Data-Driven Approaches in Concrete Science: Applications, Challenges and Future Prospects

Salim Barbhuiya[1], Bibhuti Bhusan Das[2], Dibyendu Adak[3]

1. Department of Engineering and Construction, University of East London, UK
2. Department of Civil Engineering, NIT Karnataka, Surathkal, India
3. Department of Civil Engineering, NIT Meghalaya, Shillong, India

Corresponding author: Salim Barbhuiya (email: s.barbhuiya@uel.ac.uk)

Abstract:

This review paper provides a comprehensive exploration of integrating data-driven approaches in the domain of concrete science. The paper commences with an introduction elucidating the background and context of data-driven concrete science, outlining objectives and scope, and underscoring the importance of data-driven methodologies. Subsequently, it delves into the traditional analytical approaches and the potential for data-driven methods. The paper elucidates data collection and pre-processing techniques tailored to the domain, encompassing concrete-related data types, collection methodologies, and data pre-processing strategies. Moreover, it extensively covers data-driven modelling and prediction in concrete science, presenting an overview of data-driven models, machine learning techniques, deep learning approaches, and integration of big data analytics. The review consolidates insights into diverse applications, including concrete strength prediction, durability analysis, and concrete microstructure characterisation, employing data-driven approaches. Furthermore, it highlights challenges and opportunities in this burgeoning field, encompassing data quality and availability, interpretability and explainability of models, and ethical consideration. The paper concludes with recommendations for researchers and practitioners aiming to harness the full potential of data-driven methodologies.

Keywords: Data-Driven Concrete Science; Concrete Properties Prediction; Machine Learning; Concrete Microstructure; Data Pre-processing

1. Introduction

Traditional concrete analysis, reliant on empirical formulas and experiments, falls short of understanding the intricate nature of concrete (Kelham, 1988; Kim et al., 2003; Erzar & Forquin, 2010; Debicki et al., 2012; Amriou & Bencheikh, 2017). Empirical formulas oversimplify, while experiments are time-consuming, impeding quick decision-making and innovation. In contrast, data-driven approaches, leveraging computing power and advanced machine learning (He et al., 2022; Volker et al., 2023; Nguyen & Tran, 2023), represent a transformative shift in analysing and optimizing concrete properties. By harnessing extensive datasets and advanced analytics, data-driven methods uncover intricate patterns, correlations, and insights, facilitating informed decision-making for optimized concrete composition regarding strength, durability, and sustainability.

Data-driven approaches offer a significant advantage in predictive modelling within concrete science (Xu & Feng, 2022; Cakiroglu et al. 2023). Through robust data analysis, these approaches enable accurate estimation of concrete properties, such as strength and durability, even before construction. This predictive capability not only saves time and resources but also contributes to the creation of resilient and cost-effective concrete structures, aligning with evolving construction industry needs. A transformative shift in concrete property analysis and optimization has been ushered in by data-driven approaches. Traditionally, reliance on empirical formulas and experimental methods had limitations, requiring substantial time and resources for data collection and hindering innovation in the concrete industry.

The rise of data-driven approaches, fuelled by computing advancements and machine learning, has ushered in a new era in concrete science. Leveraging extensive datasets and advanced analytics, these methods offer a more comprehensive and efficient understanding of concrete composition, behaviour, and performance. Unveiling previously elusive patterns and insights, data-driven concrete science is motivated by optimizing concrete for enhanced strength, durability, and sustainability (Imran et al. 2023; Hafez et al. 2023; Shamsabadi et al. 2023). These approaches also enhance quality control during construction, ensuring real-time adjustments for consistent and high-quality standards (Cai et al. 2014; Li et al. 2023; Zheng et al. 2023). Machine learning (ML) in concrete technology enhances material performance prediction, quality control, and mix optimization. It enables data-driven models to forecast strength, durability, and crack propagation. ML algorithms analyse large datasets, improving efficiency in construction, reducing costs, and promoting sustainability by optimizing material proportions and predicting structural behaviour more accurately

This review paper underscores the transformative impact of data-driven approaches on concrete science. Traditional methodologies often fall short of capturing the complex nature of concrete. Fuelled by computational advancements and abundant data, data-driven techniques have revolutionized concrete analysis, enhancing understanding, optimizing composition, enabling predictive modelling, and fostering sustainability. The paper emphasizes the crucial role of data-driven methods in shaping a more efficient and sustainable future for concrete construction. While providing a comprehensive exploration, it acknowledges limitations, such as a broad scope and the need for frequent updates in the rapidly evolving field. Nonetheless, it serves as a valuable starting point, stimulating further research and discussion in this dynamic domain.

The paper explores the evolution of concrete analysis from traditional empirical approaches to advanced data-driven methods. Traditional analytical techniques relied on empirical formulas and experimental observations to predict concrete properties. As technology advanced, computational and machine learning models emerged, enhancing precision and predictive capabilities. Data-driven methods, including machine learning and big data analytics, optimize mix designs, monitor real-time performance, and predict durability. Challenges such as data quality, interpretability, and ethical considerations are discussed, emphasizing the need for responsible implementation. Recommendations highlight best practices for researchers and practitioners, ensuring efficiency, sustainability, and innovation in modern concrete engineering.

2. Traditional Analytical Approaches

In the field of concrete analysis, traditional analytical approaches have held a central position in comprehending the properties and dynamics of this foundational construction material. These customary methods, deeply rooted in empirical formulas and experimental practices, served as the linchpin for evaluating and characterising concrete well before the advent of sophisticated computational techniques and data-driven methodologies. Empirical formulas, arising from meticulous observation and experimental data, represented a fundamental approach to concrete analysis. These formulas established mathematical correlations among critical constituents such as cement, aggregates, and water, offering predictive insights into various concrete properties. For example, renowned empirical relationships that correlated the water-cement ratio with compressive strength formed a bedrock for the early understanding of concrete behaviour (Popovics & Ujhelyi, 2008; ElNemr, 2020).

Analytical models had simplifying assumptions. Technological advancements drove the evolution of precise computational and data-driven methodologies in concrete analysis.

Chalioris (2013) focused on steel fibrous concrete beams, predicting the minimum fibre factor for optimal performance using an analytical approach, offering insights into fibre influence. Asutkar et al. (2017) analysed rubber aggregates in concrete beams, revealing their potential through analytical methods. Rashid et al. (2017) integrated experimental and analytical approaches for sustainable recycled concrete, showcasing the significance of varied methods. Yang et al. (2019) used analytical models to predict fracture parameters for concrete with coral aggregates in seawater, providing insights for coastal construction. Opon & Henry (2022) presented a study that introduced an analytical framework for the sustainability evaluation and comparison of concrete materials.

Building upon these analytical techniques, technological advancements have led to the emergence of computational and data-driven methodologies that enhance accuracy and predictive capabilities in concrete analysis. Machine learning, finite element modelling, and artificial intelligence now enable deeper insights into material behaviour, surpassing the limitations of empirical approaches. These innovations refine existing empirical correlations by integrating vast datasets and real-time simulations, optimizing mix designs and structural performance predictions. Studies now leverage hybrid approaches that combine experimental, analytical, and data-driven methods, fostering sustainable concrete solutions. By evolving from empirical roots, modern techniques drive efficiency, durability, and innovation in concrete engineering.

3. Potential for Data-Driven Methods

Data-driven methods in concrete science bring transformative potential by leveraging data analytics, machine learning, and artificial intelligence. These approaches revolutionize concrete property analysis, prediction, and optimization. Table 1 outlines their multifaceted advantages, emphasizing enhanced predictive modelling for precise forecasts and optimized material composition to reduce waste. These methods offer substantial improvements in concrete quality and sustainability, ensuring high-quality construction through real-time monitoring and data integration.

Table 1: Potential Benefits of Data-Driven Methods in Concrete Science

Potential Aspect	Description	Impact
Enhanced Predictive Modelling	Data-driven methods enable precise prediction of concrete properties, optimising mix designs and formulations.	Improved concrete quality and performance.
Optimised Material Composition	Understanding concrete component relationships leads to ideal mix proportions, enhancing durability and sustainability.	Reduced material waste and cost-effective solutions.
Real-time Monitoring and Control	Sensors and data analysis provide real--time quality control, ensuring high-quality concrete, and reducing resource waste.	Enhanced construction efficiency and cost savings.
Comprehensive Data Integration	Integration of diverse data sources offers a holistic understanding of concrete behaviour and characteristics.	Informed decision-making and innovative solutions.
Accelerated Research and Innovation	Data-driven analysis expedites research, facilitating the development of new formulations, sustainable practices, and construction innovations.	Faster project completion and industry advancements.

4. Data Collection and Pre-processing

Table 2 provides a concise yet comprehensive overview of the diverse data types crucial in the field of concrete science. Diverse data collection methods are vital in concrete science for meaningful insights. Laboratory testing yields precise data on properties such as compressive and tensile strength (Wright & Garwood, 1952; Darvell, 1990). Field testing, using non-destructive methods, assesses in-situ properties of operational structures (Mori et al., 2002). Instrumentation and sensors provide real-time data on structural behaviour (Yehia et al., 2014). Surveys and questionnaires offer qualitative insights, while LiDAR captures topographical data (Janowski et al., 2016). Data logging monitors concrete properties and environmental conditions continuously (McCarter et al., 1995). Material sampling and analysis in laboratories determine the chemical composition and aggregate characteristics for mix design optimization (Conciatori et al., 2014). Each method contributes uniquely, enhancing understanding, guiding decisions, and improving practices. Selection depends on research objectives, resources, and data requirements.

Table 2: Types of Concrete-Related Data and Their Significance

Type of Data	Description	Importance	Examples of Data Sources
Composition	Constituents and proportions in the concrete mix.	Directly influences concrete properties.	Lab tests, supplier specs
Strength	Mechanical properties like compressive, tensile, and flexural strength.	Vital for structural design and quality control.	Compression tests, flexural tests
Workability	Concrete's ease of mixing, placing, compacting, and finishing.	Crucial for construction processes and quality.	Slump tests, flow tests
Durability	Resistance to factors like freeze-thaw cycles and chemical attacks.	Ensures longevity and performance, especially in harsh conditions.	Weathering tests, penetration tests
Curing	Details about the curing process: duration, temperature, and humidity.	Crucial for achieving the desired strength and durability.	Curing records, environmental monitoring
Setting and Hardening	Data on concrete's setting time and hardening characteristics.	Essential for effective scheduling and achieving desired strength promptly.	Setting time records, strength gain monitoring
Microstructure	Internal structure at a microscopic level, including particle arrangement.	Provides insights into properties and behavior.	SEM, XRD, mercury intrusion
Environmental	Environmental conditions during concrete production and placement.	Affects curing and setting, impacting overall quality and performance.	Weather records, on-site monitoring

Addressing missing data poses a common challenge in research (Finch, 2008; Pani et al., 2013; Lahat et al., 2015). Techniques such as mean imputation, interpolation, or judicious deletion ensure systematic handling, creating a complete and suitable dataset. Detecting and managing anomalies or outliers caused by measurement errors is critical (Pearson, 2002; Foorthuis, 2021). Statistical approaches, visualization, or machine learning algorithms identify and address outliers, preventing undue influence on outcomes. Data transformation involves normalizing or standardizing variables for fair comparisons (Dare et al., 2002; Xu et al., 2022; Kumar & Pratap, 2023). Feature engineering enhances concrete characteristic representation, while data reduction techniques like Principal Component Analysis (PCA) promote efficient analysis (Boukhatem et al., 2012; Sadowski et al., 2015; Hameed et al., 2021).

