross-disciplinary data framework, the basic workflow of which is illustrated in Figure 8. At the base of the pyramid lies the metadata layer, which employs standardized schemas (e.g., JSON-LD, XML Schema) to describe the dataset by capturing global identifiers, textual information, and contextual details. The raw data layer consists of unprocessed outputs directly obtained from instruments, such as images, sequence files, and measurement indicators. The processed and encoded data layer contains data that have undergone preliminary treatments (e.g., denoising, calibration, normalization) as well as encoded qualitative data. The derived data and results layer includes the final datasets used to generate figures and conclusions, which must be linked in an explicit and traceable manner to the processed data layer through scripts. This ensures that others can fully reproduce the derived datasets from the processed data using the provided scripts.

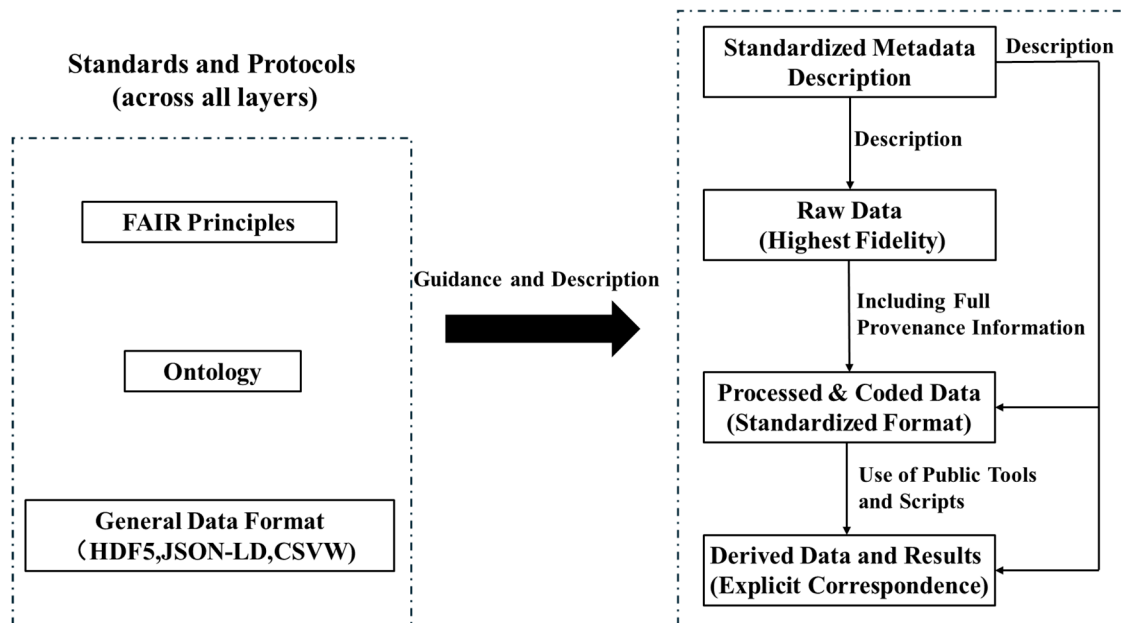


Figure 8. Fundamental workflow for dataset construction.

With continued development and broader adoption, the platform will accumulate an increasingly rich body of data resources, creating a virtuous cycle. Nonetheless, achieving standardization and comparability of cross-disciplinary data remains a large-scale, systemic undertaking that requires coordinated efforts from funding agencies, journals, academic societies, and data scientists. The core of this transformation is a paradigm shift from the current “workshop-style” research model to an open, collaborative, and reproducible model of “modern scientific infrastructure.” Although the challenges are considerable, this transition is essential for enhancing research efficiency and fostering major original discoveries. The ultimate goal is not to eliminate disciplinary differences, but to construct a “Tower of Babel” that enables the free flow, interaction, and innovation of knowledge across disciplines.

