DISSEMINATIONOF KNOWLEDGE
SvedbergOpen
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Integrated AI Frameworks for Structural Monitoring, Mechanical Performance, and Engineering Optimization

Dr. Puja Padiya [1]*, Dr. Nilesh Ratnakar Marathe [2], Dr. Vivek Khalane [3], Dr. Ekta Sarda[4], Dr. Sumithra T.V [5], Dr. Kranti Ghag [6]

[1] Associate Professor and Head, Department of IT, Xavier Institute of Engineering, Mahim Causeway, Mahim (West), Mumbai
E-MAIL ID: puja.padiya05@gmail.com , ORCID: 0000-0002-3446-3340
[2] Associate Professor, CSE (Data Science) Department, Dwarkadas J Sanghvi College of Engineering Vile-Parle Mumbai
E-MAIL ID: nilesh.marathe@djsce.ac.in
[3] Associate Professor, A C Patil College of Engineering, E-MAIL ID: vivekpkhalane@gmail.com
[4] Assistant Professor, Department of Computer Science and Engineering, Ramrao Adik Institute of Technology, D Y Patil Deemed to be University, Nerul
E-MAIL ID: ekta.sarda@rait.ac.in
[5] Assistant Professor, Department of Computer Science and Engineering, Ramrao Adik Institute of Technology, D Y Patil Deemed to be University, Nerul, E-MAIL ID: sumithratv@gmail.com
[6] Associate Professor, Department of Computer Engineering, SVKM's Dwarkadas J Sanghvi College of Engineering, Vile-Parle, Mumbai, EMAIL ID: kranti.ghag@djsce.ac.in

Abstract

This study develops an integrated artificial intelligence solution that simultaneously addresses structural health monitoring, mechanical-performance prognosis, and engineering optimization by leveraging open-sourced Indian experimental case bases. Structural monitoring assessment was based on the six-storey IIT Patna shear-building benchmark with fourth-storey damage, whereas mechanical behavior predictions were based on an innovative 188-sample experimental database of recycled-aggregate concrete mixes from IIT Bhubaneswar. The functioning of the automated XGBoost regressor was validated on the independent test set, achieving R^2=0.943 , RMSE=3.99 MPa, and MAE=2.90 MPa for the mechanical performance prognosis task. The five-fold cross-validation procedure scored R^2=0.946 ±0.009. The observed-data Pareto front analysis revealed that an observed 28-day strength of 59.0 MPa was reached with 41.2% lower cement content while still retaining 83.2% of the maximum compressive strength. This finding highlights the potential of the proposed framework to enable transparent decision-making in engineering by integrating sensing, mechanical-performance models, and design optimization in a unified data-driven paradigm.

Keywords: artificial intelligence; structural health monitoring; XGBoost; recycled aggregate concrete; explainable AI; engineering optimization

Introduction

In recent decades, the need to satisfy a growing demand for mobility, address aging infrastructure, adapt to environmental changes, and limited maintenance budgets have led civil infrastructures to increasingly complex traffic conditions. While traditional inspections are necessary, they cannot provide a constant assessment of the state of structures, such as a variation in stiffness, vibrations, degradation, or load capacity. Structural health monitoring (SHM) is a way to address this challenge by using sensors, signal processing, mechanics, and decision-making processes to recognize states of a structure associated with damage (Farrar and Worden, 2007; Anjneya and Roy, 2021a).

Artificial intelligence (AI) approaches enable SHM (structural health monitoring) ranging from threshold alarms to pattern, anomaly, damage classification, prognosis, and predictive maintenance. Deep learning models allow for directly learning patterns from vibration or images. In contrast, ensemble machine-learning approaches seem better suited to data from a table, as they can capture more complicated relationships, while still having a lower requirement for sample size compared to classical methods (Cha et al., 2024; Plevris and Papazafeiropoulos, 2024; Di Mucci et al., 2024). Current research emphasizes the importance of model interpretation, as decisions based on predictions need to be justified to ensure effective prioritization of inspections and a reasonable allocation of resources towards the most cost-effective interventions (Plevris and Papazafeiropoulos, 2024).

The Indian context gives this topic an additional level of interest. The Indian Bridge Management System was developed to ensure the country's first inventory and database about the state of its bridges. At the same time, the road sector policy calls for regular inspections, ensuring their performance, durability, safety, and cost-effective maintenance. Moreover, India possesses a considerable amount of laboratory and field research data about concrete, vibrations, recycled aggregates, or supplementary cementitious materials that can be used to create AI studies based on reality, not a theoretical model (Ministry of Road Transport and Highways, 2025; Press Information Bureau, 2016).