5. Data-Driven Modelling and Prediction

5.1 Machine Learning Techniques

Machine learning techniques have significantly transformed concrete science, constructing predictive models and extracting meaningful insights. Table 3 succinctly outlines various machine learning techniques and their applications in concrete science, offering a comprehensive overview. From regression and decision trees predicting concrete properties to clustering algorithms categorizing materials, these techniques provide valuable insights. Neural networks, like Convolutional Neural Networks (CNN), aid in microstructure analysis. Principal Component Analysis (PCA) reduces data complexity. Reinforcement learning optimizes concrete mix designs, and Genetic Algorithms fine-tune compositions. This compilation illustrates how ML contributes to understanding, analysing, and optimizing diverse aspects of concrete, advancing the field and revolutionizing the construction industry.

Table 3: Summary of applications of machine learning techniques in concrete science

ML Technique	Description	Application in Concrete Science	References
Regression Analysis	Predicts continuous concrete properties (e.g., strength) based on input features such as mix proportions and curing conditions	Predicting concrete strength, workability, and durability based on mix components and curing conditions	Atici, 2011; Omran et al. 2016; Chithra et al. 2016; Nilsen et al. 2019; Koya et al. 2022
Decision Trees	Versatile models useful for predicting concrete properties and aiding in material selection based on various parameters	Predicting concrete properties, optimising mix designs	Zhang et al. 2019; Zhang et al. 2020; Behnood & Golafshani 2020; Abbasloo et al. 2019; Taffese et al. 2015; Asghshahr et al. 2016; Chen et al. 2020.
Random Forest	Ensemble technique combining multiple decision trees to enhance prediction accuracy	Improving prediction accuracy of concrete properties, optimising mix designs	Ouyang et al. 2020; Marani & Nehdi, 2020; Oey et al. 2020; Cook et al. 2021; Pei, et al. 2020

Support Vector Machines	Versatile models for both regression and classification tasks, useful in predicting properties like compressive strength in concrete science	Predicting concrete properties, aiding in structural design based on material components	Nguyen et al. 2021; Huang et al. 2020; Nguyen-Sy et al. 2020; Yazdi et al. 2013; Ünlü, 2020; Liao et al. 2016
Clustering Algorithms	Group similar concrete data points based on features, aiding in concrete material characterisation and selection	Identifying clusters of materials with similar properties, optimising material selection	Calabrese et al. 2012; Lattanzi et al. 2014; Völker & Shokouhi 2015; Tayfur et al. 2018; Chen et al. 2021; Fan, 2021
Neural Networks	Complex models effective in concrete science, e.g., Convolutional Neural Networks (CNNs) for microstructure analysis	Analysing concrete microstructures, modelling sequential curing data	Yeh, 1998); Ouyang et al. 2020; Nguyen et al. 2021; Nasr et al. 2019; Adhikary & Mutsuyoshi, 2004; Basma, et al. 1999; Lyngdoh et al. 2020
Principal Component Analysis (PCA)	Reduces complexity by retaining essential features while reducing dimensionality of large datasets	Analysing and visualizing multi-dimensional concrete data	Boukhatem et al. 2012; Sadowski et al. 2015; Abd Elaty et al. 2017; Şimşek, 2020; Koo et al. 2021

5.2 Deep Learning Approaches

Convolutional Neural Networks (CNNs) revolutionize concrete technology by automating tasks like crack detection and real-time monitoring. Dung's study (2019) highlights CNNs' autonomy in crack detection, reducing reliance on manual methods. Dorafshan et al. (2018a) demonstrated CNNs' superiority over traditional approaches, advocating their adoption. Kim & Cho's approach (2019) using a mask and region-based CNNs improves accuracy. Despite advancements like the SDNET2018 dataset (Dorafshan et al., 2018b), addressing biases is crucial. Wang et al.'s work (2021; 2022) extends CNN utility to aggregate segmentation and monitoring, showing diverse applications. Dong et al. (2020) focused on microstructural crack segmentation, emphasizing CNNs' potential for intricate concrete analysis. Challenges like dataset biases and model robustness must be addressed for ongoing CNN advancements in concrete analysis and monitoring.

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to capture long-term dependencies in sequential data. Recent studies showcase LSTM network efficacy in concrete analysis. Ranjbar & Toufigh (2022) employed LSTM for ultrasonic damage assessment. Chen et al. (2022) predicted high-strength concrete compressive strength. Gogineni et al. (2023) explore LSTM's adaptability in strength prediction. Tanhadoust et al. (2023) extended LSTM to stress-strain under high temperatures. Tanyildizi (2021) forecasted geopolymerization in fly ash-based geopolymer. Fu et al. (2023) predicted internal humidity under varying thermal conditions, and Candelaria & Kee (2023) evaluated thermal damage using LSTM for ultrasonic waves. Despite their significance in construction, LSTM applications require further interpretability, validation, and reliability enhancements for real-world concrete industry applications.

5.3 Integration of Big Data Analytics

Big data analytics streamlines the processing and storage of vast and diverse data in the concrete industry (Sandryhaila & Moura, 2014; Elgendy & Elragal, 2014; Saggi & Jain, 2018). This encompasses material properties, construction processes, and environmental conditions. Advanced storage solutions handle structured and unstructured data for seamless analysis. Integration of big data analytics enables sophisticated techniques and predictive modeling (Gandomi & Haider, 2015; Munawar et al., 2022). Machine learning algorithms uncover patterns and correlations in extensive datasets, particularly regarding concrete properties like strength and durability. Predictive modelling aids professionals in optimizing concrete mix designs for optimal performance. Table 4 offers insights into big data analytics applications, spanning data processing, analytics, real-time monitoring, and resource optimization.

Table 4: Integration of Big Data Analytics in Concrete Science Aspects and Applications

Aspect	Description	Benefits	Applications
Data Processing and Storage	Efficient processing and storage of diverse data types including material properties, construction processes, and environmental conditions.	- Centralized data storage. - Efficient handling of structured and unstructured data.	- Centralized data repository for various projects. - Rapid retrieval and analysis of historical project data.
Advanced Analytics and Modelling	Utilising advanced analytical techniques and predictive modelling to understand concrete properties and behaviour.	- Accurate prediction of concrete properties. - Fine-tuning mix designs for optimal performance.	- Predicting concrete strength and durability. - Optimising concrete mix proportions.
Real-time Monitoring and Control	Instantaneous monitoring of construction processes and concrete performance through real-time analysis of sensor data.	- Immediate intervention for quality control. - Prevention of potential issues.	- Real-time Monitoring of ongoing construction projects. - Ensuring quality control during the construction phase.
Resource Optimisation	Data-driven decision-making to minimise resource wastage and enhance efficiency by understanding factors affecting concrete properties.	- Efficient utilisation of resources. - Cost-effective construction practices.	- Optimisation of material usage for sustainable practices. - Budget-conscious decision-making during projects.

6. Applications of Data-Driven Approaches

6.1 Prediction of fresh properties

Machine learning revolutionizes the prediction of fresh concrete properties, optimizing mix designs for enhanced workability and setting time. Algorithms forecast vital properties like workability based on mix proportions and environmental conditions, tailoring compositions to specific project needs. Dias and Pooliyadda (2001) used neural networks to predict concrete properties with admixtures, while Xie et al. (2020) focused on concrete temperature development using machine learning. Unlu (2020) assessed machine learning for slump flow, and Kina et al. (2021) compared models estimating fresh properties of hybrid fiber-reinforced self-compacting concrete. Techniques like genetic algorithms and support vector machines modelled concrete slump and fresh properties (Chandwani et al., 2015; Sonebi et al., 2016). Machine learning, particularly neural networks, exhibits the potential to predict compressive strength and slump (Öztaş et al., 2006; Timur Cihan, 2019). Artificial neural networks were applied to model the impact of additives on fresh self-consolidating cement paste rheological properties (Mohebbi et al., 2011). By enhancing prediction and understanding, machine learning provides valuable insights for quality control and optimization in construction. Table 5 summarises Machine Learning predictions for fresh concrete properties in various applications.

Table 5: Machine Learning Predictions for Fresh Concrete Properties in Various Applications

Reference	**Fresh Properties Predicted**	**Machine Learning Model(s) Used**	**Reliability**	**Application**
Dias & Pooliyadda, (2001)	Various properties with admixtures	Neural Networks	Medium	Concrete mix design
Xie et al. (2020)	Concrete temperature development	Machine Learning	High	Quality control of field curing
Unlu (2020)	Slump flow	Machine Learning	Medium	Quality control
Kina et al. (2021)	Fresh properties of SCC	Extreme Learning Machine, Deep Learning Model	High	Self-compacting concrete (SCC)
Zheng et al. (2019)	Concrete moisture level	Percussion and Machine Learning	Medium	Moisture level monitoring
Aydogmus et al. (2015)	Concrete slump flow	Ensemble Models (Bagging)	Medium	Concrete slump prediction
Chandwani et al. (2015)	Slump of ready-mix concrete	Genetic Algorithms, Artificial Neural Networks	Low	Concrete slump prediction
Sonebi et al. (2016)	Fresh properties of SCC	Support Vector Machine	Medium	Self-compacting concrete (SCC)
Öztaş et al. (2006)	Compressive strength, slump	Neural Network	Medium	Strength and slump prediction
Timur Cihan (2019)	Compressive strength, slump	Machine Learning Methods	Medium	Strength and slump prediction
Mohebbi et al., 2011	Rheological properties	Artificial Neural Network	Medium	Cement paste rheology prediction

6.2 Prediction of compressive strength

Concrete strength prediction using machine learning involves employing algorithms to forecast the compressive strength of concrete based on various input parameters. Machine learning models are trained on historical data that includes concrete mix proportions, curing conditions, material properties, and other relevant factors. Yeh pioneered strength prediction in 1998, introducing linear regression and Artificial Neural Networks (ANN) for high-performance concrete (Nunez et al., 2021). Advanced methods gained momentum over time. Deng et al. (2018) applied deep learning to efficiently predict recycled concrete compressive strength. Ghasemzadeh et al. (2016) used genetic programming for long-term compressive strength and creep predictions. Neural networks by Duan et al. (2013) and Dantas et al. (2013) forecast strength in recycled aggregate and demolition waste concrete. Luo and Paal (2018) employed the Backbone Curve Model (BCV) for cyclic loading simulation. Alipour et al. (2017) used decision trees and random modelling for bridge load capacity prediction, assessing potential post-casting failures. Contento et al. (2022) demonstrated remarkable accuracy with a probabilistic axial capacity model for load eccentricity and debonding estimation.

Feng et al. (2020) demonstrated concrete strength prediction using machine learning with an adaptive boosting approach. This involves training models on a comprehensive dataset of mix proportions, curing conditions, and material properties. Adaptive boosting allows the model to learn intricate patterns, improving prediction accuracy for concrete compressive strength. The study showcases how considering various factors enables reliable strength estimation, vital for optimizing mix designs and ensuring structural adequacy in construction. Fig. 1 plots comparing predicted values with tested values reveal AdaBoost's notably linear relationship, indicating closer proximity to actual test values. MAPE (Mean Absolute Percentage Error) is a common metric used to evaluate the accuracy of a forecasting or regression model. It measures the average percentage difference between predicted and actual values, making it useful for assessing model performance. AdaBoost's ensemble learning mechanism, aggregating outputs from multiple weak learners, enhances accuracy and robustness, resulting in superior performance across measures with an impressive R^2 value of 0.982 and a substantial MAPE decrease of 6.78%.