4.4. Keyword Co-Occurrence and Cluster Analysis

Keywords offer concise summaries of research content and highlight the core themes of a given field. Keyword co-occurrence and clustering analysis serve as powerful tools for revealing major research topics and evolving trends. In this study, a minimum occurrence threshold of 30 was applied for keyword inclusion. The resulting clusters and their attributes are presented in Table 6, Figures 9 and 10.

Table 6. Keyword information table.

Number	Source Name	Clustering Contour Value	Number of Nodes
1	Random forest	0.848	39
2	Fly ash	0.915	36
3	Flexural strength	0.882	34
4	Shapley additive explanation	0.87	31
5	Machine learning	0.954	31
6	Artificial intelligence	0.962	31
7	Concrete compressive strength	0.896	30
8	Machine learning	0.923	30
9	Geopolymer concrete	0.899	29
10	Ensemble learning	0.842	28
11	Class fly ash	0.904	24

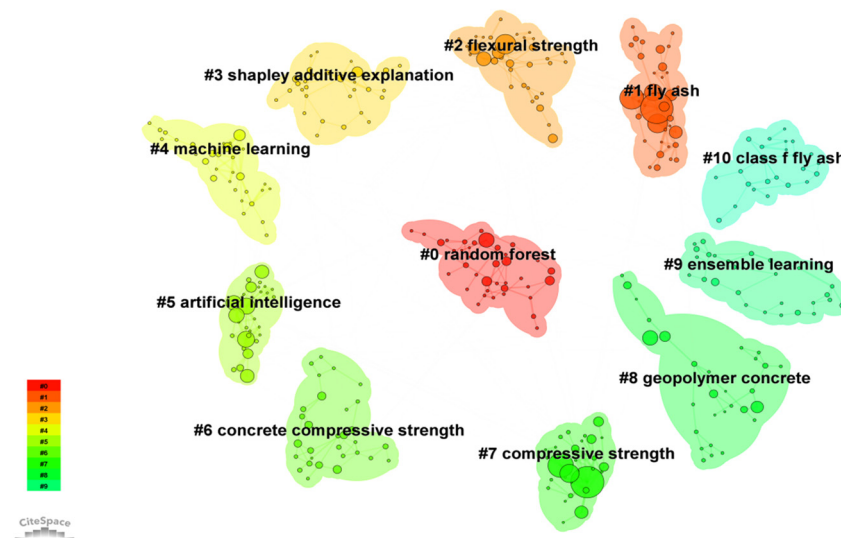


Figure 9. Keyword clustering diagram.

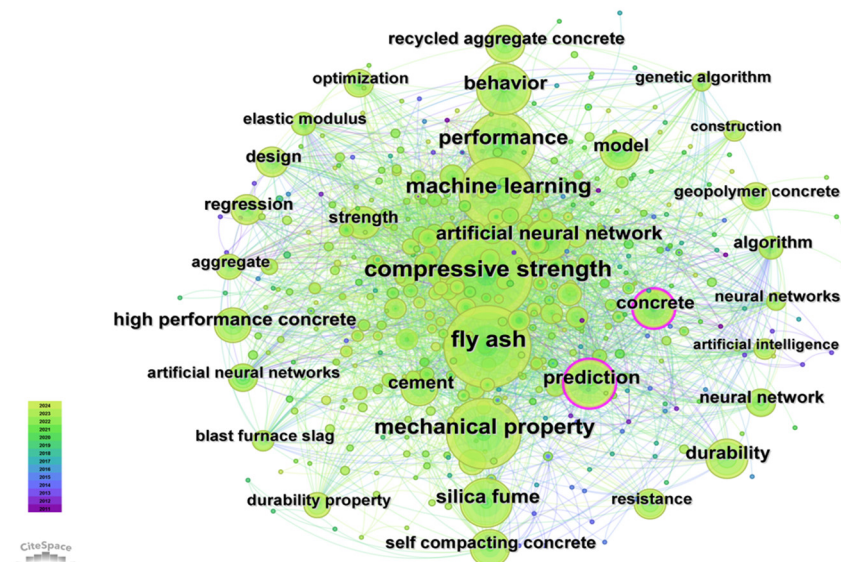


Figure 10. Keyword node graph.

