International Journal of Engineering & Artificial Intelligence Art Design

IJEAIAD Vol. 1, No. 1 (2025) pp. 1-22

Machine Learning-Driven Insights for Concrete Compressive Strength Prediction: A Bibliometric Analysis

Ahmed M. Gomaa[1,2], Khaled Samy[1], Marina O. Karam [1], Youssef A. Abd Elsatar[1], Mohamed Z. Mohamed[1], Mohamed S. Elnemr[1], Mohab W. Mosbah[1], Mohamed E. Mosbah[1], Kamal Hafez[3]

[1] Department of Civil Engineering, The Higher Institute of Engineering and Technology, Fifth Settlement, Egypt.
[2] Department of Construction and Building Engineering, Faculty of Engineering and Technology, Egyptian Chinese University, Cairo, Egypt
[3] Department of Civil Engineering, Faculty of Engineering, Suez Canal University, Ismailia, Egypt.

ARTICLE INFO

Article history:
Received 21 June 2025
Revised 13 July 2025
Accepted 19 july 2025
Available online 20 July 2025

Keywords:
Concrete Strength Prediction Machine Learning (ML) Applications
Bibliometric Study
Concrete Mechanical Characteristics
Forecasting Models.

A B S T R A C T

Predicting concrete's compressive strength through in-depth analysis is essential for improving safety in practical applications and optimizing construction processes. Numerous studies have explored methods for forecasting the mechanical properties of concrete, particularly its compressive strength. Summarizing key insights from these studies can help guide future research directions. This paper conducts a bibliometric analysis of research utilizing Machine learning (ML) algorithms for predicting concrete's compressive strength. It assesses the effectiveness of these models and offers insights into developing more efficient solutions. Additionally, it provides researchers with a comprehensive overview of key themes, emerging trends, and research gaps in this domain. To accomplish this, 1,805 articles published between 2014 and March 8, 2025, were retrieved from the Scopus Database and analyzed using VOS viewer software. The findings highlight the widespread application of ML models for this purpose, evaluating their advantages and limitations, particularly in managing complex datasets. By offering a detailed assessment of ML techniques and their practical implications, this study distinguishes itself from previous research. A major contribution of this study is its identification of leading institutions, influential authors, key countries, and major publication sources in this field. It integrates data to highlight crucial research areas, gaps, and evolving trends. Ultimately, the study establishes a solid foundation for advancing ML-driven, reliable, and sustainable structural systems in civil engineering, construction materials, and the concrete industry.

1. Introduction

Concrete is one of the most widely used construction materials due to its high compressive strength, durability, and cost-effectiveness. As global infrastructure demands continue to rise, ensuring the structural reliability of concrete remains a critical priority[1]–[3]. Predicting the compressive strength of concrete is essential for optimizing mix designs, improving quality control, and enhancing safety in civil engineering projects. Traditional methods for estimating compressive strength often rely on empirical models and experimental testing, which can be time-consuming and resource-intensive[4], [5]. With advancements in artificial intelligence and data-driven techniques, machine learning (ML) has emerged as a powerful tool for predicting concrete's mechanical properties. ML algorithms can analyze complex datasets, identify patterns, and provide accurate predictions, reducing the need for extensive physical testing. As a result, researchers have increasingly explored ML-based approaches to improve the accuracy and efficiency of concrete compressive strength prediction[6], [7]. However, predicting it accurately is challenging due to the influence of numerous factors, including the water-to-cement ratio, aggregate-to-cement ratio, air content, cement composition, cement dosage, mineral and chemical admixtures, curing conditions, hydration kinetics, and the age of the concrete[8]–[10]. These complex interactions make it difficult to develop reliable predictive models. To address these challenges, researchers have increasingly turned to Machine learning (ML) techniques for estimating concrete compressive strength[11]–[50]. ML-based models provide a promising solution, particularly for practical applications in the construction and civil engineering sectors. Recent advancements in artificial intelligence (AI) have led to the development of sophisticated models capable of predicting compressive strength with high accuracy, minimizing the reliance on expensive and labor-intensive laboratory testing[12], [23], [34], [46]. Various studies have explored different ML-based predictive approaches, making significant contributions to the field.

Despite these progresses, challenges persist due to the varied and complex nature of concrete[51]. Existing research often lacks comprehensive assessments that fully address the intricate relationships between influencing variables, limiting the generalizability of predictive models[42], [52]–[56]. Moreover, integrating ML with real-time monitoring technologies, such as the Internet of Things (IoT) and big data analytics, could further enhance accuracy and practical implementation[6], [9], [10].

To understand the current research landscape in this domain, a bibliometric analysis offers valuable insights into key trends, influential studies, and research gaps. This study systematically examines the literature on ML-driven concrete compressive strength prediction by analysing 1,805 articles published between 2014 and March 2025 from the Scopus database. Using VOS viewer software, the study identifies leading authors, institutions, and countries contributing to this field while highlighting the most prominent themes and methodologies. By providing a comprehensive overview of existing research, this bibliometric analysis aims to guide future studies, enhance the development of optimized ML models, and support the advancement of sustainable and reliable concrete structures. Ultimately, this study contributes to the growing body of knowledge in civil engineering, building materials, and artificial intelligence applications in construction.

2. Methodology

This study aims to examine research on predicting concrete compressive strength through a scientific mapping approach, highlighting key trends, existing research gaps, influential sources, leading institutions, notable authors, and contributing countries. Furthermore, it aims to facilitate strategic decision-making to shape future research directions. The methodology is structured into three main stages: data collection and selection, choosing a suitable scientific mapping method, and applying bibliometric analysis techniques.

3. Bibliometric Analysis

This review reveals the Machine Learning-Driven Insights for Concrete Compressive Strength Prediction 2014 to 2025. The bibliometric analysis method was employed to fulfil this objective. Additionally, the study adheres to the PRISMA framework [57] shown in **Fig. 1.** Bibliometric analysis involves tracking research papers focused on a specific theme and extracting insights by analysing these studies across different parameters [58]. The search in the Scopus database encompassed various search fields, including Title, Abstract, Author Keywords, and Keywords Plus, to identify related publications.

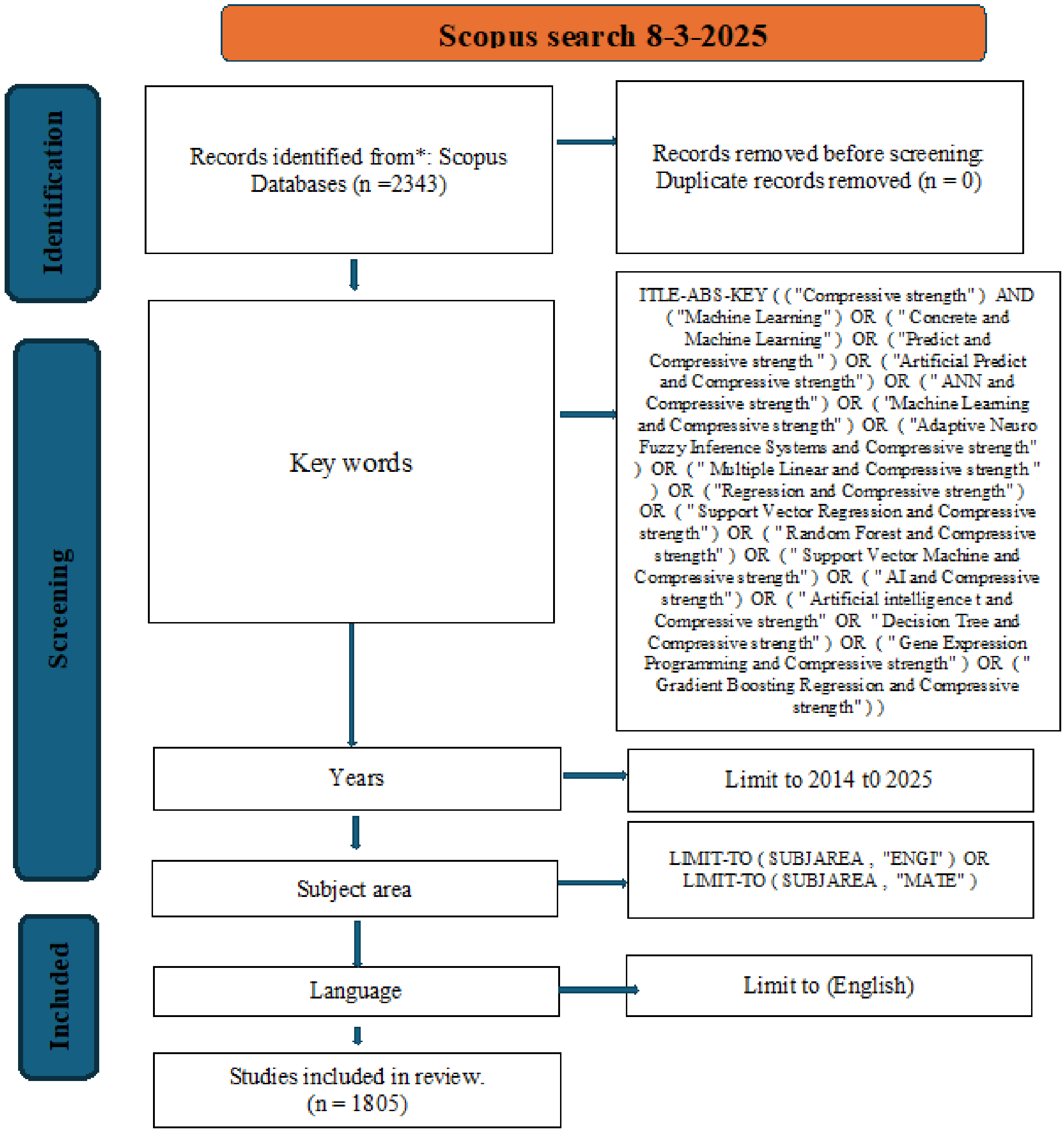

Fig. 1: PRISMA Framework for Bibliometric Analysis of Compressive Strength Prediction.

