iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** X **Month of publication:** October 2026

DOI: https://doi.org/10.22214/ijraset.2026.85310

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue X Oct 2026- Available at www.ijraset.com

Recent Advances in Sustainable Construction Materials and the Applications of Machine Learning in Construction Technology

Satej Shingan
Department of Civil Engineering, Pimpri Chinchwad College of Engineering and Research (affiliated to Savitribai Phule Pune University), Ravet, Pune 412101, Maharashtra, India

Abstract: ***The construction sector must reduce the environmental burden of its materials while keeping structures safe, durable and affordable. Sustainable construction materials—supplementary cementitious materials (SCMs), agricultural ashes, recycled aggregates, waste-derived fillers, fibres, polymer modifiers and bio-mediated self-healing systems—offer ways to cut clinker use, conserve natural resources and divert waste from landfill. Their performance, however, is sensitive to source variability, processing, dosage, curing and exposure, which makes mixture design and quality control harder than for conventional concrete. Machine learning (ML) can help by learning the nonlinear links between composition, processing and performance from experimental data. This review summarises recent advances in the main families of sustainable materials and examines how ML is being applied across construction technology: predicting strength and durability, optimising low-carbon mixtures, building fast surrogates of structural response and automating inspection. The review finds that the value of ML depends more on data quality, representative material variability and honest validation than on the choice of algorithm, and that sustainability claims should be judged on a functional, life-cycle basis rather than on waste content alone. A simple integrated framework linking material characterisation, testing, ML and environmental assessment is proposed, and priorities for future research are identified.***

Keywords: Sustainable construction materials; Supplementary cementitious materials; Recycled aggregate; Waste marble; Self-healing concrete; Machine learning; Construction technology; Life-cycle assessment.

I. INTRODUCTION

Concrete is the most widely used construction material, and Portland cement is its most carbon-intensive ingredient. Clinker production releases carbon dioxide both from fuel combustion and from the calcination of limestone, so reducing clinker content is one of the most effective levers available to the industry [1]. At the same time, extraction of natural sand and aggregate and the disposal of construction and demolition waste place further pressure on resources and land [2]. Sustainable construction therefore involves several actions together: partially replacing cement with SCMs, reusing waste streams as aggregates or fillers, extending service life through better durability, and assessing impacts over the whole life of a structure.

Many alternative materials are now available, but each brings uncertainty. Ashes, slags and recycled aggregates vary from source to source; fibres and polymers change fresh and hardened behaviour in ways that depend on dosage and dispersion; and self-healing systems depend on biological activity that is difficult to control [3, 4]. Designing with such materials traditionally requires many trial batches and long-term tests. Machine learning offers a complementary route. Since early neural-network models of high-performance concrete strength [5], ML has been used to predict mechanical properties, durability indicators and structural response from data, and to search for mixtures that balance performance, cost and carbon [6–8]. In wider construction technology, deep learning is also being used for crack detection and inspection [9, 10].

This review brings the two themes together: Section 3 reviews sustainable material families, Section 4 examines ML applications, and Sections 5–7 present an integrated framework, environmental assessment and research gaps.

II. REVIEW APPROACH

This is a narrative review intended to give engineers and students an accessible overview of the field. Peer-reviewed articles and reviews were identified through Google Scholar and publisher databases using combinations of the terms *sustainable concrete*, *supplementary cementitious material*, *rice husk ash*, *recycled aggregate*, *waste marble*, *fibre-reinforced concrete*, *polymer-modified*

©IJRASET: All Rights are Reserved

concrete, *self-healing concrete*, *machine learning*, *compressive strength prediction*, *durability prediction* and *life-cycle assessment*. Priority was given to review articles and to experimental studies that reported their materials and methods clearly. Only sources with complete and verifiable bibliographic details were retained.

III. ADVANCES IN SUSTAINABLE CONSTRUCTION MATERIALS

A. *Supplementary cementitious materials and agricultural ashes*

SCMs reduce clinker demand and refine the pore structure through pozzolanic or latent hydraulic reactions. Fly ash and ground-granulated blast-furnace slag have the longest track record. High-volume Class F fly ash concrete typically gains strength more slowly at early ages but can match or exceed plain concrete at later ages, with lower permeability and heat of hydration [11]. Eco-efficient cement strategies built on such materials, together with calcined clays and limestone, are considered among the most practical options for lowering cement-related emissions at scale [1].