A second category of challenges is connected to the materials. The mechanical performance of concrete depends on the different variables like binder, water-to-binder ratio, type of aggregates, admixture, period of curing, and the percentage of recycled aggregates. The variables present a non-linear relationship to the material's compressive strength. Moreover, the heterogeneity of the recycled aggregates and the initial moisture level also challenge the mix proportioning exercise. Therefore, it is essential to perform laboratory experiments and apply machine learning techniques to assess the compressive strength of these concrete mixtures and determine the optimal mix composition (Biswal et al., 2022; Olvera-Mayorga et al., 2025).

Table 2. Held-out regression performance on the IIT Bhubaneswar dataset.

Model	R^2	RMSE (MPa)	MAE (MPa)
Tuned XGBoost	0.943	3.99	2.90
SVR-RBF	0.907	5.10	3.38
Random Forest	0.905	5.16	3.81
Extra Trees	0.903	5.22	3.87
Gradient Boosting	0.895	5.43	4.12
Ridge	0.823	7.05	5.36

Despite significant advances in the field, many studies still focus on simplified scenarios in which structural health monitoring (SHM) data are used to classify structural conditions, constitutive models estimate the performance of candidate materials, and optimization algorithms explore a single design variable. Instead, a deployable engineering intelligence should operate at higher levels of organization by linking the information to drive from SHM, relating this information to constitutive law assumptions, and exploiting this knowledge to define a set of possible trade-off options in the optimization process. At a higher level, this approach is fully compatible with cyber-physical and digital-twin paradigms, where the response of a monitored asset, its estimated evolution, and the optimization guidance are permanently cross-referenced.

By virtue of this study, we develop an integrated artificial intelligence framework using two independently published Indian experimental databases, namely, a six-storey shear-building vibration benchmark generated at IIT Patna with repeated undamaged and damaged measurements, and an 188-mix concrete database generated at IIT Bhubaneswar for recycled aggregate concrete blended with fly ash and ground granulated blast-furnace slag and metakaolin Given that the study aims to (i) develop a structural-monitoring layer using the Indian vibration data, (ii) formulate and validate a nonlinear mechanical-performance model for compressive strength, (iii) interpret the dominant material variables, and (iv) carry out an observed-data multi-objective screening to enable strength-cement trade-off analysis for engineering decision-making, our arguments unfold around these topical underpinnings.

2. Materials and Methods

2.1 Study design and integrated framework

The research was implemented through a reproducible secondary-data computational analysis, with no fabricated measurements added into the primary validation sets. The process involves three interconnected levels: 1) a sensing and state identification layer informed by responses of acceleration; 2) a materials-performance layer, which regresses the compressive strength on the mix components; 3) an optimization layer, which identifies Pareto frontier mixtures on the basis of identified performance characteristics. Open experiment datasets have been used, so as to allow independent verification and avoid conflating fabricated values with field observations.

The structural layer may provide a condition indication that can trigger inspection or model updating. The material layer supplies a strength estimate plus variable sensitivity information for candidate concrete mixtures. The optimization layer weighs material options against competing objectives. As a practical matter, these layers can be instantiated in an asset-management framework in which sensor-driven anomaly detection triggers inspection and in which rehabilitation options are evaluated in terms of material performance and resource use.

2.2 Indian structural-health-monitoring dataset

The structural data was acquired from laboratory SHM benchmark (Anjneya & Roy, 2021a) provided by the Department of Civil and Environmental Engineering, Indian Institute of Technology Patna, Bihar, India. The test structure was a 1:20 geometric scale 3D six-storey shear-building model. a set of six piezoelectric accelerometers were mounted on the floor levels in the direction of free vibration. The number of acceleration time-history records for the undamaged and damaged structures was twenty-five each.

Damage was introduced into the structure by changing the cross-section of the columns on the fourth storey from 7.8 mm × 7.8 mm square columns to 6.5 mm × 6.5 mm ones. Flexural stiffness for a square cross-section reduces with the fourth power of the side length (for the same material and length). Therefore, the analytically identified stiffness reduction matches the experimentally identified one (51.8%) and equals approximately 51.7%. The sampling interval was 24 × 10-5 s, i.e., the sampling frequency was about 4166.7 Hz. The data can be used for vibration-based binary structural-state identification and modal analysis.

Table 1. Indian experimental datasets used in the integrated framework.