4. Results

Bibliometric analysis is a statistical approach used to quantify and evaluate the emerging trends within a particular field of study[59], [60]. Bibliometric analysis has been applied to evaluate academic outputs across multiple disciplines [61]. The search, conducted on the Scopus database from 2014 to 2025, utilized various search fields such as Author keywords, Title, Abstract, Author, and Keywords Plus. The search employed a combination of keywords using AND/OR logic, including terms like (("Compressive strength") AND ("Machine Learning") OR (" Concrete and Machine Learning") OR ("Predict and Compressive strength ") OR ("Artificial Predict and Compressive strength") OR (" ANN and Compressive strength") OR ("Machine Learning and Compressive strength") OR ("Adaptive

Neuro Fuzzy Inference Systems and Compressive strength") OR (" Multiple Linear and Compressive strength ") OR ("Regression and Compressive strength") OR (" Support Vector Regression and Compressive strength") OR (" Random Forest and Compressive strength") OR (" Support Vector Machine and Compressive strength") OR (" AI and Compressive strength") OR (" Artificial intelligence t and Compressive strength" OR " Decision Tree and Compressive strength") OR (" Gene Expression Programming and Compressive strength") OR (" Gradient Boosting Regression and Compressive strength")). The results were assessed based on titles and abstracts to ensure coherence with the article's theme and core topic.

The analysis utilized Scopus analysis and VOS viewer for data visualization. Graphs were generated using Microsoft Excel. Various details were extracted for each document, including (1) the number of documents per year, (2) average citations of articles per year, (3) author keywords and frequently used words in titles, (4) journals of publication for each article, (5) science categories, (6) most cited articles, (7) authors and co-authors for each article, (8) H-index for top 10 authors, (9) affiliation details for authors and co-authors, (10) countries of the authors, and (11) H-index for top 10 journals. Bibliographic maps were generated using VOS viewer software, encompassing keywords co-occurrence, countries co-authorship maps, and bibliographic coupling for countries and affiliations. 2343 documents were initially identified, with 1805 aligning with the study's theme. These documents were then categorized as follows: 1598 research articles, 29 review papers, 124 conference papers, and 54 documents falling into other categories. The dataset comprises 144 sources and 1723 keywords. The publications obtained showed an average growth rate of 43.60% per year. The most notable increase was observed between 2020 and 2024, reaching its peak with 687 publications in 2024, as shown in Fig. 2. The average annual citation was 50.80%, reported in 2024, as illustrated in Fig. 3. Only 15647 articles were cited for that particular year. Fig. 3 illustrates the fluctuation of journals over the years. Until 2024, the journal "Construction and Building Materials" held the top position, but it was surpassed by the "Case Studies in Construction Materials," which accumulated a total of 2,295 articles. In terms of the Cite Score (2023) of journals, the "Journal of Cleaner Production" led the rankings with a score of 20.4, followed by " Construction and Building Materials " and " Rock Mechanics and Rock Engineering " with scores of 13.8 and 10.9, respectively, as detailed in **Table 1**.

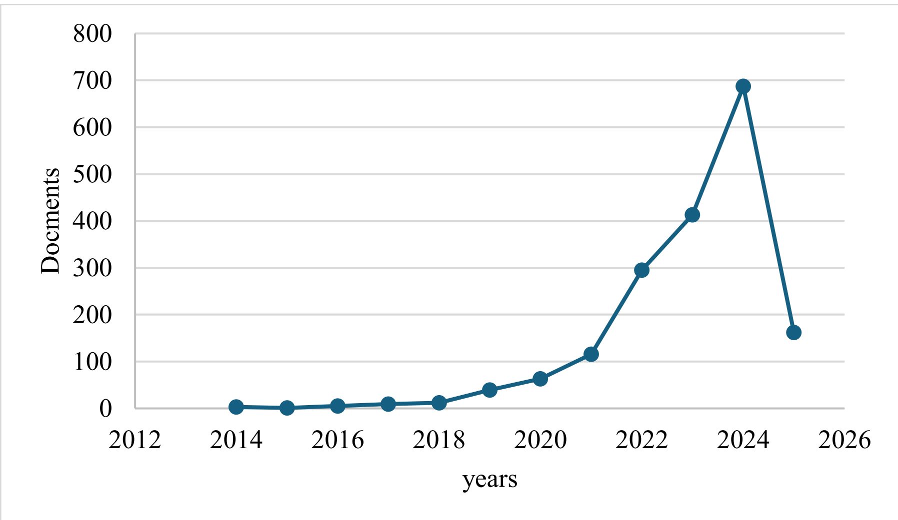

Fig. 2. Annual Distribution of Machine Learning Applications in Concrete Compressive Strength Prediction.

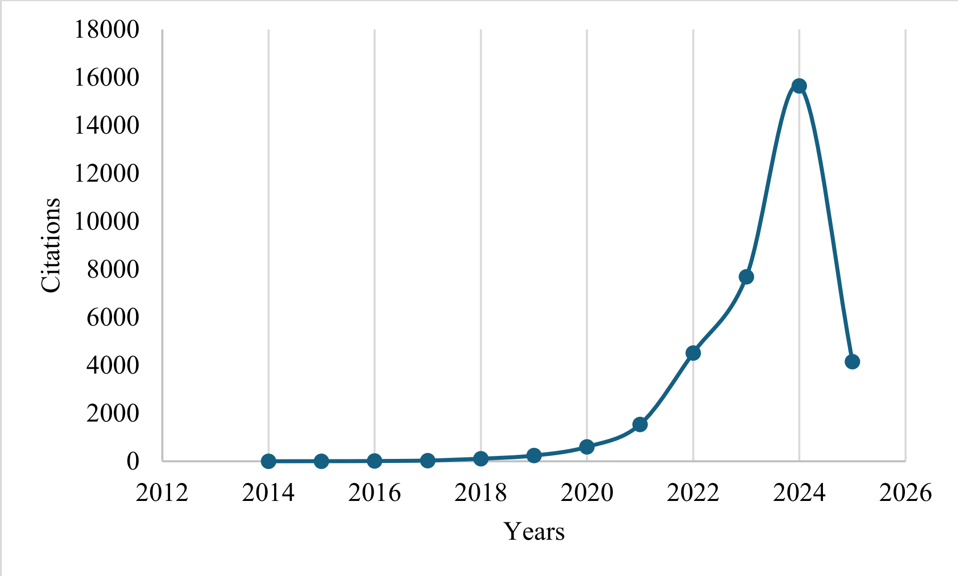

Fig. 3. Average citation per article each year.

Table 1. The top 20 highly productive journals in the Compressive Strength Prediction.

Journal	TP	TC	Cite Score (2023)	Most cited publication	Times Cited	Publisher
Construction and Building Materials	15,336	211,152	13.8	Jaf, Dilshad Kakasor Ismael, et al. (2023)	236	Elsevier
Case Studies in Construction Materials	2,295	17,401	7.6	Abdellatief, Mohamed, et al. (2023)	123	Elsevier
Materials	30,074	173,808	5.8	Wang, X., et al. (2023)	148	Multidisciplinary Digital Publishing Institute (MDPI)
Asian Journal of Civil Engineering	560	1,516	2.7	Parsamehr, Mohammadsaeid, et al (2023).	72	Springer Nature
Journal of Building Engineering	7,051	70,200	10	Moein, Mohammad Mohtasham, et al (2023).	217	Elsevier
Multiscale and Multidisciplinary Modeling, Experiments and Design	119	404	3.4	Kalita, Kanak, et al. (2023)	42	Springer Nature
Materials Today Communications	6,790	35,392	5.2	Nandhakumar, R., and K. Venkatesan (2023).	100	Elsevier