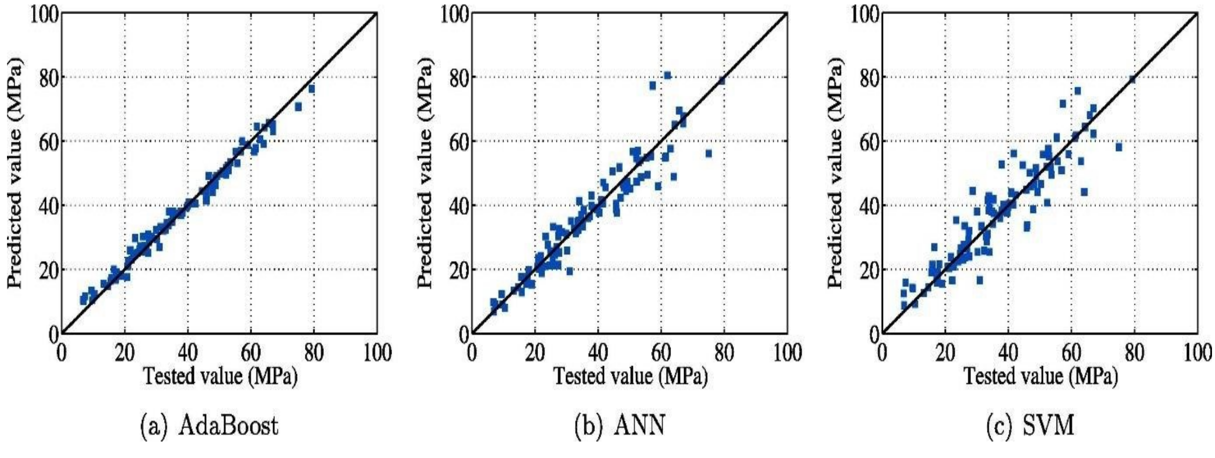

Fig. 1: Results for different machine learning techniques (Feng et al. 2020)

Pakzad et al. (2023) made a comprehensive comparison of different machine-learning algorithms for predicting the compressive strength of steel fibre-reinforced concrete. Salami et al. (2021) introduced a data-driven model for predicting ternary-blend concrete compressive strength using machine learning. LSSVM-CSA combines Least Squares Support Vector Machine (LSSVM) with Coupled Simulated Annealing (CSA) for optimized concrete strength prediction. GP (Gaussian Process) is a probabilistic model capturing data uncertainty. In Fig. 2, two models, LSSVM-CSA (A) and GP (B), demonstrate their respective fittings over the training data. The closeness of the red line to the red stars indicates the accuracy of the model's predictions, with a closer alignment signifying higher precision in predicting concrete compressive strength.

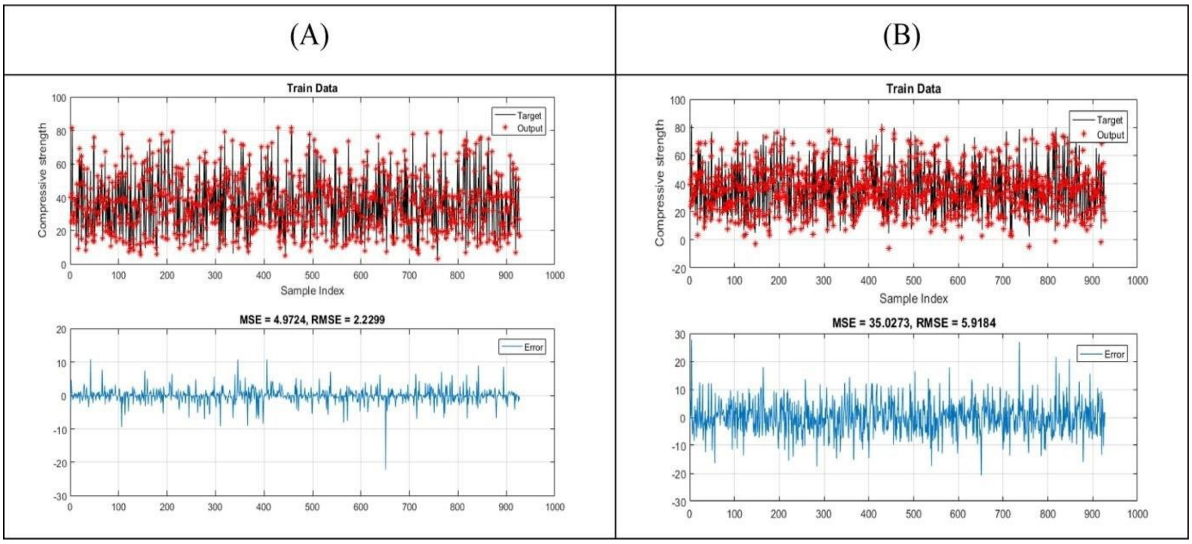

Fig. 2: Fitting of models over the train data. A) LSSVM-CSA B) GP. The target data in the red star (*) and the model prediction in the red line, respectively (Salami et al. 2021)

Ahmad et al. (2022) employed advanced machine-learning techniques to predict the compressive strength of fly ash-based geopolymer concrete. This research assessed the effectiveness of these approaches in predicting concrete strength, providing a tool for estimating geopolymer concrete compressive strength. Leveraging advanced machine learning, the study contributed to formulating geopolymer concrete, aligning with sustainable construction practices. The investigation underscored machine learning's potential in enhancing predictions for specialized concrete types, fostering innovation and efficiency in the construction industry. In Fig. 3, the Decision Tree model displays a commendable level of precision, with minimal deviation between actual and predicted values. The high R^2 value of 0.90 confirms strong accuracy in result prediction, validating the model's effectiveness.

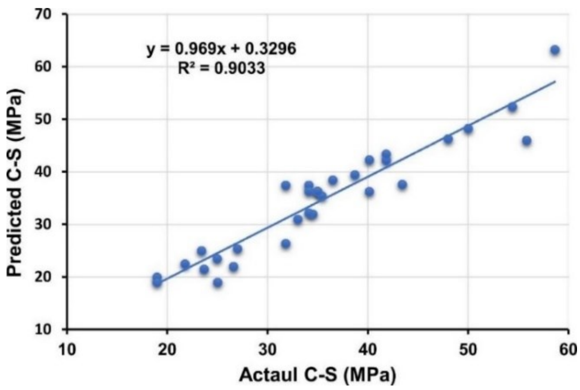

Fig. 3: Correlation between the actual and predicted results of the decision tree model (Ahmad et al. 2022)

Sevim et al. (2021) employed machine learning to develop predictive models for compressive strength in cementitious composites with fly ash. The study aimed to forecast the compressive strength of such composites, offering a valuable tool for the construction industry. Machine learning enhanced the understanding and prediction of compressive strength in these composites, fostering more efficient and sustainable construction practices. Figure 4 illustrates estimated values during training and testing, along with performance and error histograms showing Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values for both data sets. Despite the analysis, a clear correlation with experimental results proving acceptable affinity could not be established.

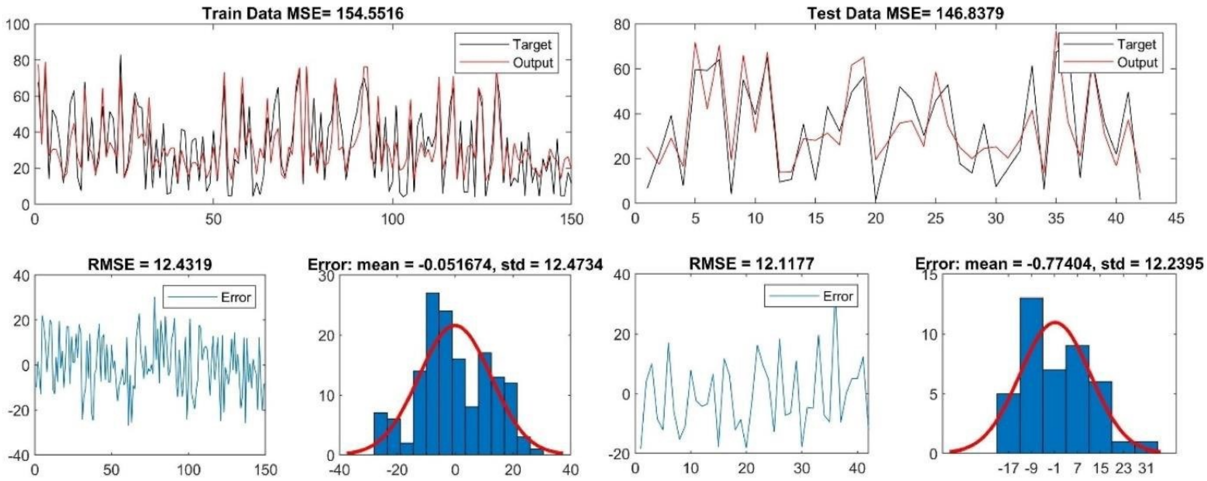

Fig. 4: Training and Test Results of MLR Model (Sevim et al. 2021)

6.3 Concrete Mix Design

The incorporation of machine learning into concrete mix design represents a significant advancement in the construction industry. Esmaeilkhanian et al. (2017) introduced Eco-SCC, optimizing low-powder self-consolidating concrete for sustainability. Ziolkowski & Niedostatkiewicz (2019) refined mix designs with machine learning, focusing on performance enhancement. Chaabene et al. (2020) highlighted machine learning's potential in predicting concrete mechanical properties for informed decision-making. Pandey et al. (2021) explored machine learning's adaptability in accommodating variations like plasticizer presence in mix designs. Nunez et al. (2020) advanced sustainable production by integrating recycled materials into mixes using a hybrid machine learning model. Zheng et al. (2023) proposed multi-objective optimization with machine learning for tailored concrete mixes. Naseri et al. (2020) introduced innovative machine-learning techniques for sustainable concrete, envisioning seamless integration of sustainability into design. Dias et al. (2021) optimized lightweight concrete using Miscanthus through machine learning, promising tailored designs for specific types. These studies collectively demonstrate machine learning's transformative role in optimizing concrete mixes for sustainability and performance enhancement.

6.4 Durability Analysis and Prediction

The incorporation of machine learning (ML) in predicting concrete durability signifies a substantial advancement in construction materials. Vital for infrastructure longevity, accurately forecasting properties like chloride resistance, carbonation depth, and corrosion rates is crucial for assessing the service life of reinforced concrete structures. Cai et al. (2020) employed ensemble ML techniques to predict the surface chloride concentration of marine concrete, a crucial factor influencing concrete durability in marine environments. This prediction aids in designing concrete structures capable of withstanding the corrosive effects of marine surroundings. Seventy-five percent of the gathered data were utilised for training six machine learning models. These models were employed to forecast Surface chloride concentration (Cs) under varying conditions related to the 12 input variables. Subsequently, the predictions were compared with the remaining 25% of the database, depicted in Fig. 5, to evaluate the models' prediction performance.