Agricultural ashes provide a local, low-cost alternative in regions where industrial by-products are scarce. Rice husk ash (RHA) burnt under controlled conditions is rich in amorphous silica and can replace part of the cement while improving later-age strength and resistance to chloride penetration [12]. Uncontrolled burning, however, leaves unburnt carbon and crystalline silica, increasing water demand and lowering reactivity [13]. The main lesson is that the benefit of an SCM depends on its chemistry, fineness and processing, so replacement levels from one study should not be adopted elsewhere without testing.

B. *Recycled aggregates and waste-derived materials*

Recycled concrete aggregate reduces demand for natural aggregate and diverts demolition waste. Its adhered mortar gives higher porosity and water absorption, which can weaken the interfacial transition zone and reduce strength and durability unless mixtures are adjusted [2]. Sustainability assessments show that the environmental benefit of recycled-aggregate concrete depends strongly on transport distances, processing energy and whether additional cement is needed to reach the target strength [14].

Waste marble from cutting and polishing is another widely available stream. Marble dust used as a partial cement replacement acts mainly as a filler and can maintain strength at low replacement levels [15, 16]. Sathe et al. examined waste marble as a partial replacement of both cement and fine aggregate and linked the mechanical and durability results to microstructural observations, showing that moderate replacement can densify the matrix while higher levels reduce performance [17]. Reviews confirm that particle size, replacement basis and dosage control the outcome [18, 19].

C. *Fibres and polymer modifiers*

Fibres control cracking and improve toughness and impact resistance, although their effect depends on fibre type, geometry, volume fraction and dispersion [20, 21]. Polypropylene fibres are popular because they are cheap, chemically inert and effective against plastic-shrinkage cracking. Kudoli et al. systematically reviewed polypropylene fibre-reinforced concrete and found that low dosages generally improve flexural and splitting tensile strength and reduce permeability-related deterioration, whereas excessive dosages impair workability and compaction [3].

Polymer modifiers change cohesion, adhesion and water resistance by forming films within the cement paste [22]. Kudoli studied concrete modified with a commercial polyvinyl-acetate adhesive (Fevicol) and reported changes in workability and strength with dosage [23]. Such results apply to the specific product tested; other polymer formulations should be evaluated separately before structural use.

D. *Bio-mediated self-healing concrete*

Self-healing concrete uses bacteria that precipitate calcium carbonate in cracks, sealing ingress paths and potentially extending service life [24, 25]. Guddad et al. incorporated *Bacillus subtilis* into concrete and reported improvements in both mechanical performance and resistance to chemical attack through microbially induced calcite precipitation [4]. Practical challenges remain: bacterial survival in the alkaline matrix, nutrient supply, the maximum crack width that can be healed and the cost of the healing agent [26]. Field evidence over long periods is still limited.

E. *Material selection as a multi-criteria problem*

Table 1 summarises the main material families. No single material is best for every application. A mixture with the lowest cement content is not necessarily the most sustainable if it needs energy-intensive processing, extra transport or more frequent repair. Selection should therefore consider strength, durability, cost, local availability and environmental impact together.

Table 1. Summary of sustainable construction materials, their benefits and their main limitations.

Material family	Main benefits	Main limitations	Key refs.
Fly ash, slag	Lower clinker use; denser pores; lower heat	Slow early strength; regional supply	[1, 11]
Rice husk ash	Local, reactive silica; better chloride resistance	Variable burning; higher water demand	[12, 13]
Recycled aggregate	Saves natural aggregate; diverts waste	High absorption; weaker transition zone	[2, 14]
Waste marble	Filler effect; uses stone-industry waste	Strength loss at high replacement	[15, 17]
Polypropylene fibres	Crack control; toughness	Lower workability at high dosage	[3, 21]
Polymer modifiers	Cohesion; water resistance	Product-specific results; cost	[22, 23]
Bacterial self-healing	Crack sealing; longer service life	Bacterial survival; limited field data	[4, 25]

IV. MACHINE LEARNING IN CONSTRUCTION TECHNOLOGY

A. *Algorithms and data*

The ML methods most often used for construction materials are artificial neural networks, support vector regression, decision trees, random forests and gradient-boosting ensembles [6, 27]. Random forests and boosted trees perform well on the small, tabular datasets typical of concrete research and are relatively robust to noise [28]. Inputs usually include binder and SCM contents, water–binder ratio, aggregate proportions, admixture dosage, curing age and, increasingly, material properties such as fineness or oxide composition. No algorithm is universally superior; the size, quality and coverage of the data matter more.