Buildings	6,258	21,439	3.4	Golewski, Grzegorz Ludwik (2023).	120	Multidisciplinary Digital Publishing Institute (MDPI)
Structures	5,109	29,065	5.7	Kaveh, Ali, and Neda Khavaninzadeh (2023).	195	Elsevier
Lecture Notes in Civil Engineering	17,058	12,939	0.8	Amoura, Nasreddine, et al. (2022).	15	Springer Nature
Applied Sciences (Switzerland)	17,058	12,939	5.3	Rahman, Md Mostafizer, and Yutaka Watanobe (2023).	422	Multidisciplinary Digital Publishing Institute (MDPI)
Journal of Cleaner Production	19,382	394,597	20.4	Mujtaba, Muhammad, et al (2023).	398	Elsevier
Structural Concrete	1,180	6,586	5.6	Ali, Reyam, et al (2023).	83	John Wiley & Sons
Engineering Structures	6,077	61,732	10.2	Hao, Hong, et al (2023).	151	Elsevier
Results in Engineering	1,555	9,006	5.8	Elfaleh, Issam, et al (2023).	320	Elsevier
Rock Mechanics and Rock Engineering	1,572	17,191	10.9	Skentou, Athanasia D., et al (2023).	77	Springer Nature
Computers and Concrete	349	3,007	8.6	Tounsi, Abdelouahed, et al (2023).	74	Techno Press
Innovative Infrastructure Solutions	1,041	3,918	3.8	Sabale, Ranjeet, B. Venkatesh, and Mathew Jose (2023)	41	Springer Nature
Advances in Civil Engineering	3,406	13,515	4.0	Praburanganathan, S., et al (2023).	84	John Wiley & Sons
Journal of Materials Research and Technology	8,170	72,186	8.8	Li, Shuang–Shuang, et al (2023).	265	Elsevier
Materials Today: Proceedings	22,276	109,461	4.9	Praveena, B. A., et al (2022).	221	Elsevier

TP= Total Publications, TC= Total Citation

Concerning scientific categories, 42.2% of total articles were categorized under Engineering, followed by materials science and Computer Science with 24.7% and 6.5% of the total articles, respectively as illustrated in **Fig. 42.** The total number of authors across all articles amounted to 159. Notably, “Amin, M.N.” authored a superior number of articles, with 46 articles. Following closely, “Javed, M.F.” contributed 44 articles, while “Khan, K.” authored 38 articles as shown in **Fig. 5**. In terms of the authors' H-index, " Nehdi, Moncef L " achieved the highest score of 65, followed by " Javed, Muhammad Faisal " with an H-index of 50, and "Aslam, Fahid" attained an H-index of 45, as detailed in **Table 2.**

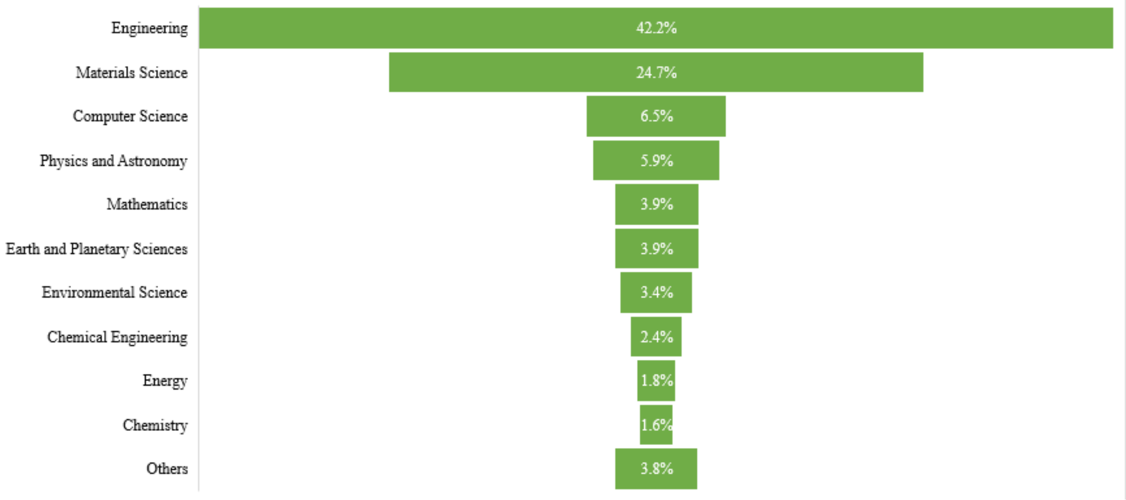

Fig. 4. Research field base publication.

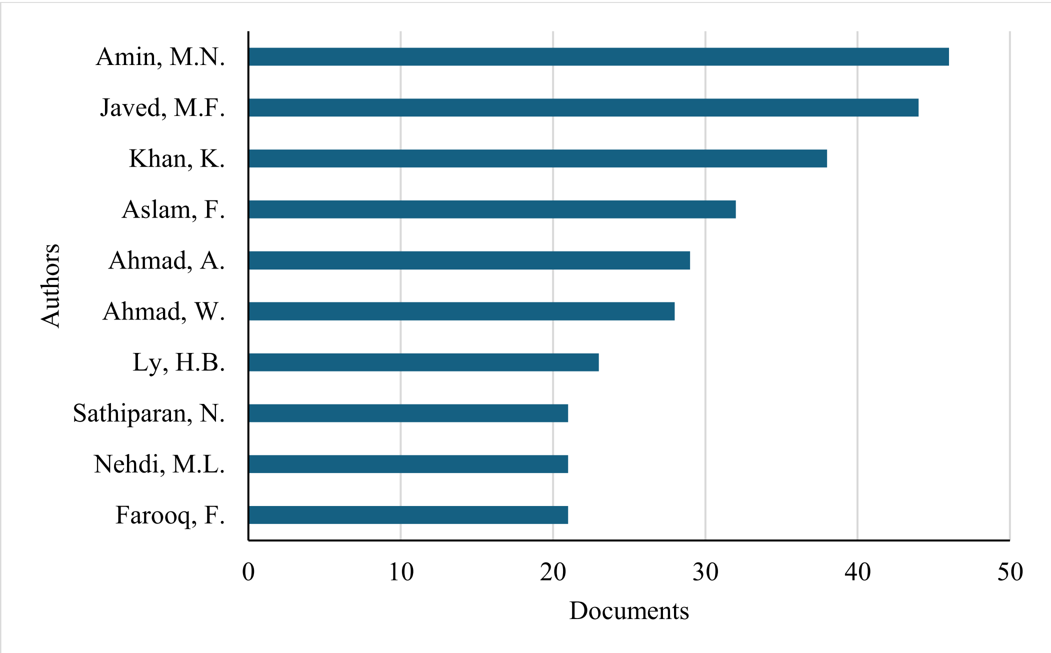

Fig. 5. Top 10 authors based on the number of articles.

Table 2. List of the 30 most prolific authors in the Compressive Strength Prediction.

No	author	TP*	h-index	Current affiliation	Country
1.	Nasir Amin, Muhammad Nasir	180	36	King Faisal UniversityThe institution will open in a new tab, Al-Ahsa, Saudi Arabia.	Saudi Arabia

2.	Javed, Muhammad Faisal	201	50	COMSATS University Islamabad, Abbottabad CampusThe institution will open in a new tab, Abbottabad, Pakistan	Pakistan
3.	Khan, Kaffayatullah M.	158	34	King Faisal UniversityThe institution will open in a new tab, Al-Ahsa, Saudi Arabia.	Saudi Arabia
4.	Aslam, Fahid	124	45	Prince Sattam Bin Abdulaziz UniversityThe institution will open in a new tab, Al Kharj, Saudi Arabia.	Saudi Arabia
5.	Ahmad, Ayaz	172	41	King Faisal UniversityThe institution will open in a new tab, Al-Ahsa, Saudi Arabia.	Saudi Arabia
6.	Ahmad, Waqas	205	41	University of Engineering and Technology, PeshawarThe institution will open in a new tab, Peshawar, Pakistan.	Pakistan
7.	Ly, Haibang	133	38	Đại học Công nghệ Giao thông vận tảiThe institution will open in a new tab, Hanoi, Viet Nam	Viet Nam
8.	Farooq, Furqan	40	27	National University of Sciences and TechnologyThe institution will open in a new tab, Islamabad, Pakistan.	Pakistan
9.	Nehdi, Moncef L.	410	65	University of GuelphThe institution will open in a new tab, Guelph, Canada	Canada
10.	Sathiparan, Navaratnarajah	84	22	University of JaffnaThe institution will open in a new tab, Jaffna, Sri Lanka.	Sri Lank
11.	Althoey, F.	112	28	Najran UniversityThe institution will open in a new tab, Najran, Saudi Arabia.	Saudi Arabia
12.	Huang, J.	111	27	Guangzhou UniversityThe institution will open in a new tab, Guangzhou, China.	China
13.	Alabduljabbar, H.	147	38	Prince Sattam Bin Abdulaziz UniversityThe institution will open in a new tab, Al Kharj, Saudi Arabia.	Saudi Arabia
14.	Nazar, S.	41	22	Shanghai Jiao Tong UniversityThe institution will open in a new tab, Shanghai, China.	China
15.	Asteris, P.G.	228	67	School of Pedagogical and Technological EducationThe institution will open in a new tab, Athens, Greece.	Greece
16.	Jeyananthan, P.	35	8	University of JaffnaThe institution will open in a new tab, Jaffna, Sri Lanka.	Sri Lanka
17.	Samui, P.	395	54	National Institute of Technology PatnaThe institution will open in a new tab, Patna, India.	India
18.	Ali, M.	113	25	Silesian University of TechnologyThe institution will open in a new tab, Gliwice, Poland.	Poland