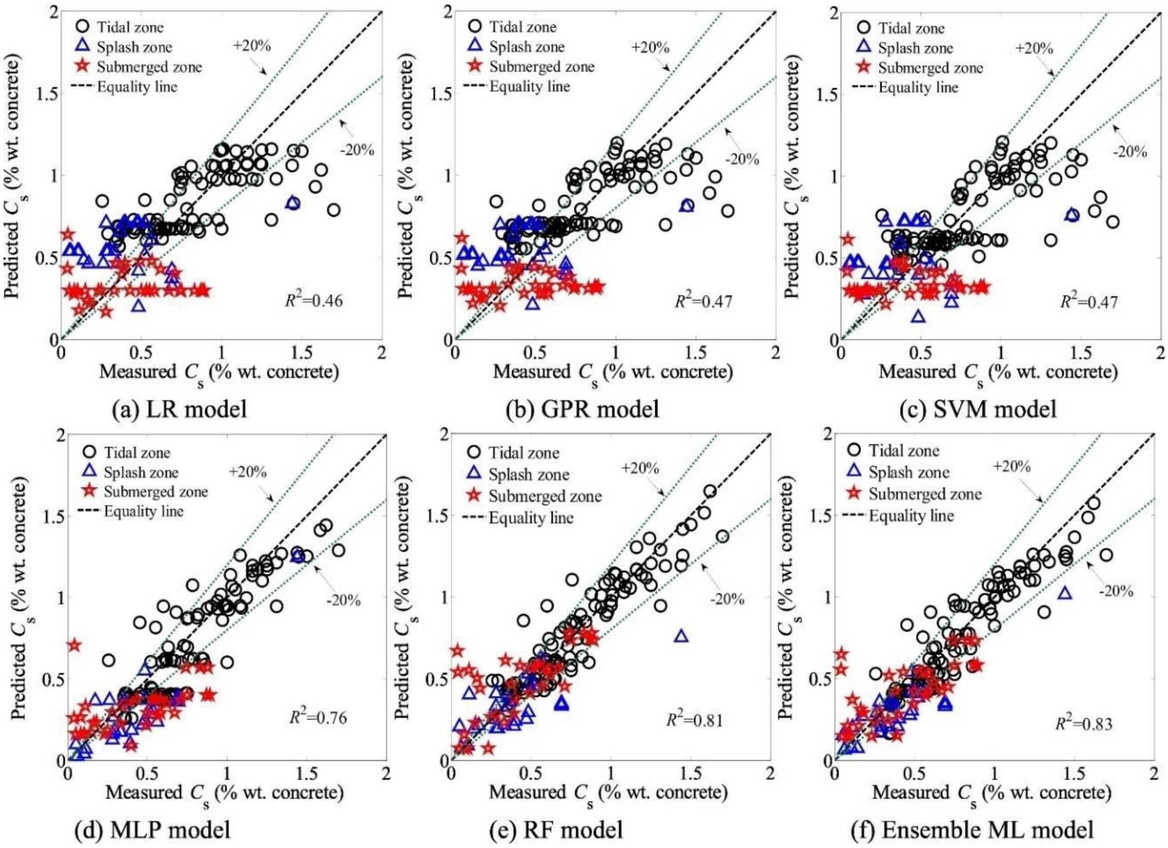

Fig. 5: Predictions of Cs made by ML models (Cai et al. 2020)

Taffese & Espinosa-Leal (2022a) introduced an ML-based predictive model for evaluating concrete's chloride resistance, essential for assessing durability and service life. Subsequently, their study (Taffese & Espinosa-Leal, 2022b) presented a specific ML method predicting the chloride migration coefficient, a key parameter influencing concrete's resistance to chloride-induced corrosion. In a comprehensive review, Taffese & Sistonen (2017) outlined recent ML advances in evaluating the durability and service life of reinforced concrete structures, highlighting progress in enhancing predictions and understanding concrete durability.

Taffese et al. (2015) pioneered the CaPrM model, utilizing ML to predict carbonation depth in reinforced concrete. Nunez & Nehdi (2021) extended this to recycled aggregate concrete with SCMs, emphasizing sustainability. Liu et al. (2021) applied hybrid ML algorithms to forecast carbonation depth in recycled aggregate concrete, showcasing ML's adaptability. Tran et al. (2023) explored carbonation depth in fly ash concrete with ML, emphasizing ML's potential in innovative mixes. Lee et al. (2020) integrated AIJ, FEM analysis, and ML for comprehensive carbonation progress assessment. Figure 6 compares machine learning-predicted carbonation depth, closely aligning with experimental data, demonstrating its efficacy.

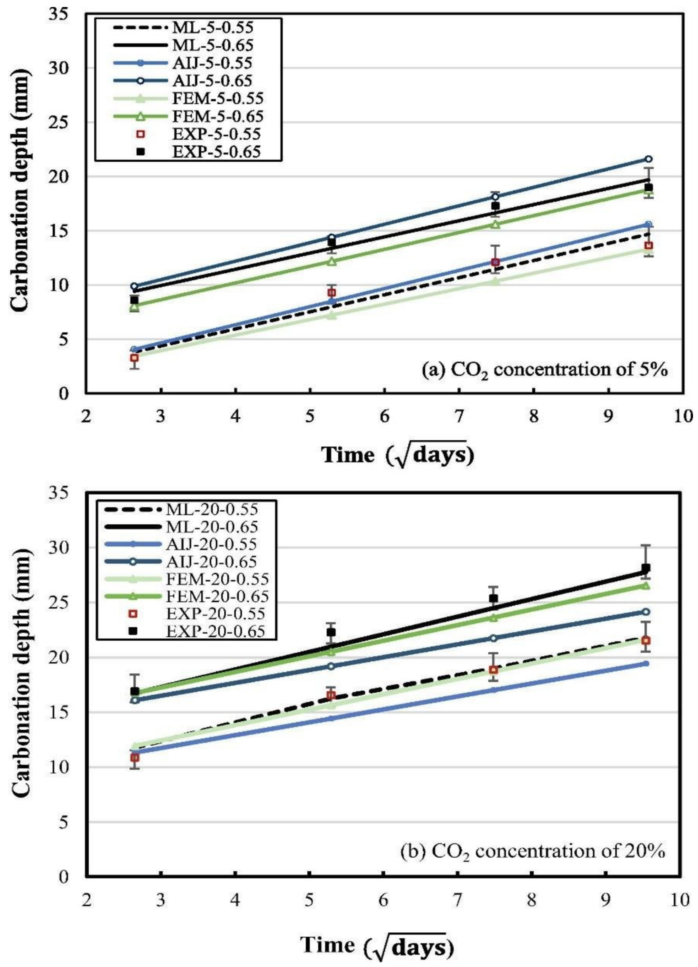

Fig. 6: Comparing carbonation rate coefficients and depth values predicted by accelerated carbonation experiments and deep learning (Lee et al. 2020)

Ji & Ye (2023) utilized ML to predict the corrosion rate of steel in carbonated cementitious mortars, offering insights into corrosion assessment in reinforced concrete. Jia et al. (2022) provided a comprehensive review on employing machine learning for evaluating environmental corrosion in reinforced concrete structures, exploring their potential in assessing corrosion-related issues. Huo et al. (2023) introduced a hybrid ensemble model predicting carbonation depth in concrete, demonstrating the efficacy of combining ML techniques for enhanced durability predictions. Zhang et al. (2023) proposed a framework incorporating ML and metaheuristic algorithms to predict the carbonation depth of concrete with fly ash, highlighting the potential of ML integration with optimization techniques for improved durability predictions.

6.5 Microstructure Characterisation

Traditional methods of concrete analysis and microstructure characterisation often require substantial manual effort and expertise. Machine learning offers an automated and data-driven approach to analyse complex microstructures with increased accuracy and efficiency. Bangaru et al. (2019) pioneered automated ML-based microstructure analysis for estimating concrete hydration degree. Lin et al. (2022) applied deep learning to characterize microstructures in graphene oxide-silica-reinforced OPC composites, showcasing its potential in identifying subtle features for tailored concrete designs. Extending this, Bangaru et al. (2022) used convolutional neural networks (CNNs) to automate microstructure segmentation in concrete through scanning electron microscopy (SEM) images. Figure 7 illustrates U-Net model assessment for concrete microstructure analysis, demonstrating its accurate segmentation and identification of components. This visual comparison highlights the U-Net model's efficiency in automating precise microstructure analysis, crucial for concrete research advancements.

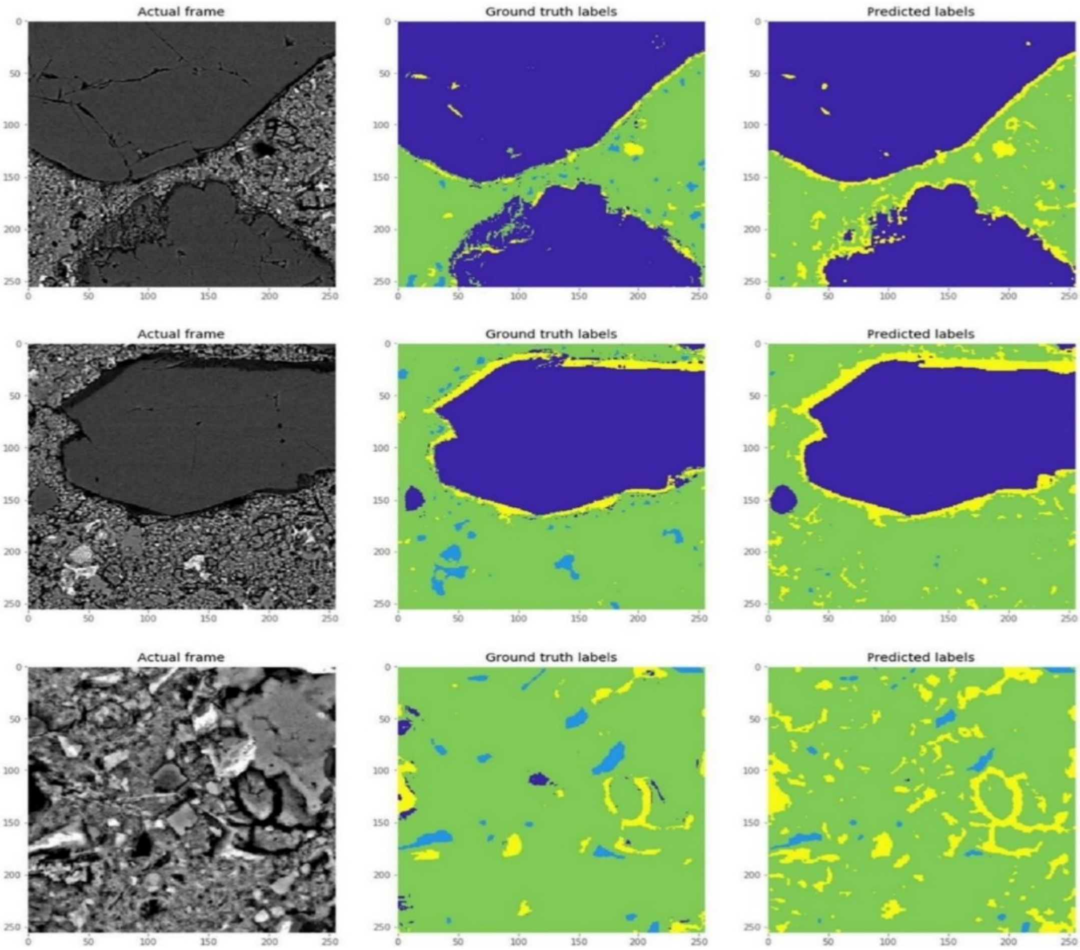

Fig. 7: Actual, Ground Truth, and Predicted images using the proposed U-Net model (Bangaru et al. 2022)

Sui et al. (2023) employed machine learning for spatial correlation and pore morphology analysis in limestone calcined clay cement (LC3), demonstrating ML's efficacy in unravelling intricate microstructures for understanding material behaviour. Qian et al. (2023) focused on cement particle segmentation and analysis through deep learning, showcasing ML's accuracy in segmenting cement particles, a crucial step for comprehending cementitious matrix composition. Lorenzoni et al. (2020) applied deep learning to micro-computed tomography scans for semantic segmentation of strain-hardening cement-based composites (SHCC), highlighting ML's capability in handling complex 3D images for insights into advanced concrete materials' microstructure. Figure 8 illustrates a 3D representation of segmented voids (blue) and fibres (red) in M1-PVA concrete achieved through deep learning, emphasizing its automated and accurate identification of key components for enhanced understanding of concrete microstructure.