Dataset	Institution/location	Observations	Primary variables	Role in framework
Shear-building acceleration benchmark	IIT Patna, Bihar, India	25 undamaged + 25 damaged records	Six-floor acceleration time histories; known fourth-storey damage	Structural-state monitoring and external AI benchmark
Recycled-aggregate concrete database	IIT Bhubaneswar, Odisha, India	188 tested concrete mixes	Binder, water, admixtures, natural/recycled aggregates, age, compressive strength	Mechanical-performance prediction and optimization

For the purpose of external benchmarking of the present structural-monitoring layer, the current study refers to the publicly available results of the independent research conducted by Sarma et al. (2025). These researchers trained an extremely lightweight 1D CNN and a Transformer model on the same IIT Patna database resulting in 99.44% and 98.87% validation accuracy, respectively. For the sake of consistency and to avoid double-counting, these accuracy measures are used in the current study as external benchmark results rather than results of the present computation. According to Sarma et al. (2025), their explainability analysis revealed that global patterns, including the response of the base sensor, contain damage-discriminatory information, thus serving as important features for vibration-based damage detection models.

2.3 Indian concrete mechanical-performance dataset

The mechanical-performance database was obtained from the open IIT Bhubaneswar concrete laboratory database of Biswal, Pasla, and Mishra related to the experimental study of Biswal et al. (2022). The database includes 188 concrete mixtures experimentally studied. It covers recycled aggregate concrete and includes the following variables: cement, fly ash, GGBS, metakaolin, total cementitious materials, water, water-to-total-cementitious-material ratio, superplasticizer, viscosity-modifying admixture, natural and recycled coarse aggregate (in fractions), sand, curing age, and compressive strength.

In the provided data file, the compressive strength accounts for 6.00 – 73.76 MPa with an average of 34.42 MPa. The range of the variable curing age (days) was 3, 7, 14, 28, 56, 90 days. The water-to-total-cementitious-material ratio varied from 0.25 to 0.75. There were no missing values in the 188 observations used to build the model, and serial number was removed from the set of predictors.

2.4 Machine-learning models and validation

Six regression approaches were considered, namely, ridge regression, radial–basis–function support vector regression, Random Forest, Extra Trees, Gradient Boosting, and Extreme Gradient Boosting (XGBoost). The study selected XGBoost as a main candidate for modeling nonlinear relationships because gradient–boosted decision trees are particularly effective in case of medium–sized tabular data and able to account for nonlinear interactions between mixture variables (Chen and Guestrin, 2016).

The data was separated into an 80% training set and a 20% held-out test set using random_state=42. The hyperparameters for the XGBoost model were selected using a randomized search with a five-fold cross-validation on the training set. The final model had 889 trees, a tree depth of 5, a learning rate of 0.0560, a subsample of 0.943, a column subsampling of 0.960, a minimum child weight of 4 and L1 and L2 regularization coefficients of 0.0197 and 0.181, respectively. The final model was evaluated using the R^2 score, root mean squared error (RMSE), and mean absolute error (MAE). Subsequently, the procedure was repeated using a second round of five-fold shuffled cross-validation on randomly split and shuffled samples.

Permutation importance was calculated on the held-out test set with 50 repeated shuffles per feature and the R^2 score as the metric. This model-agnostic procedure estimates the decrease in performance of a model when the input features are randomly permuted, thus providing an engineering interpretation of the variables responsible for the model's predictions.

2.5 Observed-data engineering optimization

The optimization procedure of mix proportioning deliberately does not aim at predicting non-observed mix designs but rather focuses on the observed experimental region. For all 28-day target records, the optimization process used two objectives to maximize the observed compressive strength and minimize the amount of cement. The Pareto front is then constructed, where a 28-day target record is a supported solution if there is no other observed mixture that has both lower cement content and higher compressive strength. The supported solutions are used to identify the mixtures that are directly comparable to the tested and observed Indian laboratory mixtures.

For a practical example of decision-making, the lowest-cement observed mixture that achieved at least 50 MPa at 28 days was compared to the corresponding 28-day maximum strength mixture. It was reported as a percentage of the cement factor reduction and the retained strengths. The intention is not to dictate a code-specified concrete mixture design with additional durability and workability criteria but to illustrate what an AI-assisted engineering system can do in terms of design space reduction prior to a detailed laboratory qualification process.

2.6 Software and reproducibility

The computations were carried out in Python programming language using pandas 2.2.3, numpy 2.3.5, scikit-learn 1.8, and XGBoost 3.1.3 libraries. For the purposes of this study, a random seed was set for both data splitting and model evaluation. The data used as the basis for this research has been made public and is available in the repositories indicated, thus allowing the reproduction of the computations.

3. Results and Discussion

3.1 Structural-monitoring evidence and physical consistency

Perhaps the most valuable Indian SHM benchmark concerns the IIT Patna case, as it involves a scenario with a known damage state, documented geometry, and multiple measured acceleration records. In this situation, the analytically identified loss of stiffness of 51.8% is close to the given value of 51.7% damage, which can be regarded as a good indication of internal consistency between the physical modification and the metadata used for AI classification.