19.	Kumar, A.	61	13	McMaster University, Faculty of EngineeringThe institution will open in a new tab, Hamilton, Canada.	Canada
20.	Tran, V.Q.	90	24	Đại học Công nghệ Giao thông vận tảiThe institution will open in a new tab, Hanoi, Viet Nam	Viet Nam
21.	Arora, H.C.	51	11	Central Building Research Institute IndiaThe institution will open in a new tab, Roorkee, India.	India
22.	Khan, M.	30	15	Southern Illinois University EdwardsvilleThe institution will open in a new tab, Edwardsville, United States.	United States
23.	Li, Y.	261	35	Beijing University of TechnologyThe institution will open in a new tab, Beijing, China.	China
24.	Sobuz, M.H.R.	85	21	Khulna University of Engineering and TechnologyThe institution will open in a new tab, Khulna, Bangladesh.	Bangladesh
25.	Subramaniam, D.N.	46	12	University of JaffnaThe institution will open in a new tab, Jaffna, Sri Lanka.	Sri Lanka
26.	Wang, X.	441	74	East China Jiaotong UniversityThe institution will open in a new tab, Nanchang, China.	China
27.	Iftikhar, B.	20	10	Universiti Teknologi Malaysia institution will open in a new tab, Johor Bahru, Malaysia.	Malaysia
28.	Ostrowski, K.A.	59	24	Politechnika KrakowskaThe institution will open in a new tab, Krakow, Poland.	Poland
29.	Wang, Y.	53	19	Curtin UniversityThe institution will open in a new tab, Perth, Australia	Australia
30.	Alyousef, R.	186	48	Prince Sattam Bin Abdulaziz UniversityThe institution will open in a new tab, Al Kharj, Saudi Arabia.	Saudi Arabia

*TP= Total Publications.

The total number of keywords used in the articles was 1723. "Compressive Strength" emerged as the most frequently utilized keyword, appearing 1438 times, as depicted in Fig. 6. This was followed by "Machine Learning" observed 1154 times, and "Machine learning" documented 686 times. As shown in Table 3, the frequently occurring keywords in the articles are grouped into six primary subject areas: mechanical properties of concrete, concrete types, modelling and analysis methods, pozzolanic additives, durability and sustainability, and other related topics. These classifications highlight the most emphasized areas in predicting concrete compressive strength and the commonly used analytical methods.

Table 3. Categorization of recurring terms in articles based on research domain.

ID	Keywords	Subject Areas	Occurrences
1.	Compressive Strength	Mechanical properties of concrete	1438
2.	Tensile Strength		150
3.	Concrete Compressive Strength		123
4.	Uniaxial Compressive Strength		63
5.	Mechanical Properties		55
6.	Shear Strength		38
7.	Fly Ash	Pozzolanic additives	218
8.	Slags		114
9.	Silica Fume		85
10.	Machine Learning	Modelling and Analysis Methods	1154
11.	Machine-learning		686
12.	Forecasting		630
13.	Machine Learning Models		255
14.	Neural Networks		254
15.	Decision Trees		247
16.	Mean Square Error		245
17.	Learning Algorithms		214
18.	Adaptive Boosting		211
19.	Support Vector Machines		198
20.	Sensitivity Analysis		191
21.	Gradient Boosting		166
22.	Artificial Neural Network		137
23.	High Performance Concrete	Concrete types	130
24.	Geopolymers		89
25.	Self-Compacting Concrete		46
26.	Sustainable Development	Durability and sustainability	84
27.	Durability		37
28.	Cost Effectiveness	Other topics	38
29.	Ultrasonic Pulse Velocity		27
30.	Ultrasonic Testing		27

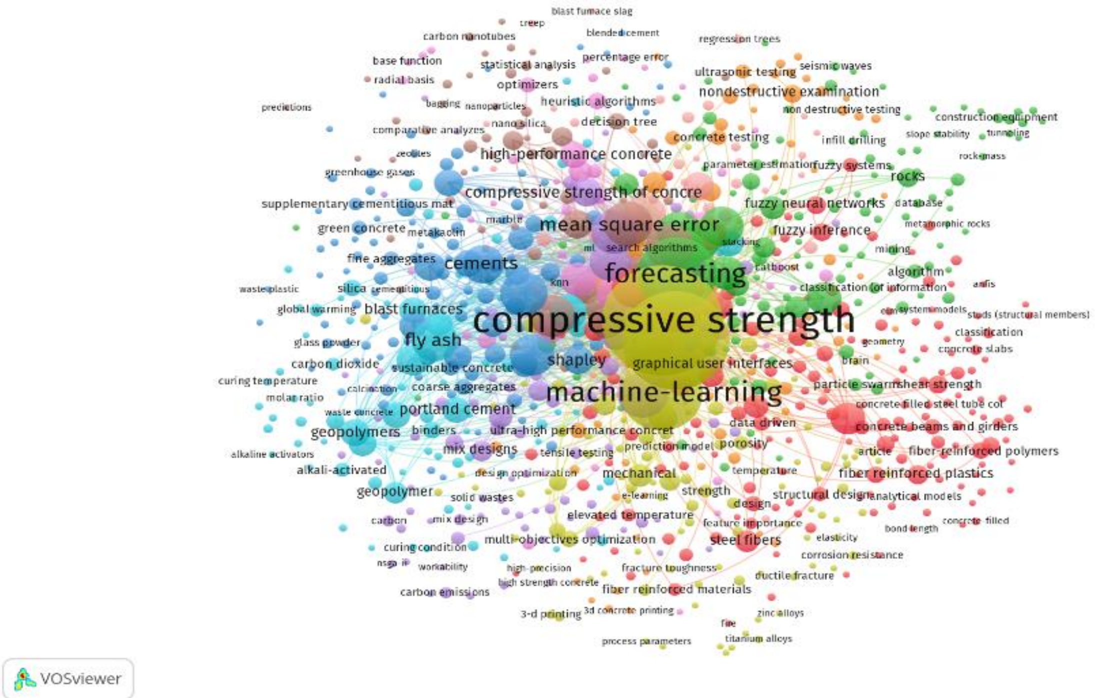

Fig. 6. Publications by keywords.

China exhibited the top contributing country, publishing a total of 576 publications, as illustrated in **Fig. 7.** Additionally, it demonstrated robust collaborative connections with other countries, as shown in **Fig. 8.** In second place, India contributed 340 publications, followed by Saudi Arabia ranked third with 200 publications, as detailed in **Table 4.**

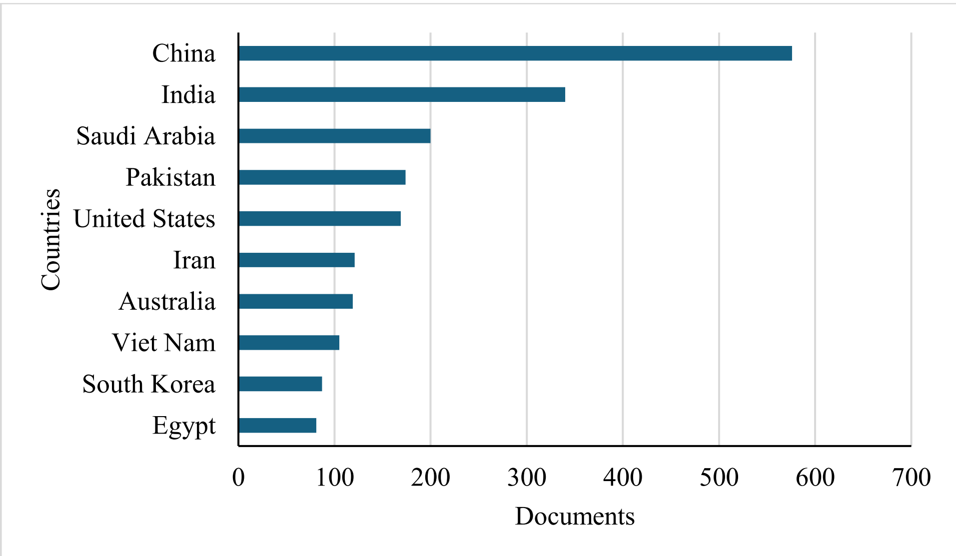

Fig. 7. Most productive countries.

