Migration Letters

Volume: 21, No: S4 (2024), pp. 271-282

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Machine Learning Algorithms For Optimizing Mix Design Of Concrete

Kewalramani, M. A[1]· Mughieda, O[2]· Alzo'ubi, A. K.[3]· Okasha, N. M.[4]·

Abstract

The procedure of concrete mix design is a multifaceted and intricate procedure aimed at determining the optimal combination of materials to produce high-quality concrete with desirable performance characteristics. In the realm of current literature and modern business practice, several approaches to concrete mix design have emerged, with the methodologies evolved from The Three Equation Method gaining significant popularity. The determination of the concrete class is contingent upon the compressive strength, which is often regarded as a pivotal characteristic of concrete. The predictability of concrete's compressive strength is crucial for the effective utilization of concrete structures since it directly influences their safety and durability. In recent times, there has been a notable surge in interest in machine learning, with projections for its future development becoming more optimistic. The field of data mining has garnered significant interest due to the advancements in machine learning algorithms, which have shown the ability to identify patterns that are challenging for human cognitive abilities to discern. In this study, we aim to use cutting-edge advancements in machine learning methodologies to optimize concrete mix design. In the course of our study, we compiled a comprehensive database consisting of several realistic recipes together with corresponding damaging laboratory experiments. This collection was then used to train the chosen optimum architecture of an Artificial Neural Network (ANN). The architectural representation of the ANN has been successfully transformed into a mathematical equation, hence enabling its practical implementation in many applications.

Keywords *Concrete · Mix design · Machine learning · ANN ·*

Introduction

The building sector accounts for about 33% of global energy consumption and has a substantial role in the release of greenhouse gases into the environment [1]. Concrete is a commonly used building material that is manufactured by the amalgamation of cement, water, fine particles, and coarse aggregates. The use of admixtures is often employed to modify the characteristics of concrete. Concrete has the characteristic of flowability, allowing it to be molded into various shapes initially in a wet state. Subsequently, when it cures and hardens, it undergoes a process of strength growth. In construction, concrete is often used as a primary material for the construction of protective structures that are exposed to various forms of severe stress [2]. Concrete is the building material that is m[1]ost extensively used and produced on-site. The composite material is formed by the combination of cement, water, and aggregate [3]. The manufacturing process

[1]Department of Civil Engineering, Abu Dhabi University (UAE)
[2]Department of Civil Engineering, Abu Dhabi University (UAE)
[3]Department of Civil Engineering, Abu Dhabi University (UAE)
[4]Department of Civil Engineering, Abu Dhabi University (UAE)

encompasses many activities that are conducted based on the current circumstances at the location. A diverse range of ingredients may be used to manufacture concrete that meets the required quality standards. The strength, durability, and many features of concrete are contingent upon the attributes of its constituents, the ratios of the mixture, the compaction technique, and further measures of control [4]. The widespread use of concrete in the building may be attributed to its composition from readily accessible materials and its ability to be customized to meet specific functional needs in various contexts. Concrete compressive strength is often regarded crucial [5]. A key factor in concrete mixture composition is workability. Other parameters including the water-cement ratio, aggregate fineness modulus, and cement specific gravity are important in mix design [6]. Concrete compressive strength is a key characteristic. The concrete mix design process involves the meticulous selection of suitable constituents for concrete and the calculation of their ratios to provide concrete that satisfies the project specifications in the most economically efficient way. This entails ensuring that the concrete possesses certain minimum compressive strength, workability, and durability. The determination of constituent proportions in concrete is a critical aspect of concrete technology since it guarantees both the quality and cost-effectiveness of the final product [7]. The process of proportioning a concrete mix is achieved by the use of certain imperial relationships that provide a relatively precise framework for selecting the optimal mixture of constituents to get the required qualities. In the realm of design, building, and maintenance of engineering systems, engineers are tasked with making many technical and marginal choices at various phases to achieve optimal outcomes. Optimization, as a process, involves striving for the most favorable result within a given set of conditions. The main goal of such opinions is to either minimize the level of work needed or to maximize the intended reward. Optimization may be designated as the process of determining the circumstances that provide the greatest or lowest value of a function since the intended impact or benefit in any practical scenario can be represented by decision variables. The evaluation of the design mix of concrete is conducted following the standards outlined by the Indian Standard (IS) regulations [8]. The acquisition of the competence to design a concrete mix is an essential aspect of early career development for civil engineers. The objective of concrete mix design is to ascertain the precise quantities of various elements of concrete necessary to achieve predefined levels of workability and compressive strength. The compressive strength of concrete is established based on its intended use. The attainment of this strength is contingent upon the relative proportions of its parts. Besides strength, the workability and durability of concrete are other factors that impact the proportions of its component materials [9].