Independent published testing on the same database confirms that raw time histories contain sufficient information to achieve extremely high levels of accuracy in state identification: the reported Fast CNN and Fast Transformer validation accuracies are 99.44% and 98.87%, respectively (Sarma et al., 2025). However, this does not mean that one can expect such accuracy in the identification of every possible field structure. The lab-bench case involves a controlled structure, a deliberately excited vibration response, while the state to be identified is binary. In real structures, many factors affecting their behavior can vary simultaneously (temperature, traffic, sensor biasing, boundary conditions, and damage mechanisms).

Nevertheless, the finding is critical for the proposed integrated framework as it demonstrates that an Indian experimental vibration dataset can be utilized for the sensing-to-diagnosis layer. In practice, the outcome of the classifier should be used as a condition indicator for initiating engineering reassessment rather than claiming structural safety by itself. This conclusion aligns with recent trends in the XAI and SHM literature that emphasize physically interpretable findings, epistemic uncertainty, and human-centered decision-making (Cha et al., 2024; Plevris and Papazafeiropoulos, 2024).

Table 3. Structural-monitoring benchmark on the IIT Patna dataset.

Evidence	Model/quantity	Result	Interpretation
Physical consistency	Analytical stiffness reduction from 7.8 mm to 6.5 mm square columns	51.8%	Matches reported fourth-storey damage severity (~51.7%)
External published benchmark	Fast 1D CNN	99.44% validation accuracy	High separability of undamaged vs damaged vibration states
External published benchmark	Fast Transformer	98.87% validation accuracy	Comparable high classification accuracy with attention-based sequence modeling

Table 4. Pareto-efficient observed 28-day mixtures for compressive strength versus cement content.

Serial no.	Cement	Fly ash	GGBS	Metakaolin	w/TCM	CS (MPa)
134	113	0	113	0	0.75	16.34
133	131	0	131	0	0.65	18.77
132	155	0	155	0	0.55	24.43
25	165	0	385	0	0.31	47.69
24	275	0	275	0	0.29	59.00
129	340	0	340	0	0.25	60.00
23	385	0	165	0	0.28	61.11
27	468	0	0	82	0.35	70.92

3.2 Mechanical-performance prediction

The tuned XGBoost model produced the strongest held-out performance, with R^2=0.943, RMSE=3.99 MPa, and MAE=2.90 MPa. Five-fold cross-validation yielded mean R^2=0.946±0.009, RMSE=4.14±0.57 MPa, and MAE=2.93±0.13 MPa. The close agreement between held-out and cross-validated results indicates that predictive performance was not dependent on a single favorable split.

The model comparisons demonstrated that the linear Ridge model performed less strongly, with R^2=0.823. At the same time, the performance of the nonlinear methods was close to or better than 0.89 for the test dataset, which suggests that the relationship between the input parameters and the target variable is indeed governed by nonlinear interactions. This is not surprising, given that the factors affecting concrete strength are numerous and complicated and that they benefit from being combined in specific ways (e.g., the amount of water depends on how much binder is used, aggregate composition and admixtures), which is challenging to capture using linear trends.

The observed versus predicted in Figure 1 falls along the identity line for the range of low, medium, and high-strength. There were residual errors, as could be expected for a heterogeneous laboratory database. From an engineering standpoint, a prediction error of about 4 MPa (RMSE) is reasonably good, and therefore, the model can be used for screening and sensitivity analyses; nevertheless, it does not replace the need for a confirmatory cube or cylinder test when the mixture is used in practice.