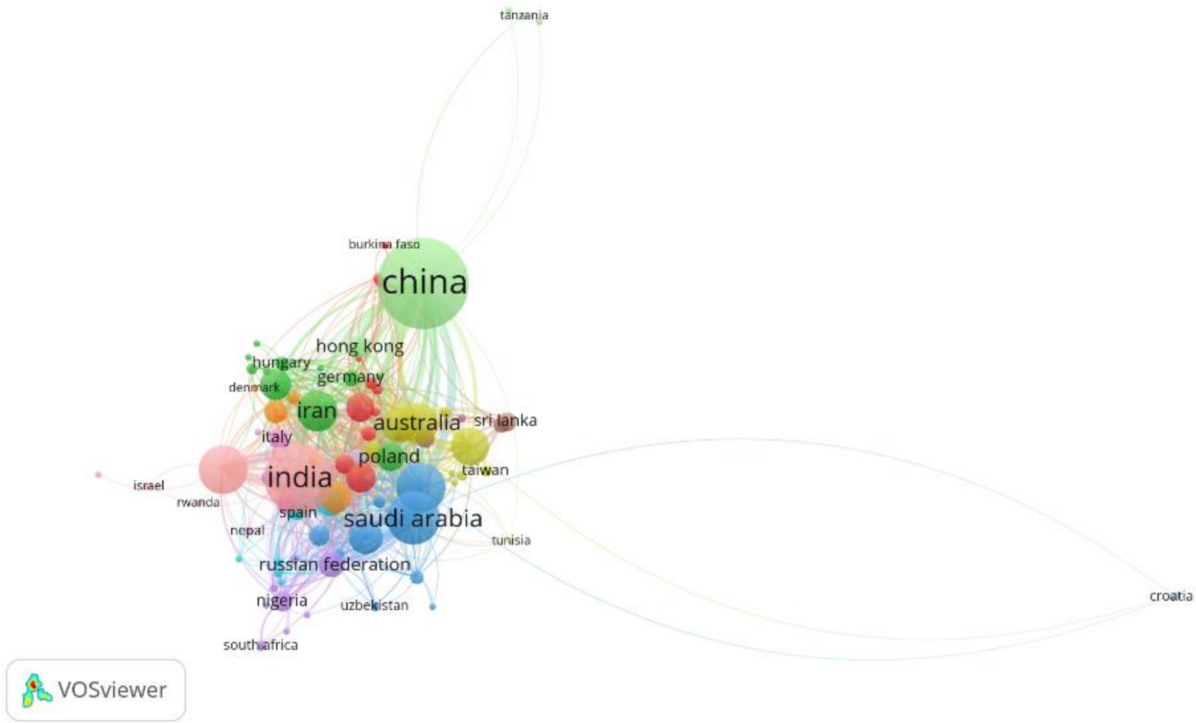

Fig. 8. Co-authorship map of countries.

Table 4. Most Productive Countries

COUNTRY	No of articles
China	576
India	340
Saudi Arabia	200
Pakistan	174
United States	169
Iran	121
Australia	119
Viet Nam	105
South Korea	87
Egypt	81
Canada	69
Malaysia	68
Iraq	64

United Kingdom	63
Poland	60
Turkey	60
Russian Federation	50
Bangladesh	37
Hong Kong	33
Jordan	31
Nigeria	29
Greece	28
Japan	27
Italy	26
Sri Lanka	26
United Arab Emirates	25
Sweden	22
Germany	21
Portugal	20
Thailand	20

The most productive affiliation was "COMSATS University Islamabad, Abbottabad Campus" with 85 articles, followed by "Ministry of Education of the People's Republic of China" with 67 articles and "Prince Sattam Bin Abdulaziz University" with 62 articles as shown in **Fig. 9**.

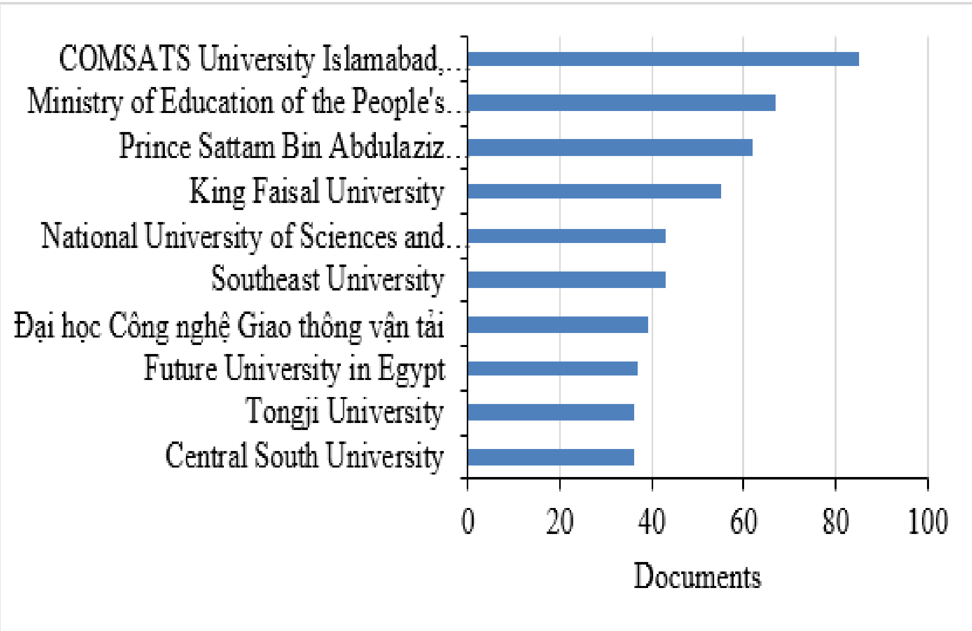

Fig. 9. Top 10 affiliations based on the number of documents.

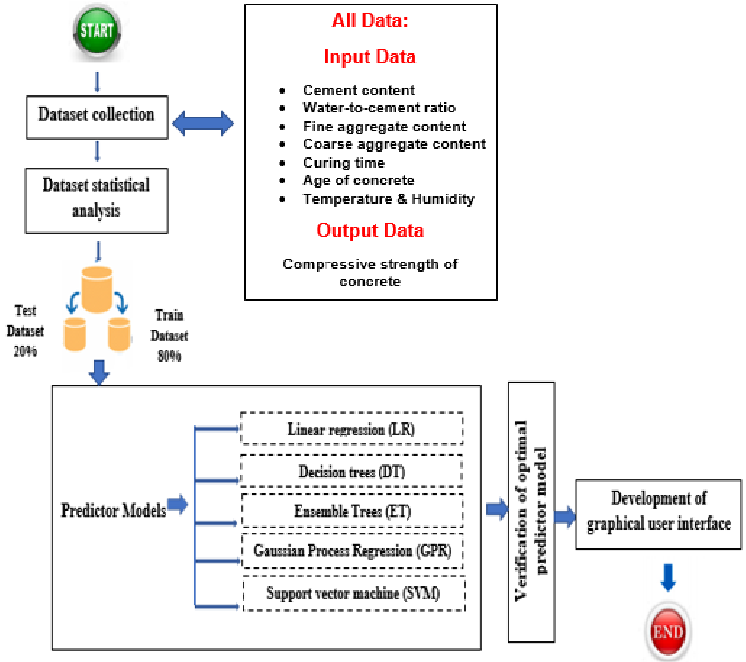

Fig. 10. Flow-work diagram for predicting concrete compressive strength using Machine learning.

The study highlights the need for large, diverse datasets to enhance ML model accuracy. Future research should focus on improving dataset availability, model interpretability, and sustainability. Innovations such as 3D printing and nanomaterials will likely drive advancements, aiding stakeholders in making informed decisions regarding sustainability, policies, and research investments. **Table 5** provides an overview of the benefits and drawbacks of ML techniques.

Table 5. An overview of the benefits and limitations of Machine learning methods.

Method	advantages	disadvantages	Summary
MLR (Multiple Linear Regression)	Quickly estimates linear relationships.	Unable to capture complex nonlinear patterns.	Fast and straightforward.
RF (Random Forest)	Improves accuracy in intricate and nonlinear datasets.	Requires substantial computational resources and processing time.	Suitable for complex, nonlinear patterns.
SVR (Support Vector Regression)	Helps minimize overfitting in nonlinear data.	Difficult to interpret, making it hard to assess variable influence.	Effective for complex, nonlinear patterns.
DT (Decision Tree)	Uses simple rules to explain parameter effects.	Prone to overfitting when too many branches are generated.	Easy to interpret and visualize.
GBR (Gradient Boosting Regression)	Delivers high accuracy for complex datasets.	Computationally intensive, especially with large datasets.	Ensures precision and optimized predictions.
ANN (Artificial Neural Network)	Accurately evaluates the influence of intricate parameters.	Large datasets increase the risk of overfitting and computational cost.	Handles complex, nonlinear relationships.

ANFIS (Adaptive Neuro-Fuzzy Inference System)	Uses fuzzy logic to analysed complex parameter interactions.	Interpretation becomes more challenging as dataset size increases.	Offers hybrid solutions with flexibility.
GEP (Gene Expression Programming)	Effectively models complex variables for precise predictions.	Requires careful parameter tuning for optimal performance.	Ensures high accuracy and refined predictions.

5. Interpretation of Results in Context

5.1. Implications of China's Dominance

The results show that China leads in publication output, contributing 576 of the 1,805 articles analysed. This trend aligns with China's national initiatives, such as the Made in China 2025 and New Infrastructure Plan, which emphasize smart cities, AI-driven construction technologies, and green building practices. These policies have incentivized universities and research institutions to invest heavily in machine learning (ML) applications for structural materials and smart infrastructure. Moreover, substantial government funding and international collaborations have helped position China as a global leader in research on AI-based concrete strength prediction.

5.2. Added Value of ML Compared to Traditional Methods

Traditional empirical models such as multiple linear regression or fixed formulas based on mix design ratios have long been used to estimate concrete compressive strength. However, these methods are often limited in scope and struggle to capture the nonlinear and complex relationships between multiple influencing variables (e.g., curing time, admixtures, environmental factors).

In contrast, machine learning models (e.g., ANN, Random Forest, Gradient Boosting) provide higher predictive accuracy, greater adaptability, and real-time learning potential. These advantages are especially useful for handling big datasets and optimizing mix design in data-rich, time-sensitive construction environments.