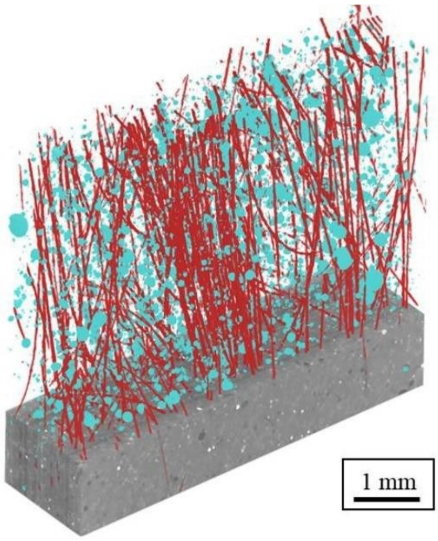

Fig. 8: Segmented 3D voids (blue) and fibres (red) in M1-PVA image by Deep Learning (Lorenzoni et al. 2020)

Ford et al. (2021) applied machine learning (ML) to microstructural chemical maps, classifying component phases in cement pastes. Using chemical information, the study showcased ML's potential to understand concrete's chemical composition and phase distribution, providing a holistic view. Qoku et al. (2023) emphasized ML's role in advancing characterisation techniques for comprehensive understanding of cementitious systems. Integrating imaging, scattering, spectroscopy, and ML presents a promising avenue for multiscale characterization of concrete microstructures. ML is transforming concrete microstructure analysis, automating processes and improving accuracy, offering a valuable tool for researchers and engineers. These studies collectively highlight ML's promising future in civil engineering and construction materials, contributing to advancements in the field.

7. Challenges and Opportunities

7.1 Data Quality and Availability

Data quality and availability profoundly influence concrete analysis, demanding accurate, up-to-date, and context-relevant information for reliable predictions and decisions. Li et al. (2022) stressed the importance of high-quality data in ML applications for concrete science, emphasizing the need for accurate datasets for effective model training. Ensuring meticulous data quality is crucial to prevent misleading ML models and ensure reliable predictions. Lyngdoh et al. (2022) addressed the concern of missing data in concrete strength prediction, highlighting the significance of accurate imputation techniques to maintain model robustness. Properly handling missing data enhances ML models' predictive power, emphasizing the completeness of datasets. In contrast, Sun et al. (2021) discussed challenges in data availability for structural design, advocating collaborative efforts to create centralized repositories for improved ML model development and validation. Collectively, these studies underscore the pivotal role of data quality and availability in advancing ML applications in concrete science, promoting efficiency and effectiveness in construction practices.

Figure 9 depicts the balance between underfitting and overfitting in concrete science, using a dataset of 40 concrete mixes with one input (water/cement ratio) and one output (compressive strength). The dataset is split into training and validation sets (80/20). Three polynomial models (p=1, p=3, and p=10) are fitted to the training data. The figure indicates the polynomial of degree three as optimal, showing good performance on the validation set. The subplot labeled "b" illustrates the prediction error for training and validation sets concerning model complexity. It underscores the challenge of finding the right complexity for optimal generalization, crucial in machine learning models' implementation and validation, particularly with smaller datasets.

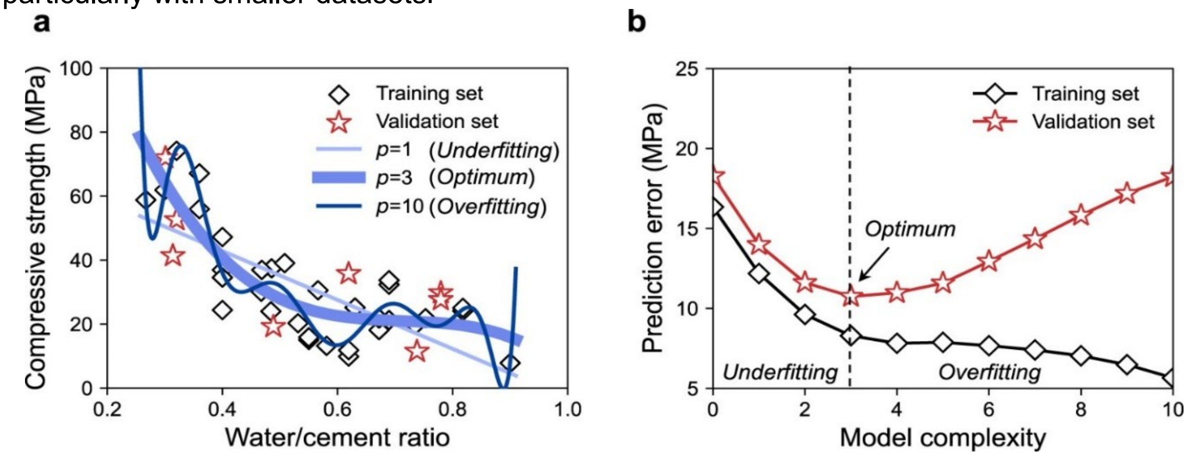

Fig. 9: Trade-off between underfitting and overfitting (Li et al. 2022)

7.2 Interpretability and Explainability of Models

Interpretability and explainability are vital in applying machine learning models to concrete science. Interpretability ensures that the model's operations and outcomes are transparent, allowing users, even those without deep machine learning knowledge, to understand them. In concrete science, interpretability involves presenting how alterations in input parameters, like mix proportions or curing conditions, impact predicted concrete strength. Examining Figure 10, two instances of concrete strength prediction reveal issues with the permutation method generating impractical mixes. Focusing on superplasticizers, known for reducing water content and enhancing flowability, a negative relationship with water content is anticipated (Pearson correlation coefficient -0.66, denoted by black circles in Fig. 10a). However, after permutation, some generated mixes (red pluses) lack workability, positioned in extremes—high water content with superplasticizer or low water content without, both impractical for real-world use. Similar challenges arise with cement and supplementary materials (SCMs) correlations, where permutation generates mixes with unviable combinations, affecting water-to-cementitious material ratio and rendering them unsuitable for practical concrete applications.

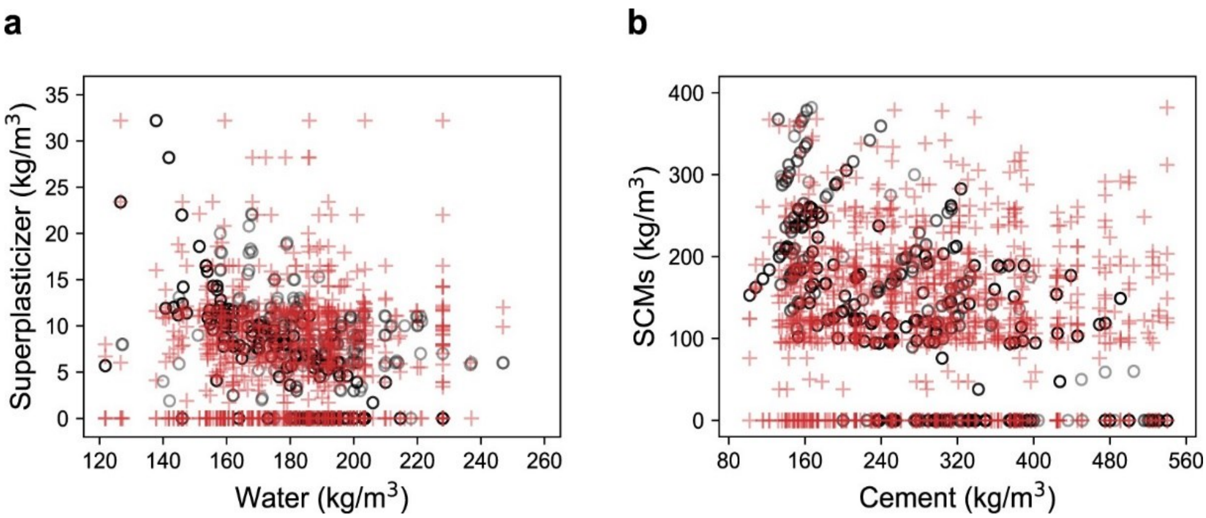

Fig. 10: Illustration of unrealistic concrete mixes generated by permutation feature importance method (Li et al. 2022)

Interpretability and explainability are indispensable in machine learning models within concrete science, offering engineers and stakeholders valuable insights into model decisions. These aspects enhance the usability and trustworthiness of predictive models, leading to substantial progress in the field. By providing clear, understandable rationales for predictions, machine learning models help optimise concrete compositions and properties. Consequently, this facilitates the construction of more resilient, sustainable, and cost-effective concrete structures, promoting innovation and efficiency in the construction industry. In summary, interpretability and explainability play pivotal roles in driving advancements in concrete science and the broader construction sector.

7.3 Ethical Considerations

Integrating machine learning (ML) into concrete science poses ethical challenges amidst a rapidly evolving technology landscape. Ethical practices necessitate respect for privacy, data ownership, and informed consent, coupled with robust security measures for sensitive data. Addressing bias is crucial to avoid perpetuating societal inequalities, ensuring fairness across demographic groups. Transparency in model predictions fosters trust and enables stakeholders to assess decisions critically. Accountability entails adherence to ethical guidelines, legal regulations, and responsible deployment. Collaborative knowledge-sharing refines ethical guidelines, fostering responsible decision-making. Considerations extend to environmental and social impacts, aligning ML integration with sustainability goals. In summary, ethical considerations are vital for responsible and informed ML integration in concrete science.

8. Recommendations for Researchers and Practitioners

Implementing data-driven approaches in concrete science requires strict adherence to key recommendations for heightened effectiveness. Priority lies in Comprehensive Data Acquisition, gathering diverse data on ingredient proportions, curing conditions, and environmental factors through sensors, lab experiments, and field measurements. Diligent Data Pre-processing and Cleaning are essential for ensuring data quality by addressing missing values and inaccuracies using statistical methods and domain knowledge.

Collaboration with concrete science experts integrates Domain Expertise, guiding analysis with their profound understanding. Emphasizing Model Interpretability instills confidence in predictions, while regular Model Validation and Updating maintain accuracy. Ethical Data Usage safeguards sensitive information. Open Collaboration and Continuous Skill Development sustain technological relevance. Benchmarking and Comparative Studies evaluate data-driven models, while Industry Engagement aligns solutions with practical needs. Following these recommendations establishes a structured framework, enhancing comprehension of concrete properties and optimizing composition. This systematic approach drives efficiency, durability, and innovation in construction, fostering sustainability. Rigorously applying these principles unlocks the full potential of data-driven methodologies, propelling the field towards deeper insights and progress.

References:

- Abadel, A., Abbas, H., Almusallam, T., Al-Salloum, Y. & Siddiqui, N., (2016) Mechanical properties of hybrid fibre-reinforced concrete–analytical modelling and experimental behaviour. Magazine of Concrete Research, 68(16), 823-843.