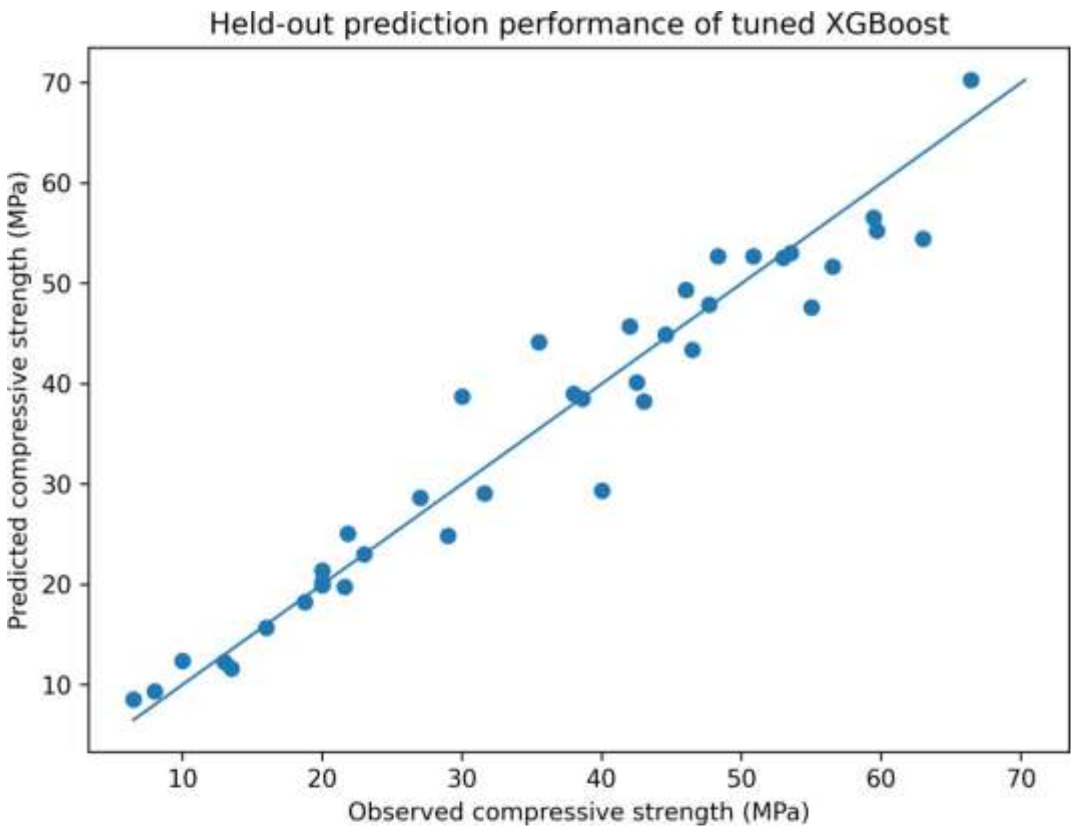


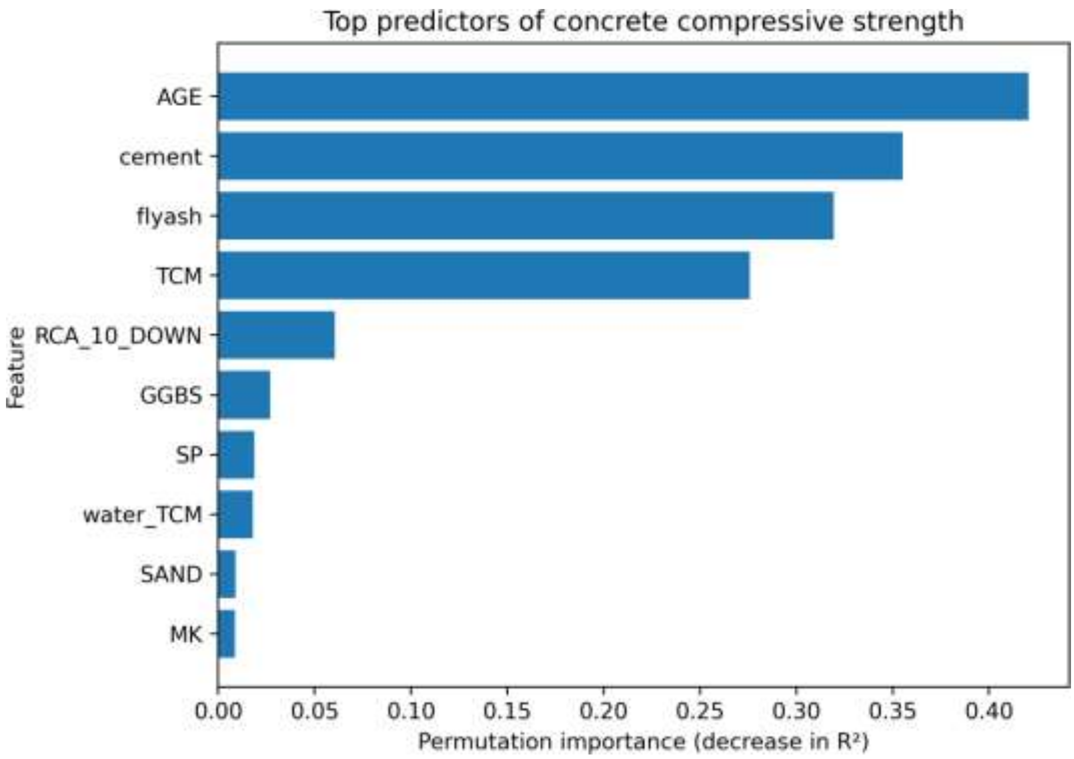
Figure 1. Observed versus predicted compressive strength for the held-out IIT Bhubaneswar test set using tuned XGBoost.