B. *Predicting mechanical properties*

Compressive strength is the most common target because it is measured in nearly every study. Kudoli and Bala compared ML with traditional empirical and regression models for predicting the physical and mechanical properties of cement and cement mortar, and showed that ML captures nonlinear effects of composition and curing that classical equations miss, provided the data are sufficient and well documented [8]. Reviews of self-compacting and sustainable concretes report similar findings [7, 29]. Young et al. cautioned, using a large industrial dataset, that mixture proportions alone limit how accurately strength can be predicted, whatever the algorithm [30]. Reporting several error measures and testing on genuinely new mixtures is therefore essential.

C. *Predicting durability*

Durability is harder to model than strength because exposure conditions, test methods and timescales differ widely, and suitable datasets are small [31]. Vishwanath et al. combined freeze–thaw experiments on sustainable concrete with AI/ML-based prediction of damage, illustrating how measured deterioration mechanisms can guide the choice of model inputs [32]. Models trained on laboratory freeze–thaw cycles still need calibration before they are used to estimate field service life.

D. *Mixture optimisation for low-carbon concrete*

Once a reliable predictive model exists, optimisation algorithms can search for mixtures that meet a target strength at minimum cost or embodied carbon [7, 33]. This can reduce the number of laboratory trial batches. However, optimisers tend to push towards the edges of the data, where predictions are least reliable, so recommended mixtures must be checked against standards and confirmed experimentally.

E. *Structural response and inspection*

ML is also used beyond materials. Numerical simulations of structural response generate data from which fast surrogate models can be trained. Gudadappanavar et al. used explicit-dynamics analysis to map the response of reinforced-concrete frames to TNT blast as a function of stand-off distance, charge weight and incidence angle [34]; parametric studies of this kind provide the training data needed for ML surrogates of blast response [35]. In construction practice, convolutional neural networks detect cracks from images [9], and computer vision is being adopted for inspection and monitoring of civil infrastructure [10].

F. *Interpretability and trust*

Explanation methods such as SHAP values show which inputs drive a prediction and help engineers spot implausible behaviour [36]. For decisions that affect safety, simpler interpretable models are often preferable to complex black-box models with similar accuracy [37]. A useful model should also state the range of materials for which it is valid.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

V. AN INTEGRATED FRAMEWORK

The greatest benefit comes from combining material science, testing and ML rather than using any one in isolation. Figure 1 shows a simple framework. It starts with documenting the material source and processing, followed by characterisation (particle size, oxide composition, microstructure), standardised testing and the assembly of a consistent dataset. Models are then trained, validated on independent data and explained, and candidate mixtures are compared against technical, economic and environmental criteria before experimental confirmation.

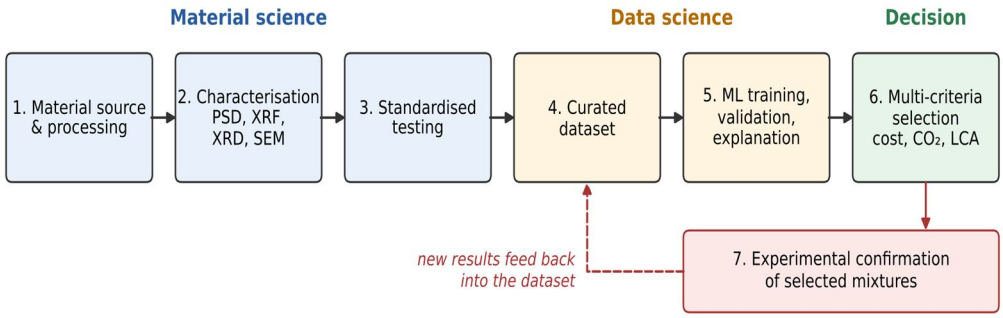


Fig. 1. Integrated framework linking sustainable material characterisation, testing, machine learning and life-cycle assessment for construction-material decisions.