- Abbasloo, A. A., Shayanfar, M. A., Pahlavan, H., Barkhordari, M. A. & Hamze-Ziabari, S. M. (2019) Prediction of shear strength of FRP-reinforced concrete members using a rule-based method. Magazine of Concrete Research, 71, 271–286.
- Abd Elaty, M. A. A., Ghazy, M. F., & Abd El Hameed, M. F. (2017). Optimization of geopolymer concrete by Principal Component Analysis. ACI Materials Journal, 114(2), 253.
- Ahmad, A., Ahmad, W., Aslam, F. & Joyklad, P., (2022) Compressive strength prediction of fly ash-based geopolymer concrete via advanced machine learning techniques. Case Studies in Construction Materials, 16, e00840.
- Ali-Benyahia, K., Sbartaï, Z.M., Breysse, D., Kenai, S. & Ghrici, M., (2017) Analysis of the single and combined non-destructive test approaches for on-site concrete strength assessment: General statements based on a real case-study. Case Studies in Construction Materials, 6, 109-119.
- Alipour, M., Harris, D. K., Barnes, L. E., Ozbulut, O. E., & Carroll, J., (2017) Loadcapacity rating of bridge populations through machine learning: Application of decision trees and random forests. Journal of Bridge Engineering, 22 (10), 04017076.
- Amriou, A. & Bencheikh, M., (2017) New experimental method for evaluating the water permeability of concrete by a lateral flow procedure on a hollow cylindrical test piece. Construction and building materials, 151, 642-649.
- Asghshahr, M. S., Rahai, A. & Ashrafi, H. (2016) Prediction of chloride content in concrete using ANN and CART. Magazine of Concrete Research, 68, 1085–1098. • Aslani, F. & Nejadi, S., (2012) Mechanical properties of conventional and selfcompacting concrete: An analytical study. Construction and Building Materials, 36, 330-347.
- Asutkar, P., Shinde, S.B., & Patel, R. (2017). Study on the behaviour of rubber aggregates concrete beams using analytical approach. Engineering Science and Technology, an International Journal, 20(1), 151-159.
- Atiş, C.D., (2003) Accelerated carbonation and testing of concrete made with fly ash. Construction and Building Materials, 17(3), 147-152.
- Austin, S., Robins, P. & Pan, Y., (1995) Tensile bond testing of concrete repairs. Materials and structures, 28, 249-259.
- Aydogmus, H. Y., Erdal, H. I., Karakurt, O., Namli, E., Turkan, Y. S., & Erdal, H., (2015) A comparative assessment of bagging ensemble models for modeling concrete slump flow. Computers and Concrete, 16 (5), 741–757.
- Bangaru, S. S., Wang, C., Hassan, M., Jeon, H. W., & Ayiluri, T. (2019). Estimation of the degree of hydration of concrete through automated machine learning based microstructure analysis–A study on effect of image magnification. Advanced Engineering Informatics, 42, 100975.
- Bangaru, S. S., Wang, C., Zhou, X., & Hassan, M. (2022). Scanning electron microscopy (SEM) image segmentation for microstructure analysis of concrete using U-net convolutional neural network. Automation in Construction, 144, 104602.
- Behnood, A. & Golafshani, E. M. (2020) Machine learning study of the mechanical properties of concretes containing waste foundry sand. Construction and Building Materials, 243, 118152.
- Boukhatem, B., Kenai, S., Hamou, A.T., Ziou, D. & Ghrici, M., (2012) Predicting concrete properties using neural networks(NN) with principal component analysis(PCA) technique. Computers & Concrete, 10(6), 557-573.
- Broomfield, J.P., Davies, K. & Hladky, K., (2002) The use of permanent corrosion monitoring in new and existing reinforced concrete structures. Cement and Concrete Composites, 24(1), 27-34.
- Cai, J.F., Ji, H., Shen, Z. & Ye, G.B., (2014) Data-driven tight frame construction and image denoising. Applied and Computational Harmonic Analysis, 37(1), 89-105.

- Cai, R., Han, T., Liao, W., Huang, J., Li, D., Kumar, A., & Ma, H. (2020). Prediction of surface chloride concentration of marine concrete using ensemble machine learning. Cement and Concrete Research, 136, 106164.
- Cakiroglu, C., Shahjalal, M., Islam, K., Mahmood, S.F., Billah, A.M. & Nehdi, M.L., (2023) Explainable ensemble learning data-driven modeling of mechanical properties of fiber-reinforced rubberized recycled aggregate concrete. Journal of Building Engineering, 76, 107279.
- Calabrese, L., Campanella, G., & Proverbio, E. (2012). Noise removal by cluster analysis after long time AE corrosion monitoring of steel reinforcement in concrete. Construction and Building Materials, 34, 362-371.
- Candelaria, M.D.E. & Kee, S.H. (2023) Evaluation of thermal damages of concrete subjected to high temperatures using recurrent neural networks for ultrasonic pulse waves. Construction and Building Materials, 407, 133416.
- Chaabene, W. B., Flah, M., & Nehdi, M. L. (2020). Machine learning prediction of mechanical properties of concrete: Critical review. Construction and Building Materials, 260, 119889.
- Chalioris, C.E. (2013). Analytical approach for the evaluation of minimum fibre factor required for steel fibrous concrete beams under combined shear and flexure. Construction and Building Materials, 43, 317-336.
- Chandwani, V., Agrawal, V., & Nagar, R., (2015) Modeling slump of ready mix concrete using genetic algorithms assisted training of Artificial Neural Networks. Expert Systems with Applications, 42 (2), 885–893.
- Chen, B., Wang, L., Feng, Z., Liu, Y., Wu, X., Qin, Y., & Xia, L. (2023). Optimization of high-performance concrete mix ratio design using machine learning. Engineering Applications of Artificial Intelligence, 122, p.106047.
- Chen, D., Montano, V., Huo, L., Fan, S. & Song, G. (2020) Detection of subsurface voids in concrete-filled steel tubular (CFST) structure using percussion approach. Construction and Building Materials, 262, 119761.
- Chen, H., Li, X., Wu, Y., Zuo, L., Lu, M. & Zhou, Y. (2022) Compressive strength prediction of high-strength concrete using long short-term memory & machine learning algorithms. Buildings, 12(3), 302.
- Chen, L., Shan, W., & Liu, P. (2021, December). Identification of concrete aggregates using K-means clustering and level set method. In Structures (Vol. 34, pp. 2069-2076). Elsevier.
- Chhachhia, A., (2020) Concrete mix design by IS, ACI and BS methods: A Comparative Analysis. Journal of Building Material Science, 2(1), 30-33.
- Conciatori, D., Grégoire, É., Samson, É., Marchand, J. & Chouinard, L., (2014) Statistical analysis of concrete transport properties. Materials and structures, 47, 89-103.
- Contento, A., Aloisio, A., Xue, J., Quaranta, G., Briseghella, B., & Gardoni, P., (2022) Probabilistic axial capacity model for concrete-filled steel tubes accounting for load eccentricity and debonding. Engineering Structures, 268, 114730.
- Cook, R. et al. (2021) Machine learning for high-fidelity prediction of cement hydration kinetics in blended systems. Materials & Design, 208, 109920.
- Dantas, A. T. A., Leite, M. B., & de Jesus Nagahama, K., (2013) Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks. Construction and Building Materials, 38, 717–722.
- Dare, P., Hanley, H., Fraser, C., Riedel, B. & Niemeier, W., (2002) An operational application of automatic feature extraction: the measurement of cracks in concrete structures. The Photogrammetric Record, 17(99), 453-464.
- Darvell, B.W., (1990) Uniaxial compression tests and the validity of indirect tensile strength. Journal of Materials Science, 25(2), 757-780.
- Das, S. & Saha, P., (2018) A review of some advanced sensors used for health diagnosis of civil engineering structures. Measurement, 129, 68-90.

- Debicki, G., Haniche, R. & Delhomme, F., (2012) An experimental method for assessing the spalling sensitivity of concrete mixture submitted to high temperature. Cement and Concrete Composites, 34(8), 958-963.
- Deng, F., He, Y., Zhou, S., Yu, Y., Cheng, H. & Wu, X., (2018) Compressive strength prediction of recycled concrete based on deep learning. Construction and Building Materials, 175, 562-569.
- Dérobert, X., Lataste, J.F., Balayssac, J.P. & Laurens, S., (2017) Evaluation of chloride contamination in concrete using electromagnetic non-destructive testing methods. NDT & E International, 89, 19-29.
- Dias, P. P., Jayasinghe, L. B., & Waldmann, D. (2021). Machine learning in mix design of Miscanthus lightweight concrete. Construction and Building Materials, 302, p.124191.
- Dias, W.P.S., Pooliyadda, S.P., (2001) Neural networks for predicting properties of concretes with admixtures. Construction and Building Materials, 15 (7), 371-379.
- Dong, Y., Su, C., Qiao, P. & Sun, L. (2020) Microstructural crack segmentation of three-dimensional concrete images based on deep convolutional neural networks. Construction and Building Materials, 253, 119185.
- Dorafshan, S., Thomas, R.J. & Maguire, M. (2018a) Comparison of deep convolutional neural networks & edge detectors for image-based crack detection in concrete. Construction and Building Materials, 186, 1031-1045.
- Dorafshan, S., Thomas, R.J. & Maguire, M. (2018b) SDNET2018: An annotated image dataset for non-contact concrete crack detection using deep convolutional neural networks. Data in brief, 21, 1664-1668.
- Dung, C.V. (2019) Autonomous concrete crack detection using deep fully convolutional neural network. Automation in Construction, 99, 52-58.
- Duan, Z.-H., Kou, S.-C., & Poon, C.-S., (2013) Prediction of compressive strength of recycled aggregate concrete using artificial neural networks. Construction and Building Materials, 40, 1200–1206.
- Elgendy, N. & Elragal, A. (2014) Big data analytics: a literature review paper. In Advances in Data Mining. Applications and Theoretical Aspects: 14th Industrial Conference, ICDM 2014, St. Petersburg, Russia, July 16-20, 2014. Proceedings 14 (pp. 214-227). Springer International Publishing.
- ElNemr, A., (2020) Generating water/binder ratio-to-strength curves for cement mortar used in Masonry walls. Construction and Building Materials, 233, 117249.
- Erzar, B. & Forquin, P., (2010) An experimental method to determine the tensile strength of concrete at high rates of strain. Experimental Mechanics, 50(7), 941-955.
- Esmaeilkhanian, B., Khayat, K., & Wallevik, O. H. (2017). Mix design approach for lowpowder self-consolidating concrete: Eco-SCC—content optimization and performance. Materials and Structures, 50(2), 124–218.
- Fan, C. L. (2021). Detection of multidamage to reinforced concrete using support vector machine-based clustering from digital images. Structural Control and Health Monitoring, 28(12), e2841.
- Feng, D.C., Liu, Z.T., Wang, X.D., Chen, Y., Chang, J.Q., Wei, D.F. & Jiang, Z.M., (2020) Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. Construction and Building Materials, 230, 117000.
- Feroz, S. & Abu Dabous, S., (2021) UAV-based remote sensing applications for bridge condition assessment. Remote Sensing, 13(9), 1809. • Finch, H., (2008) Estimation of item response theory parameters in the presence of missing data. Journal of Educational Measurement, 45(3), 225-245.
- Foorthuis, R., (2021) On the nature and types of anomalies: a review of deviations in data. International journal of data science and analytics, 12(4), 297-331.