A total of ten keyword clusters were identified, with Cluster #0 emerging as the most significant. It achieved a Silhouette Score (S) of 0.848, indicating a high level of clustering reliability. In the visual map, contour shapes represent the degree of similarity between clustered keywords. Clusters #0, #3, #4, #5, and #9 primarily focus on ML algorithms, including topics such as model selection, optimization, and multi-model integration. Representative keywords include random forest, neural networks, ML, artificial intelligence, and deep learning. Clusters #1, #8, and #10 are associated with various types of waste concrete, such as geopolymer concrete, recycled aggregates, rubber concrete, and coal gangue powder concrete. Clusters #2, #6, and #7 focus on output indicators predicted by ML models, including compressive strength, durability, carbon footprint, and workability.

These clusters collectively reflect the growing diversity and interdisciplinary scope of ML applications in waste concrete research. The main research focus lies in algorithmic performance enhancement and multi-model fusion, with dominant approaches including Random Forest, XGBoost, ANN, and hybrid models such as genetic algorithm–neural network combinations. Research emphasis has shifted from single-target predictions (e.g., compressive strength) to multi-objective optimization, including durability, slump, and carbon emissions. In particular, integration with digital twin technology is facilitating

full-cycle prediction across material design, construction, operation, and maintenance, thereby advancing the industry toward net-zero emission goals.

However, a significant challenge remains: due to the limited availability of long-term datasets, prediction errors for time-dependent indicators such as durability and carbonation depth remain high (e.g., MAE > 15%). To address this issue, it is recommended to combine accelerated aging test data with field monitoring results to construct spatio-temporally enriched datasets. This would support the development of Transformer-based sequence prediction models capable of capturing long-term degradation patterns in concrete performance.

4.5. Reference Co-Citation Cluster Analysis

In academic research, prior studies serve as foundational references for ongoing scientific inquiry. A co-citation relationship is established when two documents are cited together in the same reference list, reflecting thematic or methodological similarity. Co-citation analysis provides valuable insights into the structure and evolution of a research field, as frequently co-cited articles tend to indicate closely related areas of investigation.

Using Cite Space, this study conducted a reference co-citation analysis and identified 10 distinct co-citation clusters, as visualized in Figure 11. The clustering structure achieved a high average silhouette value ($S = 0.902$), indicating excellent clustering quality and reliability. Table 7 summarizes the attributes of each identified cluster.

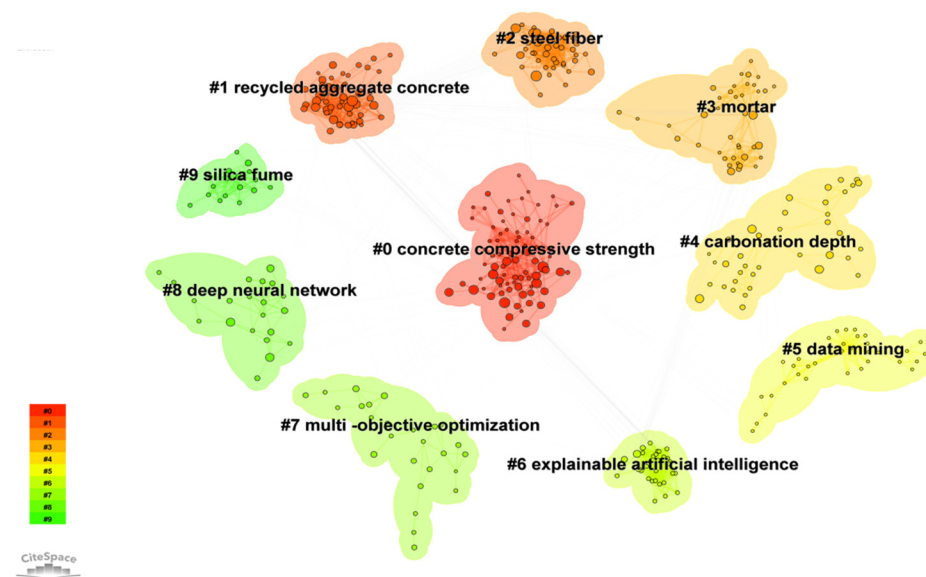


Figure 11. A cluster analysis of the co-cited literature.