Microstructural studies such as the waste-marble work of Sathe et al. [17] help explain why similar waste materials behave differently and indicate which descriptors models need. Likewise, fibre dosage, polymer content and bacterial concentration must be explicit model inputs if predictions are to cover those materials [3, 4, 23].

VI. ENVIRONMENTAL ASSESSMENT

Sustainability should be demonstrated, not assumed from waste content. Life-cycle assessment accounts for raw-material extraction, processing, transport, construction, maintenance and end of life. Comparisons must use a common functional unit—for example, a volume of concrete with a defined strength and service life—otherwise a low-carbon mix with poorer durability may appear better than it is [14]. The availability of by-products such as fly ash and slag is also changing as coal power and steelmaking evolve, which affects long-term planning [1].

VII. RESEARCH GAPS AND FUTURE DIRECTIONS

Several gaps recur in the literature:

1) Fragmented data. Datasets differ in materials, test standards and reporting, which limits model transfer between laboratories and regions [27].
2) Overstated accuracy. Small datasets and random train–test splits can make models look more general than they are [30].
3) Focus on strength. Durability, service life and field performance receive far less attention than compressive strength [31].
4) Incomplete material description. Waste-derived materials are often characterised inconsistently, so their variability is not captured in models.
5) Separate treatment of sustainability. Environmental and cost objectives are rarely linked with technical predictions.

Future work should develop shared datasets with full material, curing and testing information; validate models across laboratories; combine prediction with uncertainty estimates and physical knowledge; link mechanical, durability and life-cycle objectives in optimisation; and confirm optimised mixtures in the laboratory and in field trials.

VIII. CONCLUSIONS

Sustainable construction materials can reduce cement use, conserve natural resources and divert waste, but their benefits depend on material quality, processing, dosage and service life. SCMs and agricultural ashes, recycled aggregates, waste marble, fibres, polymers and bacterial self-healing systems each offer clear advantages alongside practical limitations, and none is universally best. Machine learning is now applied across construction technology—to predict strength and durability, optimise low-carbon mixtures, build fast structural surrogates and automate inspection.

©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

Its usefulness depends on representative data, honest validation and interpretable outputs rather than on algorithm complexity. An integrated approach that combines characterisation, standardised testing, validated ML and life-cycle assessment offers the most reliable path towards construction materials that are both high-performing and genuinely sustainable. ML should be treated as a decision-support tool that complements experiments and engineering judgement.

A. Declaration of competing interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

B. Funding and data availability

This research received no specific grant from any funding agency. No new data were generated; all information discussed is available in the cited literature.