- Ford, E., Maneparambil, K., & Neithalath, N. (2021). Machine learning on microstructural chemical maps to classify component phases in cement pastes. Journal of Soft Computing in Civil Engineering, 5(4), 1-20.
- Fu, W., Sun, B., Noguchi, T., Zhao, W. & Ye, J. (2023) Prediction of internal relative humidity of concrete under different thermal conditions using an enhanced long short-term memory network. Thermal Science and Engineering Progress, 38, 101629.
- Gandomi, A. & Haider, M. (2015) Beyond the hype: Big data concepts, methods, & analytics. International journal of information management, 35(2), 137-144.
- Ghasemzadeh, F., Manafpour, A., Sajedi, S., Shekarchi, M., & Hatami, M., (2016) Predicting long-term compressive creep of concrete using inverse analysis method. Construction and Building Materials, 124, 496–507.
- Gogineni, A., Rout, M.D. & Shubham, K. (2023) Evaluating machine learning algorithms for predicting compressive strength of concrete with mineral admixture using long short-term memory (LSTM) Technique. Asian Journal of Civil Engineering, 1-13.
- Gudimettla, J. & Crawford, G., (2016) Resistivity tests for concrete-recent field experience. ACI Materials Journal, 113(4), 505.
- Gupta, M., Khan, M.A., Butola, R. & Singari, R.M., (2022) Advances in applications of Non-Destructive Testing (NDT): A review. Advances in Materials and Processing Technologies, 8(2), 2286-2307.
- Hafez, H., Teirelbar, A., Tošić, N., Ikumi, T. & de la Fuente, A., (2023) Data-driven optimization tool for the functional, economic, and environmental properties of blended cement concrete using supplementary cementitious materials. Journal of Building Engineering, 67, 106022.
- Hameed, M.M., AlOmar, M.K., Baniya, W.J. & AlSaadi, M.A., (2021) Incorporation of artificial neural network with principal component analysis and cross-validation technique to predict high-performance concrete compressive strength. Asian Journal of Civil Engineering, 22, 1019-1031.
- He, J., Gao, R. & Tang, Z., (2022) A data-driven multi-scale constitutive model of concrete material based on polynomial chaos expansion and stochastic damage model. Construction and Building Materials, 334, 127441.
- Huang, Y., Zhang, J., Tze Ann, F. & Ma, G. (2020) Intelligent mixture design of steel fibre reinforced concrete using a support vector regression and firefly algorithm based multi-objective optimization model. Construction and Building Materials, 260, 120457.
- Huo, Z., Wang, L., & Huang, Y. (2023). Predicting carbonation depth of concrete using a hybrid ensemble model. Journal of Building Engineering, 76, 107320.
- Imran, M., Khushnood, R.A. & Fawad, M., (2023) A hybrid data-driven and metaheuristic optimization approach for the compressive strength prediction of high-performance concrete. Case Studies in Construction Materials, 18, e01890.
- Janowski, A., Nagrodzka-Godycka, K., Szulwic, J. & Ziolkowski, P., (2016) Remote sensing and photogrammetry techniques in diagnostics of concrete structures. Computers and Concrete, 18(3), 405-420.
- Ji, H. & Ye, H. (2023). Machine learning prediction of corrosion rate of steel in carbonated cementitious mortars. Cement and Concrete Composites, 143, 105256.
- Jia, H., Qiao, G., & Han, P. (2022). Machine learning algorithms in the environmental corrosion evaluation of reinforced concrete structures-A review. Cement and Concrete Composites, 104725.
- Johann, S., Strangfeld, C., Müller, M., Mieller, B. & Bartholmai, M., (2017) RFID sensor systems embedded in concrete–requirements for long–term operation. Materials Today: Proceedings, 4(5), 5827-5832.

- Kim, B. & Cho, S. (2019) Image-based concrete crack assessment using mask & region-based convolutional neural network. Structural Control and Health Monitoring, 26(8), e2381.
- Kim, K.H., Jeon, S.E., Kim, J.K. & Yang, S., (2003) An experimental study on thermal conductivity of concrete. Cement and Concrete Research, 33(3), 363-371.
- Kina, C., Turk, K., Atalay, E., Donmez, I., & Tanyildizi, H., (2021) Comparison of extreme learning machine and deep learning model in the estimation of the fresh properties of hybrid fiber-reinforced SCC. Neural Computing and Applications, 33 (18), 11641–11659.
- Koo, S., Shin, D., & Kim, C. (2021). Application of principal component analysis approach to predict shear strength of reinforced concrete beams with stirrups. Materials, 14(13), 3471.
- Kumar, P. & Pratap, B., (2023) Feature engineering for predicting compressive strength of high-strength concrete with machine learning models. Asian Journal of Civil Engineering, 1-14.
- Lahat, D., Adali, T. & Jutten, C., (2015) Multimodal data fusion: an overview of methods, challenges, and prospects. Proceedings of the IEEE, 103(9), 1449-1477.
- Lattanzi, D., & Miller, G. R. (2014). Robust automated concrete damage detection algorithms for field applications. Journal of Computing in Civil Engineering, 28(2), 253- 262.
- Lee, H., Lee, H. S., & Suraneni, P. (2020). Evaluation of carbonation progress using AIJ model, FEM analysis, & machine learning algorithms. Construction and Building Materials, 259, 119703.
- Liao, K. W., Chen, C. T., Wu, B. H., Chen, W. L. & Yeh, C. M. (2016) Investigation of chloride diffusion in cement mortar via statistical learning theory. Magazine of Concrete Research, 68, 237–249.
- Li, F., Laili, Y., Chen, X., Lou, Y., Wang, C., Yang, H., Gao, X. & Han, H., (2023) Towards big data driven construction industry. Journal of Industrial Information Integration, 100483.
- Li, Z., Yoon, J., Zhang, R., Rajabipour, F., Srubar III, W.V., Dabo, I., & Radlińska, A. 2022. Machine learning in concrete science: applications, challenges, and best practices. npj Computational Materials, 8(1), p.127.
- Lin, J., Liu, Y., Sui, H., Sagoe-Crentsil, K., & Duan, W. (2022). Microstructure of graphene oxide–silica-reinforced OPC composites: Image-based characterization and nano-identification through deep learning. Cement and Concrete Research, 154, 106737.
- Liu, K., Alam, M. S., Zhu, J., Zheng, J., & Chi, L. (2021). Prediction of carbonation depth for recycled aggregate concrete using ANN hybridized with swarm intelligence algorithms. Construction and Building Materials, 301, 124382.
- Lorenzoni, R., Curosu, I., Paciornik, S., Mechtcherine, V., Oppermann, M., & Silva, F. (2020). Semantic segmentation of the micro-structure of strain-hardening cementbased composites (SHCC) by applying deep learning on micro-computed tomography scans. Cement and Concrete Composites, 108, 103551.
- Luo, H., & Paal, S. G., (2018) Machine learning–based backbone curve model of reinforced concrete columns subjected to cyclic loading reversals. Journal of Computing in Civil Engineering, 32 (5), 04018042.
- Lyngdoh, G.A., Zaki, M., Krishnan, N.A., & Das, S. 2022. Prediction of concrete strengths enabled by missing data imputation and interpretable machine learning. Cement and Concrete Composites, 128, p.104414. Martínez, I. & Andrade, C., (2009) Examples of reinforcement corrosion monitoring by embedded sensors in concrete structures. Cement and Concrete Composites, 31(8), 545-554.
- Matos, L.M., Barros, J.A., Ventura-Gouveia, A. & Calçada, R.A., (2021) A new inverse analysis approach for predicting the fracture mode I parameters of fibre reinforced concrete. Engineering Fracture Mechanics, 246, 107613.

- McCarter, W.J., Emerson, M. & Ezirim, H., (1995) Properties of concrete in the cover zone: developments in monitoring techniques. Magazine of Concrete Research, 47(172), 243-251.
- Mohebbi, A., Shekarchi, M., Mahoutian, M., & Mohebbi, S. (2011). Modeling the effects of additives on rheological properties of fresh self-consolidating cement paste using artificial neural network. Computers and Concrete, 8 (3), 279–292.
- Mori, K., Spagnoli, A., Murakami, Y., Kondo, G. & Torigoe, I., (2002) A new non-contacting non-destructive testing method for defect detection in concrete. NDT & E International, 35(6), 399-406.
- Munawar, H.S., Ullah, F., Qayyum, S. & Shahzad, D. (2022) Big data in construction: current applications and future opportunities. Big Data and Cognitive Computing, 6(1), 18.
- Naseri, H., Jahanbakhsh, H., Hosseini, P., & Nejad, F. M. (2020). Designing sustainable concrete mixture by developing a new machine learning technique. Journal of Cleaner Production, 258, p.120578.
- Nguyen, H.L. & Tran, V.Q., (2023) Data-driven approach for investigating and predicting rutting depth of asphalt concrete containing reclaimed asphalt pavement. Construction and Building Materials, 377, 131116.
- Nguyen, H., Vu, T., Vo, T. P. & Thai, H. T. (2021) Efficient machine learning models for prediction of concrete strengths. Construction and Building Materials, 266, 120950.
- Nguyen-Sy, T. et al. (2020) Predicting the compressive strength of concrete from its compositions and age using the extreme gradient boosting method. Construction and Building Materials, 260, 119757.
- Nikbin, I.M., Rahimi, S., Allahyari, H. & Damadi, M., (2016) A comprehensive analytical study on the mechanical properties of concrete containing waste bottom ash as natural aggregate replacement. Construction and Building Materials, 121, 746-759.
- Nunez, I., Marani, A., Flah, M., & Nehdi, M. L., (2021) Estimating compressive strength of modern concrete mixtures using computational intelligence: A systematic review. Construction and Building Materials, 310, 125279.
- Nunez, I., Marani, A., & Nehdi, M. L. (2020). Mixture optimization of recycled aggregate concrete using hybrid machine learning model. Materials, 13(19), 4331.
- Nunez, I. & Nehdi, M. L. (2021). Machine learning prediction of carbonation depth in recycled aggregate concrete incorporating SCMs. Construction and Building Materials, 287, 123027.
- Oey, T., Jones, S., Bullard, J. W. & Sant, G. (2020) Machine learning can predict setting behavior and strength evolution of hydrating cement systems. Journal of the American Ceramic Society, 103, 480–490.
- Omar, T. & Nehdi, M.L., (2017) Remote sensing of concrete bridge decks using unmanned aerial vehicle infrared thermography. Automation in Construction, 83, 360-371.
- Opon, J., & Henry, M. (2022). Implementation of a multicriteria analytical framework for the sustainability evaluation and comparison of concrete materials considering methodological uncertainties. Journal of Cleaner Production, 344, 131057.
- Öztaş, A., Pala, M., Özbay, E. a., Kanca, E. a., Çagõlar, N., & Bhatti, M. A., (2006) Predicting the compressive strength and slump of high strength concrete using neural network. Construction and Building Materials, 20 (9), 769–775.
- Pakzad, S.S., Roshan, N. & Ghalehnovi, M., (2023) Comparison of various machine learning algorithms used for compressive strength prediction of steel fiber-reinforced concrete. Scientific Reports, 13(1), 3646.
- Pandey, S., Kumar, V., & Kumar, P. (2021). Application and analysis of machine learning algorithms for design of concrete mix with plasticizer and without plasticizer. Journal of Soft Computing in Civil Engineering, 5(1), 19–37.