By highlighting this contrast, our study not only maps current ML research trends but also reinforces the practical and scientific justification for transitioning from empirical models to data-driven techniques in concrete strength prediction.

6. Comparison with Related Bibliometric Studies

To contextualize the findings of this study, it is useful to compare them with other bibliometric reviews focused on concrete research and the application of Machine learning (ML) in civil engineering. For instance, Abdellatief et al. (2025) [71]conducted a bibliometric review on Machine learning applications in ultra-high-performance concrete (UHPC), analyzing 1,035 documents from the Scopus database. Similar to our study, they found China, India, and Saudi Arabia to be dominant contributors; however, our analysis, based on a broader dataset of 1,805 documents from 2014 to 2025, reveals a more extensive global collaboration network and a wider range of ML techniques being applied.

Another study by Mouhamadou Amar et al. (2025)[41] explored AI-based applications in concrete durability assessment and highlighted neural networks and support vector machines as the most frequently used models. Our review confirms these findings but expands the scope by including recent trends such as gene expression programming (GEP), adaptive neuro-fuzzy inference systems (ANFIS), and ensemble learning approaches, reflecting the evolution of predictive modeling in recent years.

Furthermore, compared to earlier reviews [72], [73]which typically focused on a specific concrete type (e.g., geopolymer or fiber-reinforced concrete), our study provides a more comprehensive domain-level analysis encompassing different concrete compositions, sustainability considerations, and advanced modeling techniques. This broader perspective enables the identification of emerging research hotspots and interdisciplinary integration, particularly with sustainability, nanomaterials, and 3D printing technologies, which have not been sufficiently emphasized in prior bibliometric reviews.

7. Conclusion

The prediction of concrete compressive strength is a critical research area with global significance. Although extensive studies have been conducted, there remains a gap in comprehensive reviews that systematically analyze, summarize and track recent advancements while providing strategic directions for future research. This study aims to bridge that gap by offering valuable insights to advance predictive modelling in concrete strength assessment. Through a detailed analysis, this research contributes to improving safety in practical applications and enhancing work efficiency. Additionally, it provides both theoretical and practical contributions by evaluating Machine learning (ML) models that offer higher prediction accuracy. Identifying these models will support further advancements, ultimately strengthening research and real-world applications in the field of concrete compressive strength prediction.

7.1. Study Contributions

This study conducts an in-depth literature review on predicting concrete compressive strength, categorizing research into six major domains: mechanical properties of concrete, different concrete types, modeling, and analytical techniques, pozzolanic additives, durability, and sustainability. These classifications provide insight into the primary research priorities in strength prediction and the predominant methodologies employed in the field. Research activity in this area has grown steadily since 2020, reaching its peak in 2024, with projections suggesting continued expansion in 2025 and beyond.

Key contributors to this research include China, India, Saudi Arabia, Pakistan, the United States, and Iran, reflecting their active role in advancing sustainable construction materials, environmental impact assessments, and AI-driven applications in engineering. Among the most influential researchers, Nasir Amin and Muhammad Nasir from King Faisal University stand out for their high number of publications and citations, demonstrating their significant impact on the field. Their affiliation with Saudi academic institutions highlights the nation's increasing investment in construction research. Additionally, the journal Construction and Building Materials has emerged as a leading publication, serving as a primary platform for advancements in construction technology.

The study also underscores the growing role of Machine learning (ML) in predicting concrete compressive strength due to its ability to model complex relationships with high accuracy and efficiency. Various ML models, including artificial neural networks (ANN), random forests (RF), gradient boosting regression (GBR), multiple linear regression (MLR), and decision trees (DT), have proven effective in predicting compressive strength. More advanced approaches, such as support vector regression (SVR) and adaptive neuro-fuzzy inference systems (ANFIS), are particularly useful for capturing nonlinear patterns in data. However, certain challenges persist, including high computational demands, difficulties in interpretability, and potential overfitting. Each ML technique has unique strengths and limitations, making the selection of an appropriate model crucial for achieving optimal predictive performance in specific applications.

7.2. Suggestions for Academia and Industry Practice

This study is anticipated to drive advancements in civil engineering, construction materials, and the concrete industry by emphasizing the significance of Machine learning (ML) in predicting concrete compressive strength. Based on the findings, the following key recommendations are proposed to enhance both academic research and industry applications:

- ML models will serve as the foundation for developing more precise and reliable predictive techniques for concrete compressive strength.
- Continuous enhancement of these models will lead to improvements in accuracy, robustness, and real-world applicability.
- This research supports the advancement of non-destructive testing (NDT) methods, fostering their broader adoption in construction settings.
- Digital simulations powered by ML will enable optimized planning and execution of construction projects.
- The study aids in forecasting the strength of concrete containing sustainable materials like recycled aggregates, olivine, and wastewater treatment sludge ash, fostering eco-friendly construction practices.

- Future research will emphasize ML-driven quality control and safety methodologies in construction.
- The datasets used for strength prediction will facilitate further studies on structural strength degradation over time and reinforcement requirements.
- Expanding and diversifying datasets is crucial, especially in cases with limited data availability.
- Time-dependent modeling techniques will be developed to refine predictive accuracy across different concrete aging phases.
- Future research will focus on sustainable approaches to minimize the carbon footprint of concrete production.

- The integration of 3D technology and nanomaterials may lead to the development of novel algorithms and hybrid models for predicting concrete compressive strength.
- ML models will not only enhance predictive accuracy but also improve interpretability, offering deeper insights into the factors influencing compressive strength.

7.3. Limitations of This Study

While this study provides valuable insights, it has several limitations:

- The analysis is based on the Scopus database, chosen for its extensive coverage and credibility. However, some relevant studies may have been omitted due to indexing constraints.
- The study initially identified 2343 articles, but after refining the selection to research explicitly focused on concrete compressive strength prediction, the dataset was reduced to 1805 articles. This narrowing may have excluded some broader or interdisciplinary studies.
- The research specifically focuses on publications from 2014 to March 8, 2025, as the use of ML in concrete compressive strength prediction gained substantial traction post-2014. This timeframe ensures the inclusion of contemporary research but may exclude earlier foundational work.
- The study's bibliometric approach provides insights into research trends, influential authors, and institutions but does not conduct experimental validations of ML models, meaning practical implementation challenges may not be fully addressed.

References

[1] S. Barbhuiya, F. Kanavaris, B. B. Das, and M. Idrees, "Decarbonising cement and concrete production: Strategies, challenges and pathways for sustainable development," *J. Build. Eng.*, vol. 86, no. February, p. 108861, 2024, doi: 10.1016/j.jobe.2024.108861.

[2] M. Ibrahim, B. A. Salami, Z. Khallaf, A. A. Bahraq, and A. A. Adewumi, "Evaluating long-term durability of nanosilica-enhanced alkali-activated concrete in sulfate environments towards sustainable concrete development," *Constr. Build. Mater.*, vol. 438, no. June, p. 137315, 2024, doi: 10.1016/j.conbuildmat.2024.137315.

[3] B. A. Salami *et al.*, "Polymer-enhanced concrete: A comprehensive review of innovations and pathways for resilient and sustainable materials," *Next Mater.*, vol. 4, no. May, p. 100225, 2024, doi: 10.1016/j.nxmate.2024.100225.

[4] M. K. Anwar, M. A. Qurashi, X. Zhu, S. A. R. Shah, and M. U. Siddiq, "A comparative performance analysis of machine learning models for compressive strength prediction in fly ash-based geopolymers concrete using reference data," *Case Stud. Constr. Mater.*, vol. 22, no. August 2024, p. e04207, 2025, doi: 10.1016/j.cscm.2025.e04207.

[5] R. K. Tipu, V. Batra, Suman, K. S. Pandya, and V. R. Panchal, "Efficient compressive strength prediction of concrete incorporating recycled coarse aggregate using Newton's boosted backpropagation neural network (NB-BPNN)," *Structures*, vol. 58, no. November, p. 105559, 2023, doi: 10.1016/j.istruc.2023.105559.

[6] R. Kumar Tipu, V. R. Panchal, and K. S. Pandya, "An ensemble approach to improve BPNN model precision for predicting compressive strength of high-performance concrete," *Structures*, vol. 45, no. September, pp. 500–508, 2022, doi:

10.1016/j.istruc.2022.09.046.

[7] D. Coffetti, E. Crotti, G. Gazzaniga, M. Carrara, T. Pastore, and L. Coppola, "Pathways towards sustainable concrete," *Cem. Concr. Res.*, vol. 154, no. November 2021, p. 106718, 2022, doi: 10.1016/j.cemconres.2022.106718.

[8] S. A. Alavi, M. Noel, F. Moradi, and H. Layssi, "Development of a machine learning model for on-site evaluation of concrete compressive strength by SonReb," *J. Build. Eng.*, vol. 82, no. October 2023, p. 108328, 2024, doi: 10.1016/j.jobe.2023.108328.

[9] A. Shishegaran, H. Varaee, T. Rabczuk, and G. Shishegaran, "High correlated variables creator machine: Prediction of the compressive strength of concrete," *Comput. Struct.*, vol. 247, p. 106479, 2021, doi: 10.1016/j.compstruc.2021.106479.