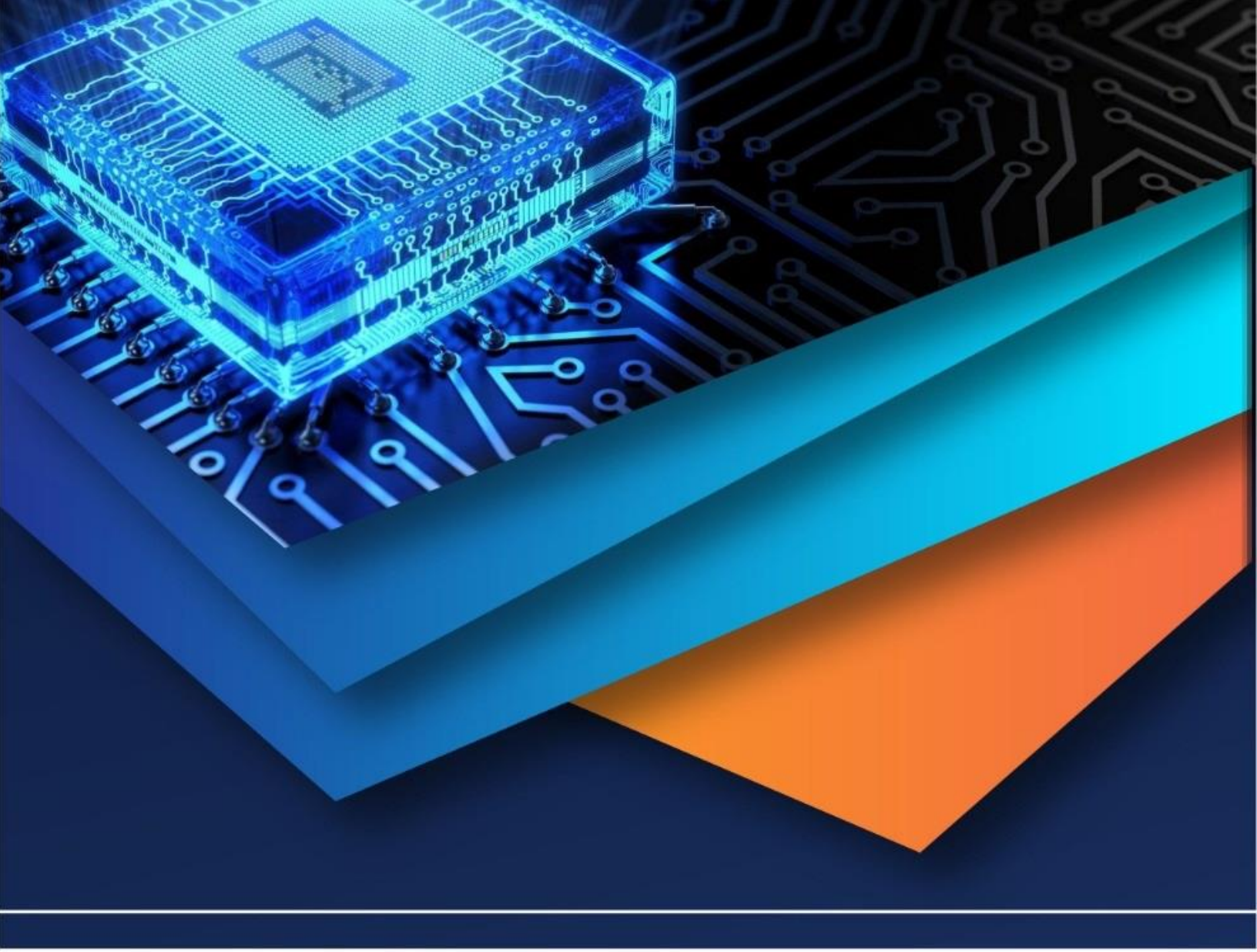
C. Declaration of generative AI use

During the preparation of this work the author used Catgut to assist with language editing, structuring and preparation of the conceptual figure. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