- Pani, A.K., Vadlamudi, V.K. & Mohanta, H.K., (2013) Development and comparison of neural network based soft sensors for online estimation of cement clinker quality. ISA transactions, 52(1), 19-29.
- Pearson, R.K., (2002) Outliers in process modeling and identification. IEEE Transactions on control systems technology, 10(1), 55-63.
- Pei, L. et al. (2020) Pavement aggregate shape classification based on extreme gradient boosting. Construction and Building Materials, 256, 119356.
- Popovics, S. & Ujhelyi, J., (2008) Contribution to the concrete strength versus water-cement ratio relationship. Journal of Materials in Civil Engineering, 20(7), 459-463.
- Qian, H., Li, Y., Yang, J., Xie, L., & Tan, K. H. (2023). Segmentation and analysis of cement particles in cement paste with deep learning. Cement and Concrete Composites, 136, 104819.
- Qoku, E., Xu, K., Li, J., Monteiro, P. J., & Kurtis, K. E. (2023). Advances in imaging, scattering, spectroscopy, and machine learning-aided approaches for multiscale characterization of cementitious systems. Cement and Concrete Research, 174, 107335.
- Ranjbar, I. & Toufigh, V. (2022) Deep long short-term memory (LSTM) networks for ultrasonic-based distributed damage assessment in concrete. Cement and Concrete Research, 162, 107003.
- Rashid, K., Razzaq, A., Ahmad, M., Rashid, T., & Tariq, S. (2017). Experimental and analytical selection of sustainable recycled concrete with ceramic waste aggregate. Construction and Building Materials, 154, 829-840.
- Sadowski, Ł., Nikoo, M., & Nikoo, M. (2015). Principal component analysis combined with a self-organization feature map to determine the pull-off adhesion between concrete layers. Construction and Building Materials, 78, 386-396.
- Sagar, B. & Sivakumar, M.V.N., (2021) Compressive properties and analytical modelling for stress-strain curves of polyvinyl alcohol fiber reinforced concrete. Construction and Building Materials, 291, 123192.
- Salami, B.A., Olayiwola, T., Oyehan, T.A. & Raji, I.A., (2021) Data-driven model for ternary-blend concrete compressive strength prediction using machine learning approach. Construction and Building Materials, 301, 124152.
- Saggi, M.K. & Jain, S. (2018) A survey towards an integration of big data analytics to big insights for value-creation. Information Processing & Management, 54(5), 758-790.
- Sandryhaila, A. & Moura, J.M. (2014) Big data analysis with signal processing on graphs: Representation and processing of massive data sets with irregular structure. IEEE signal processing magazine, 31(5), 80-90.
- Sevim, U.K., Bilgic, H.H., Cansiz, O.F., Ozturk, M. & Atis, C.D., (2021) Compressive strength prediction models for cementitious composites with fly ash using machine learning techniques. Construction and Building Materials, 271, 121584.
- Shamsabadi, E.A., Salehpour, M., Zandifaez, P. & Dias-da-Costa, D., (2023) Data-driven multicollinearity-aware multi-objective optimisation of green concrete mixes. Journal of Cleaner Production, 390, 136103.
- Sifan, M., Nguyen, H., Nagaratnam, B., Thamboo, J., Poologanathan, K., & Makul, N. (2023, September). Efficient mix design method for lightweight high strength concrete: A machine learning approach. In Structures (Vol. 55, pp. 1805-1822). Elsevier.
- Şimşek, B. (2020). Multi-walled carbon nanotubes with different features reinforced cement pastes: A compressive and systematic approach using principal component analysis. Journal of Building Engineering, 32, 101792.
- Sonebi, M., Cevik, A., Grünewald, S., & Walraven, J., (2016) Modelling the fresh properties of self-compacting concrete using support vector machine approach. Construction and Building Materials, 106, 55–64.

- Sui, H., Wang, W., Lin, J., Tang, Z. Q., Yang, D. S., & Duan, W. (2023). Spatial correlation and pore morphology analysis of limestone calcined clay cement (LC3) via machine learning and image-based characterisation. Construction and Building Materials, 401, 132721.
- Sun, H., Burton, H.V., & Huang, H. 2021. Machine learning applications for building structural design and performance assessment: State-of-the-art review. Journal of Building Engineering, 33, p.101816.
- Taffese, W. Z. & Espinosa-Leal, L. (2022a). Prediction of chloride resistance level of concrete using machine learning for durability and service life assessment of building structures. Journal of Building Engineering, 60, 105146.
- Taffese, W. Z. & Espinosa-Leal, L. (2022b). A machine learning method for predicting the chloride migration coefficient of concrete. Construction and Building Materials, 348, 128566.
- Taffese, W. Z. & Sistonen, E. (2017). Machine learning for durability and service-life assessment of reinforced concrete structures: Recent advances and future directions. Automation in Construction, 77, 1-14.
- Taffese, W. Z., Sistonen, E., & Puttonen, J. (2015). CaPrM: Carbonation prediction model for reinforced concrete using machine learning methods. Construction and Building Materials, 100, 70-82.
- Tanhadoust, A., Yang, T.Y., Dabbaghi, F., Chai, H.K., Mohseni, M., Emadi, S.B. & Nasrollahpour, S. (2023) Predicting stress-strain behavior of normal weight and lightweight aggregate concrete exposed to high temperature using LSTM recurrent neural network. Construction and Building Materials, 362, 129703.
- Tanyildizi, H. (2021) Predicting the geopolymerization process of fly ash-based geopolymer using deep long short-term memory & machine learning. Cement and Concrete Composites, 123, 104177.
- Tayfur, S., Alver, N., Abdi, S., Saatcı, S., & Ghiami, A. (2018). Characterization of concrete matrix/steel fiber de-bonding in an SFRC beam: Principal component analysis and k-mean algorithm for clustering AE data. Engineering Fracture Mechanics, 194, 73-85.
- Timur Cihan, M., (2019) Prediction of concrete compressive strength and slump by machine learning methods. Advances in Civil Engineering, 2019, 1–11.
- Tran, V. Q., Mai, H. V. T., To, Q. T., & Nguyen, M. H. (2023). Machine learning approach in investigating carbonation depth of concrete containing Fly ash. Structural Concrete, 24(2), 2145-2169.
- Tsioulou, O., Lampropoulos, A. & Paschalis, S., (2017) Combined non-destructive testing (NDT) method for the evaluation of the mechanical characteristics of ultra high performance fibre reinforced concrete (UHPFRC). Construction and Building Materials, 131, 66-77.
- Unlu, R., (2020) An assessment of machine learning models for slump flow and examining redundant features. Computers and Concrete, 25 (6), 565–574.
- Völker, C., & Shokouhi, P. (2015). Clustering based multi-sensor data fusion for honeycomb detection in concrete. Journal of Nondestructive Evaluation, 34, 1-10.
- Völker, C., Torres, B.M., Rug, T., Firdous, R., Zia, G.A.J., Lüders, S., Scaffino, H.L., Höpler, M., Böhmer, F., Pfaff, M. & Stephan, D., (2023) Data driven design of alkali-activated concrete using sequential learning. Journal of Cleaner Production, 418, 138221.
- Wang, D., Ren, B., Cui, B., Wang, J., Wang, X. & Guan, T. (2021) Real-time monitoring for vibration quality of fresh concrete using convolutional neural networks & IoT technology. Automation in Construction, 123, 103510.
- Wang, W., Su, C. & Zhang, H. (2022) Automatic segmentation of concrete aggregate using convolutional neural network. Automation in Construction, 134, 104106.

- Witkowski, H. & Koniorczyk, M., (2018) New sampling method to improve the reliability of FTIR analysis for Self-Compacting Concrete. Construction and Building Materials, 172, 196-203.
- Wright, P.J.F. & Garwood, F., (1952) The effect of the method of test on the flexural strength of concrete. Magazine of Concrete Research, 4(11), 67-76.
- Xie, H., Shi, W., Issa, R. R., Guo, X., Shi, Y., & Liu, X., (2020) Machine learning of concrete temperature development for quality control of field curing. Journal of Computing in Civil Engineering, 34 (5), 04020031.
- Xu, J.G., Feng, D.C., Mangalathu, S. & Jeon, J.S., (2022) Data-driven rapid damage evaluation for life-cycle seismic assessment of regional reinforced concrete bridges. Earthquake Engineering & Structural Dynamics, 51(11), 2730-2751.
- Xu, S., Hao, M., Liu, G., Meng, Y., Han, J. & Shi, Y., (2022) Concrete crack segmentation based on convolution–deconvolution feature fusion with holistically nested networks. Structural Control and Health Monitoring, 29(8), e2965.
- Yang, S., Zhang, X., Yu, M., & Yao, J. (2019). An analytical approach to predict fracture parameters of coral aggregate concrete immersed in seawater. Ocean Engineering, 191, 106508.
- Yazdi, J. S., Kalantary, F. & Yazdi, H. S. (2013) Prediction of Elastic Modulus of Concrete Using Support Vector Committee Method. Journal of Materials in Civil Engineering, 25, 9–20.
- Yeh, I.-C., (1998) Modeling of strength of high-performance concrete using artificial neural networks. Cement and Concrete Research, 28 (12), 1797–1808.
- Yehia, S., Landolsi, T., Hassan, M. & Hallal, M., (2014) Monitoring of strain induced by heat of hydration, cyclic and dynamic loads in concrete structures using fiber-optics sensors. Measurement, 52, 33-46.
- Yin, Y. & Ren, Q., (2018) Studying the representative volume of concrete using the entropy weight–grey correlation model. Magazine of Concrete Research, 70(15), 757- 769.
- Yu, T., Twumasi, J.O., Le, V., Tang, Q. & D'Amico, N., (2017) Surface and subsurface remote sensing of concrete structures using synthetic aperture radar imaging. Journal of Structural Engineering, 143(10), 04017143.
- Zheng, L., Cheng, H., Huo, L., & Song, G., (2019) Monitor concrete moisture level using percussion and machine learning. Construction and Building Materials, 229, 117077.
- Ziolkowski, P., & Niedostatkiewicz, M. (2019). Machine learning techniques in concrete mix design. Materials, 12(8), 1256.
- Zheng, W., Shui, Z., Xu, Z., Gao, X., & Zhang, S. (2023). Multi-objective optimization of concrete mix design based on machine learning. Journal of Building Engineering, 76, p.107396.
- Ziolkowski, P. (2023). Computational Complexity and Its Influence on Predictive Capabilities of Machine Learning Models for Concrete Mix Design. Materials, 16(17), p.5956.
- Zarate Garnica, G.I., Lantsoght, E.O.L. & Yang, Y., (2022) Monitoring structural responses during load testing of reinforced concrete bridges: A review. Structure and Infrastructure Engineering, 18(10-11), 1558-1580.
- Zhang, J., Li, D. & Wang, Y. (2020) Toward intelligent construction: Prediction of mechanical properties of manufactured-sand concrete using tree-based models. Journal of Cleaner Production, 258, 120665.
- Zhang, K., Zhang, K., Bao, R., & Liu, X. (2023). A framework for predicting the carbonation depth of concrete incorporating fly ash based on a least squares support vector machine and metaheuristic algorithms. Journal of Building Engineering, 65, 105772.

- Zhang, M., Li, M., Shen, Y., Ren, Q. & Zhang, J. (2019) Multiple mechanical properties prediction of hydraulic concrete in the form of combined damming by experimental data mining. Construction and Building Materials, 207, 661–671.
- Zheng, Z., Wang, F., Gong, G., Yang, H. & Han, D., (2023) Intelligent technologies for construction machinery using data-driven methods. Automation in Construction, 147, 104711