[10] S. A. Alavi and M. Noel, "Effect of model architecture and input parameters to improve performance of artificial intelligence models for estimating concrete strength using SonReb," *Eng. Struct.*, vol. 323, no. PA, p. 119285, 2025, doi: 10.1016/j.engstruct.2024.119285.

[11] H. Moussa, A. M. B. Elabeidy, and T. Akçaoğlu, "Predicting the compressive strength of rubberized concrete containing silica fume using stacking ensemble learning model," *Constr. Build. Mater.*, vol. 449, no. May, pp. 0–2, 2024, doi: 10.1016/j.conbuildmat.2024.138254.

[12] H. A. Dahish and A. D. Almutairi, "Compressive strength prediction models for concrete containing nano materials and exposed to elevated temperatures," *Results Eng.*, vol. 25, no. January, p. 103975, 2025, doi: 10.1016/j.rineng.2025.103975.

[13] F. Zulkarnain, "Analysis of The Addition Polypropylene Fibre and 8670 Mn Viscocrete added Material on The Split Tensile Strength and Modulus of Elasticity of Concrete," *J. Penelit. Pendidik. IPA*, vol. 9, no. 10, pp. 8798–8806, 2023, doi: 10.29303/jppipa.v9i10.4808.

[14] B. Sankar and P. Ramadoss, "Assessment of mechanical and durability performance of silica fume and metakaolin as cementitious materials in high-performance concrete," *Int. Rev. Appl. Sci. Eng.*, vol. 15, no. 1, pp. 44–54, 2024, doi: 10.1556/1848.2023.00638.

[15] G. Lizia Thankam and N. T. Renganathan, "Ideal supplementary cementing material - Metakaolin: A review," *Int. Rev. Appl. Sci. Eng.*, vol. 11, no. 1, pp. 58–65, 2020, doi: 10.1556/1848.2020.00008.

[16] M. K. Anwar, M. A. Qurashi, X. Zhu, S. A. R. Shah, and M. U. Siddiq, "A comparative performance analysis of machine learning models for compressive strength prediction in fly ash-based geopolymers concrete using reference data," *Case Stud. Constr. Mater.*, vol. 22, no. August 2024, pp. 1–24, 2025, doi: 10.1016/j.cscm.2025.e04207.

[17] Y. Dong *et al.*, "A new method to evaluate features importance in machine-learning based prediction of concrete compressive strength," *J. Build. Eng.*, vol. 102, no. July 2024, pp. 1–21, 2025, doi: 10.1016/j.jobe.2025.111874.

[18] K. Aswed, M. Hassan, and H. Al-Quraishi, "Effects of Curing Temperature and Chemical Admixture Type on Fresh Properties and Compressive Strength of Ultra High-performance Concrete," *Eng. Technol. J.*, vol. 40, no. 11, pp. 1448–1454, 2022, doi: 10.30684/etj.2022.132300.1103.

[19] Q. Tian *et al.*, "Building the future: Smart concrete as a key element in next-generation construction," *Constr. Build. Mater.*, vol. 429, no. March, 2024, doi: 10.1016/j.conbuildmat.2024.136364.

[20] Y. T. Altuncı, "A Comprehensive Study on the Estimation of Concrete Compressive Strength Using Machine Learning Models," *Buildings*, vol. 14, no. 12, 2024, doi: 10.3390/buildings14123851.

[21] "1-s2.0-S2773207X25000284-main.pdf." .

[22] M. Mejdi, M. Saillio, T. Chaussadent, L. Divet, and A. Tagnit-Hamou, "Hydration mechanisms of sewage sludge ashes used as cement replacement," *Cem. Concr. Res.*, vol. 135, no. May, p. 106115, 2020, doi: 10.1016/j.cemconres.2020.106115.

[23] Y. Ji, D. Wang, and J. Wang, "Study of recycled concrete properties and prediction using machine learning methods," *J. Build. Eng.*, vol. 94, no. June, p. 110067, 2024, doi:

10.1016/j.jobe.2024.110067.

[24] D. Shakya, V. Deshpande, M. J. S. Safari, and M. Agarwal, "Performance evaluation of machine learning algorithms for the prediction of particle Froude number (Frn) using hyper-parameter optimizations techniques," *Expert Syst. Appl.*, vol. 256, no. July, p. 124960, 2024, doi: 10.1016/j.eswa.2024.124960.

[25] Y. Zhou, Y. Zhang, R. Pang, and B. Xu, "Seismic fragility analysis of high concrete faced rockfill dams based on plastic failure with support vector machine," *Soil Dyn. Earthq. Eng.*, vol. 144, no. 2, p. 106587, 2021, doi: 10.1016/j.soildyn.2021.106587.

[26] D. Sinkhonde, T. Bezabih, D. Mirindi, D. Mashava, and F. Mirindi, "Ensemble machine learning algorithms for efficient prediction of compressive strength of concrete containing tyre rubber and brick powder," *Clean. Waste Syst.*, vol. 10, no. February, p. 100236, 2025, doi: 10.1016/j.clwas.2025.100236.

[27] M. Saridemir, I. B. Topçu, F. Özcan, and M. H. Severcan, "Prediction of long-term effects of GGBFS on compressive strength of concrete by artificial neural networks and fuzzy logic," *Constr. Build. Mater.*, vol. 23, no. 3, pp. 1279–1286, 2009, doi: 10.1016/j.conbuildmat.2008.07.021.

[28] I. Galan, A. Baldermann, W. Kusterle, M. Dietzel, and F. Mittermayr, "Durability of shotcrete for underground support– Review and update," *Constr. Build. Mater.*, vol. 202, pp. 465–493, 2019, doi: 10.1016/j.conbuildmat.2018.12.151.

[29] A. Hammoudi, K. Moussaceb, C. Belebchouche, and F. Dahmoune, "Comparison of artificial neural network (ANN) and response surface methodology (RSM) prediction in compressive strength of recycled concrete aggregates," *Constr. Build. Mater.*, vol. 209, pp. 425–436, 2019, doi: 10.1016/j.conbuildmat.2019.03.119.

[30] M. R. Kaloop, D. Kumar, P. Samui, J. W. Hu, and D. Kim, "Compressive strength prediction of high-performance concrete using gradient tree boosting machine," *Constr. Build. Mater.*, vol. 264, p. 120198, 2020, doi: 10.1016/j.conbuildmat.2020.120198.

[31] "1-s2.0-S0950061824039333-main.pdf." .

[32] M. Sathurshan, H. Derakhshan, J. Thamboo, J. Gill, C. Inglis, and T. Zahra, "Compressive strength in grouted dry-stack concrete block masonry: Experimental and analytical predictions," *Constr. Build. Mater.*, vol. 467, no. November 2024, p. 140411, 2025, doi: 10.1016/j.conbuildmat.2025.140411.

[33] U. Atici, "Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 9609–9618, 2011, doi: 10.1016/j.eswa.2011.01.156.

[34] E. M. Lotfy, A. M. Gomaa, S. Hosny, A. Sherif, and M. A. Ahmed, "Predicting of Punching Shear Capacity of Corroded Reinforced Concrete Slab-column Joints Using Artificial Intelligence Techniques," doi: 10.4186/ej.20xx.xx.x.xx.

[35] Y. Gao, Z. Li, Y. Li, Z. Zhu, and J. Zhu, "Development of chemistry-informed interpretable model for predicting compressive strength of recycled aggregate concrete containing supplementary cementitious materials," *J. Clean. Prod.*, vol. 425, no. July, p. 138733, 2023, doi: 10.1016/j.jclepro.2023.138733.

[36] S. Ray, M. Haque, T. Ahmed, and T. T. Nahin, "Comparison of artificial neural network (ANN) and response surface methodology (RSM) in predicting the compressive and splitting tensile strength of concrete prepared with glass waste and tin (Sn) can fiber," *J. King Saud Univ. - Eng. Sci.*, vol. 35, no. 3, pp. 185–199, 2023, doi: 10.1016/j.jksues.2021.03.006.

[37] A. Bushenkova, P. M. M. Soares, F. Johannsen, and D. C. A. Lima, "Towards an improved representation of the urban heat island effect : A multi-scale application of XGBoost for madrid," *Urban Clim.*, vol. 55, no. June, p. 101982, 2024, doi: 10.1016/j.uclim.2024.101982.

[38] W. Zhang, D. Liu, and K. Cao, "Prediction of concrete compressive strength using support vector machine regression and non-destructive testing," *Case Stud. Constr.*

Mater., vol. 21, no. June, p. e03416, 2024, doi: 10.1016/j.cscm.2024.e03416.

[39] Q. Li, R. Su, H. Qiao, and L. Su, "Jo u rn a l P of," 2025, doi: 10.1016/j.mtcomm.2025.112080.

[40] H. Monteiro, B. Moura, and N. Soares, "Advancements in nano-enabled cement and concrete: Innovative properties and environmental implications," *J. Build. Eng.*, vol. 56, no. June, p. 104736, 2022, doi: 10.1016/j.jobe.2022.104736.

[41] M. Amar, "Comparative use of different AI methods for the prediction of concrete compressive strength," *Clean. Mater.*, vol. 15, no. November 2024, p. 100299, 2025, doi: 10.1016/j.clema.2025.100299.