REFERENCES

[1] K.L. Scrivener, V.M. John, E.M. Gartner, Eco-efficient cements: potential economically viable solutions for a low-CO2 cement-based materials industry, Cem. Concr. Res. 114 (2018) 2–26. https://doi.org/10.1016/j.cemconres.2018.03.015
[2] R.V. Silva, J. de Brito, R.K. Dhir, Properties and composition of recycled aggregates from construction and demolition waste suitable for concrete production, Constr. Build. Mater. 65 (2014) 201–217. https://doi.org/10.1016/j.conbuildmat.2014.04.117
[3] A.B. Kudoli, R.S. Patil, M.M. Yeole, Recent advances in polypropylene fibre-reinforced concrete: a systematic review on mechanical characteristics and durability performance, J. Mines Met. Fuels 73 (2025) 2887–2896. https://doi.org/10.18311/jmmf/2025/49411
[4] M.V. Guddad, M. Selvakumar, G.M. Basavanagowda, M.M. Yeole, D.B. Firake, Y. Dibdalli, P. Sunagar, Microbially induced calcite precipitation (MICP)-based bio-mediated self-repairing concrete incorporating Bacillus subtilis: mechanical performance and chemical durability enhancement, SSRG Int. J. Civ. Eng. 13 (8) (2026) 362–374. https://doi.org/10.14445/23488352/IJCE-V13I8P122
[5] I.-C. Yeh, Modeling of strength of high-performance concrete using artificial neural networks, Cem. Concr. Res. 28 (12) (1998) 1797–1808. https://doi.org/10.1016/S0008-8846(98)00165-3
[6] W. Ben Chaabene, M. Flah, M.L. Nehdi, Machine learning prediction of mechanical properties of concrete: critical review, Constr. Build. Mater. 260 (2020) 119889. https://doi.org/10.1016/j.conbuildmat.2020.119889
[7] S. Wang, P. Xia, K. Chen, F. Gong, H. Wang, Q. Wang, Y. Zhao, W. Jin, Prediction and optimization model of sustainable concrete properties using machine learning, deep learning and swarm intelligence: a review, J. Build. Eng. 80 (2023) 108065. https://doi.org/10.1016/j.jobe.2023.108065
[8] A.B. Kudoli, A. Bala, A comprehensive review of machine learning and traditional models for predicting the physical and mechanical properties of cement and cement mortar, J. Mines Met. Fuels 73 (2025) 2923–2931. https://doi.org/10.18311/jmmf/2025/49408
[9] Y.-J. Cha, W. Choi, O. Büyüköztürk, Deep learning-based crack damage detection using convolutional neural networks, Comput.-Aided Civ. Infrastruct. Eng. 32 (5) (2017) 361–378. https://doi.org/10.1111/mice.12263
[10] B.F. Spencer Jr., V. Hoskere, Y. Narazaki, Advances in computer vision-based civil infrastructure inspection and monitoring, Engineering 5 (2) (2019) 199–222. https://doi.org/10.1016/j.eng.2018.11.030
[11] R. Siddique, Performance characteristics of high-volume Class F fly ash concrete, Cem. Concr. Res. 34 (3) (2004) 487–493. https://doi.org/10.1016/j.cemconres.2003.09.002
[12] B.S. Thomas, Green concrete partially comprised of rice husk ash as a supplementary cementitious material – a comprehensive review, Renew. Sustain. Energy Rev. 82 (2018) 3913–3923. https://doi.org/10.1016/j.rser.2017.10.081
[13] B.A. Tayeh, R. Alyousef, H. Alabduljabbar, A.M. Alaskar, Recycling of rice husk waste for a sustainable concrete: a critical review, J. Clean. Prod. 312 (2021) 127734. https://doi.org/10.1016/j.jclepro.2021.127734
[14] S. Marinković, I. Josa, S. Braymand, N. Tošić, Sustainability assessment of recycled aggregate concrete structures: a critical view on the current state-of-knowledge and practice, Struct. Concr. 24 (2) (2023) 1956–1979. https://doi.org/10.1002/suco.202201245
[15] A.A. Aliabdo, A.E.M. Abd Elmoaty, E.M. Auda, Re-use of waste marble dust in the production of cement and concrete, Constr. Build. Mater. 50 (2014) 28–41. https://doi.org/10.1016/j.conbuildmat.2013.09.005
[16] A. Ergün, Effects of the usage of diatomite and waste marble powder as partial replacement of cement on the mechanical properties of concrete, Constr. Build. Mater. 25 (2) (2011) 806–812. https://doi.org/10.1016/j.conbuildmat.2010.07.002
[17] S. Sathe, M. Sonawane, M. Yeole, S. Shekokar, P.D. Gunaware, Effects of waste marble as partial replacement of cement and fine aggregate on the mechanical, durability and microscopic properties of concrete, Mag. Concr. Res. 78 (17–18) (2026) 1064–1088. https://doi.org/10.1680/jmacr.25.00443
[18] B. Prakash, T.J. Saravanan, K.I.S.A. Kabeer, K. Bisht, Exploring the potential of waste marble powder as a sustainable substitute to cement in cement-based composites: a review, Constr. Build. Mater. 401 (2023) 132887. https://doi.org/10.1016/j.conbuildmat.2023.132887