3.3 Explainability and dominant material variables

Permutation importance ranked curing age as the most important predictor, followed by cement content, fly ash, total cementitious material and 10-mm-down recycled coarse aggregate fraction. The contribution of GGBS, the superplasticizer dosage and the water-to-total-cementitious-material ratio was also non-negligible. The ranking is in line with mechanistic considerations, since age determines the degree of binder hydration, cement and fly ash contents define the reactivity of the binder system, and different types of aggregates affect the properties of interfacial transition zones and the effective stiffness of the mortar.

The fly ash content and total amount of cementitious material were found to contribute to prediction, but not necessarily positively to increased strength in all cases; permutation importance does not identify monotone features. The permutation importance quantifies the variable's contribution to the prediction, but it does not establish a monotone relationship. For instance, fly ash may benefit particular concrete elements at given ages, replacement levels, and water-to-binder ratios but harm others. Therefore, the model's explanation should be combined with domain knowledge to understand how the changes in explanatory variables affect the response.

This distinction is critically important for integrated engineering AI. A model that forecasts accurately but cannot specify which physical variables drive its results is not readily interpretable. The importance of individual predictors provides a useful degree of transparency, while future work can employ SHAP values, partial-dependence analysis, or monotonicity constraints, as appropriate, to enhance understanding (Lundberg and Lee,



2017).

Figure 2. Permutation importance of the ten most influential concrete predictors on the held-out test set.

3.4 Engineering optimization and Pareto trade-offs

Among the 28-day experimental records, the maximum observed compressive strength was 70.92 MPa at 468 kg/m^3 cement. In contrast, the lowest-cement observed mixture exceeding 50 MPa used 275 kg/m^3 cement and 275 kg/m^3 GGBS, with a water-to-total-cementitious ratio of 0.29 and a measured 28-day strength of 59.00 MPa.

The alternative used 41.2% less cement than the mixture with the highest strength. Its compressive strength was 83.2% of the maximum mixture's strength. It can be concluded that the mixture with the highest strength is not necessarily the best option if a project only requires a specific strength level. The Pareto frontier in Figure 3 below represents mixtures for which there is no better alternative in terms of both strength and decreased amount of cement used.

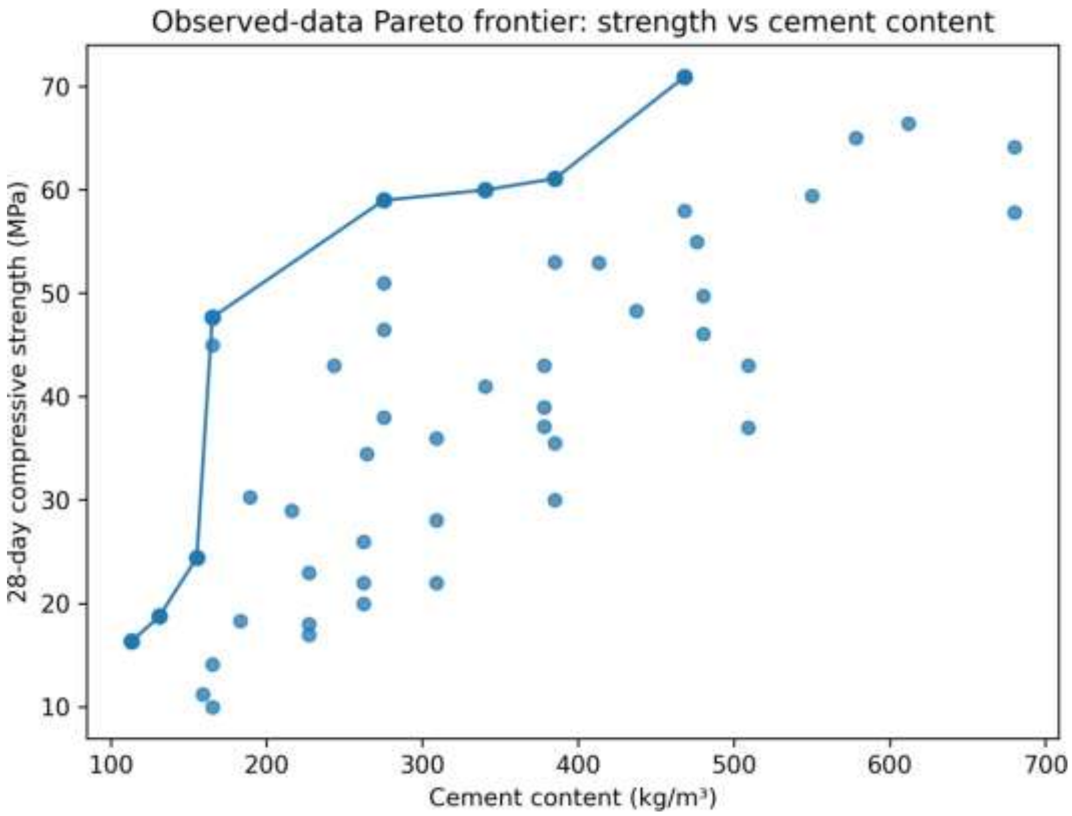


Figure 3. Pareto-efficient frontier among observed 28-day mixtures, maximizing compressive strength while minimizing cement content.