Table 7. Co-citation clustering information table.

Number	Source Name	The Number of Published	Number of Citations
1	Concrete compressive strength	0.82	317
2	Recycled aggregate concrete	0.872	274
3	Steel fiber	0.916	69
4	Mortar	0.891	341
5	Carbonation depth	0.926	121
6	Data mining	0.962	135
7	Explainable artificial intelligence	0.935	107
8	Multi-objective optimization	0.962	104
9	Deep neural network	0.902	283
10	Silica fume	0.968	328

Eight key clusters were particularly relevant to the integration of ML and waste concrete research:

Cluster 0 (Concrete Compressive Strength) represents the core research area. As one of the most cited clusters, it confirms that compressive strength remains the central mechanical property for performance prediction in waste concrete studies.

Clusters 1 (Recycled Concrete), 2 (Steel Fiber), and 9 (Silica Fume) highlight increasing attention paid to sustainable resource utilization, particularly through the use of recycled aggregates, FA, and other industrial waste materials.

Clusters 3 (Mortar) and 4 (Carbonation Depth) focus on the mechanical behavior and durability performance of cementitious materials under varying environmental conditions.

Clusters 5 (Data Mining), 6 (Artificial Intelligence), and 8 (Neural Networks) emphasize the growing role of advanced algorithmic approaches such as deep learning, ensemble modeling, and optimization strategies in predicting the behavior of waste-based concrete materials.

Cluster 7 (Multi-Objective Optimization) indicates a shift from single-variable analysis toward models that balance multiple design goals, such as structural performance, cost-efficiency, and environmental impact.

Despite these advancements, the co-citation network reveals some critical limitations. Notably, there is a lack of integration between mechanical and durability-focused clusters. For example, compressive strength (Cluster 0) and carbonation depth (Cluster 4) show weak linkages, suggesting that long-term durability aspects are often excluded from ML-based predictive models. This fragmentation hinders the development of holistic frameworks necessary for real-world engineering applications. In addition, although clusters related to carbon footprint and silica fume reflect a strong interest in sustainability, most of the studies remain at the laboratory research stage. The practical implementation of ML-based design approaches in construction remains limited, and the technology adoption rate is relatively low.

In summary, the co-citation clusters provide a comprehensive framework for understanding the thematic structure of ML applications in waste concrete research. These findings reveal key trends, highlight research gaps, and offer valuable guidance for future studies aiming to promote interdisciplinary collaboration, resource-efficient design, and practical engineering integration.

4.6. Analysis of Evolutionary Trends

Building upon the previous co-citation, keyword, and category analyses, this section provides a comprehensive overview of the evolutionary trends in the application of ML to waste concrete. Using Cite Space, the study tracks research progress, identifies current hotspots, and outlines development trajectories in this interdisciplinary domain (Figure 12).

First, the overall publication trend shows a strong positive correlation with time, indicating growing academic interest. The number of related publications has increased rapidly, a trend expected to continue in the coming years. Influential journals—such as *Construction and Building Materials*, *Journal of Civil Engineering*, *Green Sustainability*, and *Environmental Science and Technology*—have become key platforms for disseminating advancements in this field. These journals were identified based on metrics including publication counts, H-index, average total local citation score (ATLCS), and average total global citation score (ATGCS). Second, in terms of international contributions, countries such as the United States, China, and India play a leading role. These nations have not only published the most research but have also maintained high levels of international collaboration. Institutions such as the Chinese Academy of Sciences, Southeast University, the Egyptian Knowledge Bank, and Kasetsart University in Thailand have made significant