[19] O. Turk, S. Yehia, A. Abdelfatah, M. Elchalakani, Sustainable concrete production: the potential of utilizing recycled waste materials, J. Build. Eng. 98 (2024) 111467. https://doi.org/10.1016/j.jobe.2024.111467
[20] R.F. Zollo, Fiber-reinforced concrete: an overview after 30 years of development, Cem. Concr. Compos. 19 (2) (1997) 107–122. https://doi.org/10.1016/S0958-9465(96)00046-7
[21] J. Ahmad, Z. Zhou, Mechanical properties of natural as well as synthetic fiber reinforced concrete: a review, Constr. Build. Mater. 333 (2022) 127353. https://doi.org/10.1016/j.conbuildmat.2022.127353
[22] Y. Ohama, Polymer-based admixtures, Cem. Concr. Compos. 20 (2–3) (1998) 189–212. https://doi.org/10.1016/S0958-9465(97)00065-6
[23] A.B. Kudoli, To study the properties of concrete by adding Fevicol, Int. J. Res. Appl. Sci. Eng. Technol. 5 (11) (2017) 2063–2066. https://doi.org/10.22214/ijraset.2017.11298
[24] H.M. Jonkers, A. Thijssen, G. Muyzer, O. Copuroglu, E. Schlangen, Application of bacteria as self-healing agent for the development of sustainable concrete, Ecol. Eng. 36 (2) (2010) 230–235. https://doi.org/10.1016/j.ecoleng.2008.12.036
[25] N. De Belie, E. Gruyaert, A. Al-Tabbaa, P. Antonaci, C. Baera, D. Bajare, et al., A review of self-healing concrete for damage management of structures, Adv. Mater. Interfaces 5 (17) (2018) 1800074. https://doi.org/10.1002/admi.201800074
[26] K. Vijay, M. Murmu, S.V. Deo, Bacteria based self healing concrete – A review, Constr. Build. Mater. 152 (2017) 1008–1014. https://doi.org/10.1016/j.conbuildmat.2017.07.040
[27] I. Nunez, A. Marani, M. Flah, M.L. Nehdi, Estimating compressive strength of modern concrete mixtures using computational intelligence: a systematic review, Constr. Build. Mater. 310 (2021) 125279. https://doi.org/10.1016/j.conbuildmat.2021.125279
[28] L. Breiman, Random forests, Mach. Learn. 45 (1) (2001) 5–32. https://doi.org/10.1023/A:1010933404324
[29] S. Terlumun, M.E. Onyia, F.O. Okafor, Predicting the compressive strength of self-compacting concrete using artificial intelligence techniques: a review, AI Civ. Eng. 3 (1) (2024) 14. https://doi.org/10.1007/s43503-024-00029-3
[30] B.A. Young, A. Hall, L. Pilon, P. Gupta, G. Sant, Can the compressive strength of concrete be estimated from knowledge of the mixture proportions?: New insights from statistical analysis and machine learning methods, Cem. Concr. Res. 115 (2019) 379–388. https://doi.org/10.1016/j.cemconres.2018.09.006
[31] W.Z. Taffese, E. Sistonen, Machine learning for durability and service-life assessment of reinforced concrete structures: recent advances and future directions, Autom. Constr. 77 (2017) 1–14. https://doi.org/10.1016/j.autcon.2017.01.016
[32] K.N. Vishwanath, M.M. Yeole, A. Ananthi, D. Parameswari, S.T. Ramya, M. Vijayakumar, Freeze–thaw resistance of sustainable concrete: experimental investigation, damage mechanisms, and AI/ML-based performance prediction, Int. J. Artif. Intell. Mach. Learn. 6 (13s) (2026) 218–230. https://doi.org/10.51483/IJAIML.6.13s.2026.218-230
[33] M.A. DeRousseau, J.R. Kasprzyk, W.V. Srubar, Computational design optimization of concrete mixtures: a review, Cem. Concr. Res. 109 (2018) 42–53. https://doi.org/10.1016/j.cemconres.2018.04.007
[34] B. Gudadappanavar, M. Selvakumar, M.M. Yeole, V.A. Hosur, Y. Dibdalli, C. Morales-Verdejo, P. Sunagar, Explicit-dynamics assessment of reinforced concrete frame response under TNT blast: stand-off, charge weight and incidence angle effects, SSRG Int. J. Civ. Eng. 13 (3) (2026) 255–273. https://doi.org/10.14445/23488352/IJCE-V13I3P119
[35] M.K. Almustafa, M.L. Nehdi, Machine learning model for predicting structural response of RC slabs exposed to blast loading, Eng. Struct. 221 (2020) 111109. https://doi.org/10.1016/j.engstruct.2020.111109
[36] S.M. Lundberg, G. Erion, H. Chen, A. DeGrave, J.M. Prutkin, B. Nair, R. Katz, J. Himmelfarb, N. Bansal, S.-I. Lee, From local explanations to global understanding with explainable AI for trees, Nat. Mach. Intell. 2 (1) (2020) 56–67. https://doi.org/10.1038/s42256-019-0138-9
[37] C. Rudin, Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead, Nat. Mach. Intell. 1 (5) (2019) 206–215. https://doi.org/10.1038/s42256-019-0048-x



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)