The optimization outcome that has to be read as a design-support statement rather than a final mixing recommendation comes from the fact that cement reduction affects workability, early strength, carbonation resistance, chloride ingress, shrinkage, and sensitivity to curing. Indian long-term exposure data that include the IIT Madras ten-year natural carbonation database for blended cements show that the durability function needs to be added to the mix-design multi-objective function (Hule et al., 2024). A competent engineering optimizer would have to address strength, durability, carbon footprint, cost, workability, and process variability.

3.5 Integrated deployment pathway for Indian infrastructure

The main contribution of the present work is the link between the structural-state intelligence and the material-design intelligence. Specifically, in a closed-loop infrastructure monitoring-assessment-upgrade framework, accelerometers or other response sensors provide the in-situ continuous condition assessment. An anomaly classifier determines whether the event needs investigation. The event is then subjected to a combination of model-based physics-informed diagnosis, inspection information, and history of the asset to determine if it requires repair. The material performance model then identifies candidate properties, and a multiobjective optimizer selects the best upgrade options based on the design criteria relevant to the project's needs.

Such a workflow would be appropriate to the intent of bridge-management and infrastructure-maintenance systems in India, where the condition information is intended to be used to prioritize maintenance activities. Thus, AI is most useful when it allows to make shorter work of the period between acquiring raw measurements and arriving at a set of justified recommendations; it should not replace the structural engineer, laboratory qualification, code checking, and field inspection.

The framework presented is also scalable; the structural layer can be adapted from a binary lab-scale benchmark to multi-class field damage states, transfer learning based health-state identification or anomaly detection, or digital-twin model updating; the material layer can be expanded to predict beyond compressive strength to other material response functions such as tensile strength, modulus, durability, and remaining service-life indices; and the optimization layer can then account for life-cycle costs and maintenance scheduling. Connecting all these contributions is traceability, from data to models to physics to actions.

3.6 Limitations

The structural data set is a laboratory-scale shear building benchmark, not a full-scale field bridge or building. Its controlled binary damage state is useful for validation, but a real-world structure would have more nuanced performance degradation states that are not captured by such a simplified model. The CNN and transformer accuracies reported in this paper are independent published results on the same dataset; they are not the results of the present computation.

The concrete database consists of 188 mixtures, which is sufficient for the careful validation using tabular machine learning, but it represents a relatively narrow data set for general industrial applications. In this database, a random train/test split can result in the same family of mixes in both data sets. It is recommended to perform a grouped validation with mixes of the same base blend or campaign if the data set contains this information. Finally, the Pareto front analysis used only the 28-day-old mixes and optimized two objectives, but in reality, it is necessary to optimize more than one objective, while ensuring code compliance, durability, cost, and sustainability.

4. Conclusion

The developed framework was evaluated using the IIT Patna Structural Health Monitoring (SHM) benchmark dataset, which provides a physically documented damage scenario with replicable acceleration measurements, and the IIT Bhubaneswar database, which enables the nonlinear prediction of the compressive strength of recycled aggregate concrete.

The tuned XGBoost model achieved R^2=0.943, RMSE=3.99 MPa, and MAE=2.90 MPa on held-out data, with five-fold mean R^2=0.946. Permutation importance showed that age and binder-related variables dominated prediction. Observed-data Pareto screening identified a 59.0 MPa, 28-day mixture using 41.2% less cement than the maximum-strength mix while retaining 83.2% of its strength.

The general conclusion is that the main benefit of AI for engineering comes from linking separate tasks of prediction into a transparent decision chain. Monitoring data can provide information about change in structure behavior. Material models can evaluate potential interventions. Multiobjective screening can make trade-offs in multiple objectives explicit. The framework is thus best interpreted as a decision support system for engineers rather than as a safety assessment tool.