[42] B. I. Bulgakov, V. Q. D. Nguyen, A. V. Aleksandrova, O. A. Larsen, and N. A. Galtseva, "High-performance concrete produced with locally available materials," *Mag. Civ. Eng.*, vol. 117, no. 1, 2023, doi: 10.34910/MCE.117.2.

[43] P. Bober, K. Zgodavová, M. Čička, M. Mihaliková, and J. Brindza, "Predictive Quality Analytics of Surface Roughness in Turning Operation Using Polynomial and Artificial Neural Network Models," *Processes*, vol. 12, no. 1, 2024, doi: 10.3390/pr12010206.

[44] I. Izonin, R. Tkachenko, O. Berezsky, I. Krak, M. Kováč, and M. Fedorchuk, "Improvement of the ANN-Based Prediction Technology for Extremely Small Biomedical Data Analysis," *Technologies*, vol. 12, no. 7, 2024, doi: 10.3390/technologies12070112.

[45] M. Adamu, S. Chhetri, S. Das, P. Saha, and Y. E. Ibrahim, "An explainable boosting-based ensemble machine learning model for predicting the properties of date palm fiber reinforced concrete," vol. 44, no. February, pp. 1–24, 2025.

[46] A. M. Gomaa, E. M. Lotfy, S. A. Khafaga, S. Hosny, and A. Manar, "Advanced Sciences and Technology Studying the Effect of RC Slab Corrosion on Punching Behavior Using Artificial Neural Networks," vol. 1, 2024.

[47] D. Van Dao, H. Ly, S. H. Trinh, T. Le, and B. T. Pham, "Artificial Intelligence Approaches for Prediction of Compressive Strength of Geopolymer Concrete," 2019, doi: 10.3390/ma12060983.

[48] A. M. Gomaa *et al.*, "Comparative study of models predicting punching shear capacity of strengthened corroded RC slab- column joints," *HBRC J.*, vol. 20, no. 1, pp. 257–274, 2024, doi: 10.1080/16874048.2024.2310936.

[49] A. M. Gomaa, E. M. Lotfy, S. A. Khafaga, S. Hosny, and M. A. Ahmed, "Experimental , numerical , and theoretical study of punching shear capacity of corroded reinforced concrete slab-column joints," *Eng. Struct.*, vol. 289, no. May, p. 116280, 2023, doi: 10.1016/j.engstruct.2023.116280.

[50] A. R. Ghanizadeh, H. Abbaslou, A. T. Amlashi, and P. Alidoust, "Modeling of bentonite/sepiolite plastic concrete compressive strength using artificial neural network and support vector machine," *Front. Struct. Civ. Eng.*, vol. 13, no. 1, pp. 215–239, 2019, doi: 10.1007/s11709-018-0489-z.

[51] F. Farooq and M. N. Amin, "applied sciences A Comparative Study of Random Forest and Genetic Engineering Programming for the Prediction of Compressive Strength of High Strength Concrete."

[52] V. Stoyanov, V. Petkova, K. Mihaylova, and M. Shopska, "A Study of the Influence of Thermoactivated Natural Zeolite on the Hydration of White Cement Mortars," *Materials (Basel).*, vol. 17, no. 19, 2024, doi: 10.3390/ma17194798.

[53] J. Bian, R. Huo, Y. Zhong, and Z. Guo, "XGB-Northern Goshawk Optimization: Predicting the Compressive Strength of Self-Compacting Concrete," *KSCE J. Civ. Eng.*, vol. 28, no. 4, pp. 1423–1439, 2024, doi: 10.1007/s12205-024-1647-6.

[54] J. Wang, Y. Xie, T. Guo, and Z. Du, "Predicting the Influence of Soil–Structure Interaction on Seismic Responses of Reinforced Concrete Frame Buildings Using Convolutional Neural Network," *Buildings*, vol. 13, no. 2, 2023, doi: 10.3390/buildings13020564.

[55] K. Meena and S. Luhar, "Effect of wastewater on properties of concrete," *J. Build. Eng.*, vol. 21, no. 4, pp. 106–112, 2019, doi: 10.1016/j.jobe.2018.10.003.

[56] A. M. Mansor, A. M. M. Hamed, and R. P. Borg, "Effect of Silica Fume on High Performance Concrete Strength."

[57] M. J. Page *et al.*, "The PRISMA 2020 statement : An updated guideline for reporting systematic reviews Asbj ø rn Hr o," vol. 88, no. March, 2021, doi: 10.1016/j.ijsu.2021.105906.

[58] J. Martí-parreño, D. Seguí-mas, and E. Seguí-mas, "Teachers ' Attitude towards and Actual Use of Gamification," *Procedia - Soc. Behav. Sci.*, vol. 228, no. June, pp. 682–688, 2016, doi: 10.1016/j.sbspro.2016.07.104.

[59] H. Abuhassna and N. Yahaya, "Paper-Strategies for Successful Blended Learning-A Bibliometric Analysis and Reviews Strategies for Successful Blended Learning-A Bibliometric Analysis and Reviews Strategies for Successful Blended Learning — A Bibliometric Analysis and Reviews," no. July, 2022, doi: 10.3991/ijim.v16i13.30739.

[60] H. Abuhassna, F. Awae, K. Bayoumi, and D. U. Alzitawi, "Understanding Online Learning Readiness among University Students : A Bibliometric Analysis," vol. 16, no. 13, pp. 81–94, 2022.

[61] X. Chen, G. Yu, G. Cheng, and T. Hao, "technology over the past 40 years : a bibliometric analysis," *J. Comput. Educ.*, vol. 6, no. 4, pp. 563–585, 2019, doi: 10.1007/s40692-019-00149-1.

[62] M. Abdellatief, Y. M. Hassan, M. T. Elnabwy, L. S. Wong, R. J. Chin, and K. H. Mo, "Investigation of machine learning models in predicting compressive strength for ultra-high-performance geopolymer concrete: A comparative study," *Constr. Build. Mater.*, vol. 436, no. June, p. 136884, 2024, doi: 10.1016/j.conbuildmat.2024.136884.

[63] M. S. Rana, M. M. Hossain, and F. Li, "Comparative analysis of machine learning models for predicting the compressive strength of ultra-high-performance steel fiber reinforced concrete," *J. Eng. Res.*, no. September 2024, 2025, doi: 10.1016/j.jer.2025.01.004.

[64] N. Miyan, N. M. A. Krishnan, and S. Das, "Integrating data imputation and augmentation with interpretable machine learning for efficient strength prediction of fly ash-based alkali-activated concretes," *J. Build. Eng.*, vol. 98, no. September, p. 111248, 2024, doi: 10.1016/j.jobe.2024.111248.

[65] Y. Shao *et al.*, "Comprehensive Utilization of Industry By-Products in Precast Concrete: A Critical Review from the Perspective of Physicochemical Characteristics of Solid Waste and Steam Curing Conditions," *Materials (Basel).*, vol. 17, no. 19, 2024, doi: 10.3390/ma17194702.

[66] A. C. Through, "Optimized Machine Learning Model for Predicting Compressive," pp. 1–34, 2024.

[67] J. de-Prado-Gil, C. Palencia, N. Silva-Monteiro, and R. Martínez-García, "To predict the compressive strength of self compacting concrete with recycled aggregates utilizing ensemble machine learning models," *Case Stud. Constr. Mater.*, vol. 16, no. April, p. e01046, 2022, doi: 10.1016/j.cscm.2022.e01046.

[68] K. AL-Bukhaiti, Y. Liu, S. Zhao, and H. Abas, "An Application of BP Neural Network to the Prediction of Compressive Strength in Circular Concrete Columns Confined with CFRP," *KSCE J. Civ. Eng.*, vol. 27, no. 7, pp. 3006–3018, 2023, doi: 10.1007/s12205-023-1542-6.

[69] H. Y. Jaramillo, J. A. Gómez Camperos, and N. Afanador García, "Development of a Non-Structural Prefabricated Panel Based on Construction and Demolition Waste for Sustainable Construction," *Infrastructures*, vol. 9, no. 8, 2024, doi: 10.3390/infrastructures9080135.

[70] S. H. Park, H. S. Ryu, and W. J. Park, "Influence of Unit Water Content Control on Concrete Performance in the Ready-Mixed Concrete Production Process," *Materials (Basel).*, vol. 17, no. 4, 2024, doi: 10.3390/ma17040834.

[71] M. Abdellatief, G. Murali, and S. Dixit,

"Leveraging machine learning to evaluate the effect of raw materials on the compressive strength of ultra-high-performance concrete," *Results Eng.*, vol. 25, no. January, 2025, doi: 10.1016/j.rineng.2025.104542.

[72] I. Y. Hakeem, O. Zaid, M. M. Arbili, M. Alyami, A. Alhamami, and M. Alharthai, "A state-of-the-art review of the physical and durability characteristics and microstructure behavior of ultra-high-performance geopolymer concrete," *Heliyon*, vol. 10, no. 2, p. e24263, 2024, doi: 10.1016/j.heliyon.2024.e24263.

[73] M. Amar, "Comparative use of different AI methods for the prediction of concrete compressive strength," *Clean. Mater.*, vol. 15, no. November 2024, 2025, doi: 10.1016/j.clema.2025.100299.