contributions through both independent and collaborative projects. Third, the integration of ML with waste concrete research reflects a highly interdisciplinary endeavor. It spans fields such as civil engineering, materials science, construction and building materials, environmental engineering, metallurgical engineering, green and sustainable science and technology, computer science, artificial intelligence, and applied physics. This diversity demonstrates the complex nature of the challenge and the necessity of cross-disciplinary approaches. Finally, to achieve the long-term goals of green, low-carbon, and sustainable development, continued effort is required in areas such as technology innovation, engineering validation, standardization, policy formulation, and industrial scaling. Strengthening interdisciplinary collaboration will be key to identifying more effective and scalable solutions. A robust integration of scientific, technical, and regulatory frameworks will further accelerate the adoption of ML-driven waste concrete applications in real-world scenarios.

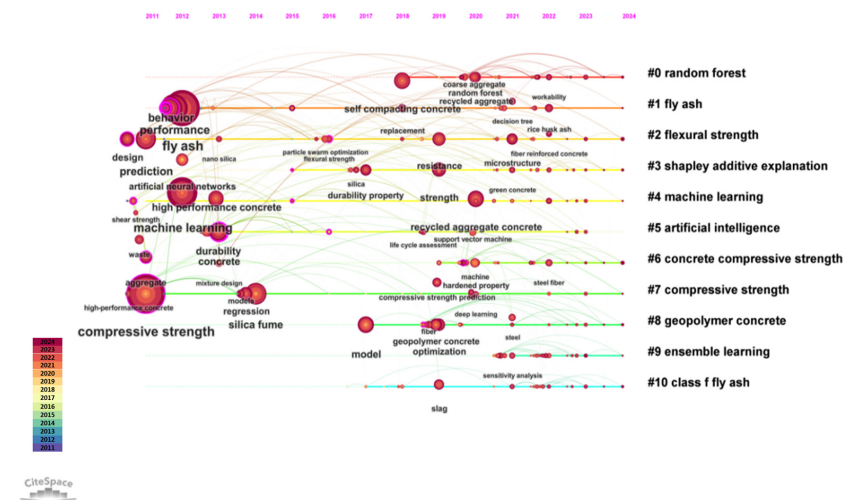


Figure 12. A keyword clustering time slice diagram.

5. Conclusions and Future Prospects

Based on the scientometric analysis and literature review, the following key conclusions are drawn:

- (1) The number of publications on ML in waste concrete applications has steadily increased, particularly after 2015, reflecting both the growing maturity of ML technologies and their adaptability for predicting material performance.
- (2) Research has expanded from standard concrete to various waste-based types (e.g., recycled aggregate, FA, rubberized, and ceramic concrete), while predictive targets have extended beyond compressive strength to include durability, permeability, carbonation, and freeze–thaw resistance.
- (3) Widely used ML models include artificial neural networks, decision trees, support vector machines, and hybrid metaheuristic algorithms. Their ability to handle nonlinear, multi-parameter data makes them well suited for complex material systems.
- (4) Most studies rely on laboratory-scale datasets with standard specimens. Performance prediction in real engineering environments remains limited, underscoring the need for broader validation and practical implementation.
- (5) Despite the interdisciplinary nature of the field, collaboration across civil engineering, materials science, and computer science is still fragmented. Data inconsistency and the absence of unified standards hinder model generalization and comparative evaluation.
- (6) Future research priorities should include (i) developing generalizable and interpretable ML models, (ii) integrating field-scale monitoring data, (iii) shifting from the prediction of single properties to multi-objective optimization, and (iv) strengthening

cross-disciplinary cooperation to achieve scalable and sustainable applications in the construction industry.

- (7) In addition, more emphasis should be placed on improvement strategies, multi-objective optimization frameworks, and sustainable applications of ML in waste concrete. Specifically, future studies should explore advanced optimization approaches to balance mechanical, economic, and environmental objectives, and promote sustainable mix designs that maximize the utilization of solid wastes while reducing carbon emissions. This direction will enhance both the depth and the practical relevance of ML research in the field.

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