References

1. Alvandi, A., and Cremona, C. (2006). Assessment of vibration-based damage identification techniques. Journal of Sound and Vibration, 292(1-2), 179-202. https://doi.org/10.1016/j.jsv.2005.07.036
2. Anjneya, K., and Roy, K. (2021a). Acceleration time history dataset for a 3D miniature model of a shear building with structural damage. Data in Brief, 38, 107377. https://doi.org/10.1016/j.dib.2021.107377
3. Anjneya, K., and Roy, K. (2021b). Response surface-based structural damage identification using dynamic responses. Structures, 29, 1047-1058. https://doi.org/10.1016/j.istruc.2020.11.033
4. Azad, M. M., Kim, S., Cheon, Y. B., and Kim, H. S. (2024). Intelligent structural health monitoring of composite structures using machine learning, deep learning, and transfer learning: A review. Advanced Composite Materials, 33(2), 162-188. https://doi.org/10.1080/09243046.2023.2215474
5. Biswal, U. S., Mishra, M., Singh, M. K., and Pasla, D. (2022). Experimental investigation and comparative machine learning prediction of the compressive strength of recycled aggregate concrete incorporated with fly ash, GGBS, and metakaolin. Innovative Infrastructure Solutions, 7, 242. https://doi.org/10.1007/s41062-022-00844-6
6. Breiman, L. (2001). Random forests. Machine Learning, 45, 5-32. https://doi.org/10.1023/A:1010933404324
7. Brincker, R., Zhang, L., and Andersen, P. (2001). Modal identification of output-only systems using frequency domain decomposition. Smart Materials and Structures, 10(3), 441-445. https://doi.org/10.1088/0964-1726/10/3/303
8. Bureau of Indian Standards. (2019). IS 10262:2019 Concrete mix proportioning - Guidelines. New Delhi, India: BIS.
9. Cha, Y.-J., Ali, R., Lewis, J., and Büyüköztürk, O. (2024). Deep learning-based structural health monitoring. Automation in Construction, 161, 105328. https://doi.org/10.1016/j.autcon.2024.105328
10. Chen, T., and Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785-794. https://doi.org/10.1145/2939672.2939785
11. Chen, X., Jia, J., Yang, J., Bai, Y., and Du, X. (2023). A vibration-based 1DCNN-BiLSTM model for structural state recognition of RC beams. Mechanical Systems and Signal Processing, 203, 110715. https://doi.org/10.1016/j.ymssp.2023.110715
12. Chitkeshwar, A. (2024). Revolutionizing structural engineering: Applications of machine learning for enhanced performance and safety. Archives of Computational Methods in Engineering, 31(8), 4617-4632. https://doi.org/10.1007/s11831-024-10117-3

13. Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182-197. https://doi.org/10.1109/4235.996017
14. Di Mucci, V. M., Cardellicchio, A., Ruggieri, S., Nettis, A., Renò, V., and Uva, G. (2024). Artificial intelligence in structural health management of existing bridges. Automation in Construction, 167, 105719. https://doi.org/10.1016/j.autcon.2024.105719
15. Farrar, C. R., and Worden, K. (2007). An introduction to structural health monitoring. Philosophical Transactions of the Royal Society A, 365(1851), 303-315. https://doi.org/10.1098/rsta.2006.1928
16. Hule, U., Rathnarajan, S., Pillai, R. G., Gettu, R., and Santhanam, M. (2024). 10-year natural carbonation data of concretes with limestone, fly ash, volcanic ash, and slag and exposed to tropical climate in India. Data in Brief, 57, 111006. https://doi.org/10.1016/j.dib.2024.111006
17. Lundberg, S. M., and Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765-4774.
18. Ministry of Road Transport and Highways. (2025). Annual Report 2024-25. Government of India, New Delhi.
19. Olvera-Mayorga, C. E., López-Martínez, M. J., Rodríguez-Rodríguez, J. A., Vázquez-Reyes, S., Solís-Sánchez, L. O., de la Rosa-Vargas, J. I., Duarte-Correa, D., González-Aviña, J. V., and Olvera-Olvera, C. A. (2025). AI-Based inference system for concrete compressive strength: Multi-dataset analysis of optimized machine learning algorithms. Applied Sciences, 15(23), 12383. https://doi.org/10.3390/app152312383
20. Plevris, V., and Papazafeiropoulos, G. (2024). AI in structural health monitoring for infrastructure maintenance and safety. Infrastructures, 9(12), 225. https://doi.org/10.3390/infrastructures9120225
21. Press Information Bureau. (2016). Shri Gadkari launches Indian Bridge Management System: Says it is a major step towards ensuring safety of bridges. Government of India, Ministry of Road Transport and Highways.
22. Sarma, I. V., Chanda, S., and Reddy, M. S. (2025). Interpretable AI for vibration-based structural health monitoring: A comparative study of CNN and transformer architectures on a benchmark shear building. Asian Journal of Civil Engineering, 26, 4615-4628. https://doi.org/10.1007/s42107-025-01446-0
23. Yeh, I.-C. (1998). Modeling of strength of high-performance concrete using artificial neural networks. Cement and Concrete Research, 28(12), 1797-1808. https://doi.org/10.1016/S0008-8846(98)00165-3