Machine learning (ML) is a component of a subfield within the domain of Artificial Intelligence (AI) that focuses on the examination of computer algorithms capable of autonomously acquiring knowledge and improving performance via experience and analysis of past data [10]. The process involves the development of a model that uses training data to generate predictions or judgments, without requiring explicit programming. ML has been used to enhance comprehension of concrete behavior and to devise novel methodologies for forecasting its attributes by using insights from past data. ML has the potential to be used for the analysis of both the physical and chemical characteristics of concrete, as well as its performance under diverse environmental conditions. Furthermore, this technology may be used to facilitate the development of novel models for accurately forecasting the strength and longevity of concrete, as well as to enhance the efficiency of concrete structure designs [11]. Furthermore, there is ongoing research aimed at development of novel techniques for detection and diagnosis of flaws in concrete, as well as the prediction of the anticipated lifespan of concrete buildings. Additionally, ML can detect fractures in concrete, therefore aiding engineers in the early identification of possible issues before they escalate into significant concerns. Engineers may use machine learning algorithms to leverage predictive models for the expedited and precise identification of cracks in concrete, hence mitigating the need for expensive repairs.

In this paper, based on the results of Fukushima et al.
[3] and Kasuga et al. [4], we analyze these process data by using multivariate linear

analyses, i.e. correlation analysis, principal component analysis, and multiple regression analysis. At this time, we clarify the relationship among QCD management metrics and derive useful software management models, i.e. development-period estimation, software product quality prediction, and delivery-delay prediction models. From the derived prediction models, we make the factors affecting software product quality and delivery-delay clear.

Literature Review

(Tipu, Panchal, & Pandya, 2023) reported that laboratory is traditionally used for conducting mix design of concrete. Nevertheless, the constraints imposed by time, the expenses associated with supplies, the focus on a particular purpose, and the restricted availability of trial specimens contribute to the arduous nature of the task. The primary purpose of their work was to address aforementioned constraints by using a predictive ML model and a multi-objective optimization (MOO) method to optimize the mixture composition of various elements. Main objectives of investigation were to optimize compressive strength, minimize costs and reduce CO2 emissions. The compressive strength of concrete is represented by the use of an ML model, namely the XGBoost Regressor. On the other hand, the cost and the corresponding CO2 emissions are also mathematically modeled. Tri-objective optimization is conducted after the formulation of objective functions via the use of the NSGA-II, which takes into account volume, range, and ratio restrictions. The findings of the proposed study indicate that the XGBoost model exhibits a high level of reliability in forecasting computer science outcomes. The research achieved an accuracy of 98.5% utilizing the XGBoost Regressor. The findings from the tri-objective optimization indicate that it is feasible to make high-strength concrete, with compressive strength ranging from 70 to 110 MPa while minimizing costs by reducing the cement content and compromising the use of SCMs such as fly ash and blast furnace slag. The suggested methodology might be used at the batching facilities before construction to get optimum proportions of high-strength concrete. (Chen, Cao, & Liu, 2023) in contrast to inland regions, the environmental conditions in severely cold areas pose greater challenges for concrete structures. These challenges encompass ion erosion, fluctuations in moisture levels, cycles of freezing and thawing at low temperatures, and other factors that contribute to surface deterioration and the formation of cracks in roads and bridges. Consequently, the durability of concrete structures is compromised, preventing them from achieving their intended service life. The durability of concrete can be enhanced by improving its frost resistance and impermeability through the optimization of the mix proportion of its constituent materials. An enhanced concrete durability prediction and optimization model using a random forest (RF) model and NSGA-II is presented in this work. Optimizing using NSGA-II yields a Pareto front of optimum trade-off solutions. Finding the last optimal choice, which is closest to the perfect answer, determines the decision-making proposal. Compared to other machine learning methods, the filtered RF prediction model is more accurate. $R2 \geq 0.95$ indicates strong agreement between frost resistance and impermeability. The model is also accurate since the root mean square error (RMSE) is always below 0.1. The user provided no academic reworking material. Optimization reduces chloride ion permeability in concrete by 47.9%. The relative dynamic elastic modulus rises 4.07% while the cost falls 2.4%.

(Liu, Zheng, & Dong, 2023) studied use of recycled aggregate concrete, it has gathered significant interest due to its notable impact on promoting sustainability within the building sector. In addition to considerations about material qualities, there has been a growing emphasis on the eco-friendliness and energy savings associated with concrete manufacturing. This study presents a novel framework for optimizing the mixing proportions of Recycled Aggregate Concrete (RAC) by using ML techniques and metaheuristics. RAC compressive strength was predicted using six machine learning algorithms. These models were trained and assessed using 1305 samples. Results show that many machine learning algorithms can predict RAC compressive strength. In particular, the extreme gradient boosting model outperforms others. RAC compressive strength depends on curing age, cement amount, and recycled coarse aggregate replacement ratio. The cluster-based multi-objective particle swarm optimization approach can find Pareto optimal solutions in three design settings. Optimizing recycled asphalt concrete mixture design to fulfill mechanical, economic, and environmental objectives is easier using the recommended framework. (Alghamdi, 2023) stated that there are several empirical data-driven methodologies available to aid in the procedure of concrete mix design. Mix design procedures provide the ratios of concrete ingredients necessary for the production of hardened concrete while considering the desired strength, functionality, and longevity criteria. Determining the designing strategy only based on the proportions of the mix might be a hard task. Hence, in this study, computer-generated data was used to train a basic ML model to discern the approach employed in designing a normal-strength concrete mixture. The ML model that has been constructed demonstrates that it can properly estimate the design technique of a mix by just considering the ratios of its constituents, namely cement, water, sand, and gravel. The study revealed that a basic ML model, namely a decision tree, showed a notable capability to accurately identify the mix design process. Furthermore, via the use of main components analysis and other analogous methodologies, researchers have shown that the quantity of cement exhibits the highest level of predictive capability in determining the appropriate mix design strategy. The results of this study provide a methodology for assessing mixed design techniques and advocating for the integration of machine learning within the realm of civil engineering. (Sadrossadat, Basarir, & Karrech, 2022) analyzed ultra-high-performance concrete (UHPC) compared to conventional concrete. UHPC typically has superior mechanical, rheological, and durability characteristics. Extremely high-priced components including cement, quartz powder, silica fume, fibers, and superplasticizers contribute to astronomically high manufacturing cost of UHPC. Properly adjusting component quantities of UHPC is essential for achieving certain objectives, such as the target manufacturing cost, strength, and flowability. Extensive, expensive, and labor-intensive trial programs are necessary for the conventional concrete mixture design process. Statistical mixture design, mathematical optimization and design of experiments have therefore been used more often in the last several years, especially when attempting to accomplish many goals at once. Depending on the needs, objective functions in conventional approaches are derived from basic regression models, such as multiple linear regression models. After the model is built, the best solutions are often found using mathematical programming and simplex algorithms. In this paper, we will show how to optimize UHPC reinforced with steel fibers using a metaheuristic algorithm called PSO, as well as how to build high-accuracy models using ML algorithms like artificial neural networks (ANN) and Gaussian process regression (GPR). To build the models and provide justification for the outcomes, a trustworthy experimental dataset was used. By comparing the theoretical predictions with the actual data, it was demonstrated that suggested method can successfully optimize steel fiber-reinforced UHPC mixtures for several objectives. Optimal mixes are produced when the designer encounters strength-flowability-cost dilemmas, and the suggested technique also reduces the work required for UHPC experimental design.

(Liu, Liu, & Zheng, 2022) intended in the design phase of asphalt concrete, the development of rutting in the real pavement is often not taken into consideration. The accuracy of predicting rut depth on real-world pavement under realistic climatic conditions and traffic is challenging using traditional simulative wheel-tracking experiments, often used for evaluating the rutting resistance of planned asphalt concrete. To formulate an asphalt mix design methodology that mitigates the occurrence of premature and significant pavement degradation, namely rutting, the relevant data about rut depth in asphalt concrete pavements were taken from the Long-Term Pavement Performance (LTPP) program. A total of 27 input characteristics about climatic conditions, traffic patterns, pavement structure, and qualities of pavement materials were chosen for inclusion in the study. The selection process included the use of collinearity diagnostics and impurity-based feature significance approaches. This research further examined the impact of various imputation techniques used for managing missing values within the dataset on the efficacy of machine learning models. The models' abilities were assessed using the computation of several performance assessment scoring metrics, including the coefficient of determination (R2), RMSE, MAE, MAPE, and scatter index (SI). In conclusion, a novel asphalt mix design technique was introduced, using the most optimal machine learning model. The findings indicate that, in comparison to other imputation approaches, the mean imputation method yields superior performance in machine learning models. (Pandey, Kumar, & Kumar, 2021) identified an alternate approach to the traditional way of concrete mix design. The multi-variable linear regression model may be considered a rudimentary baseline model, whereas support vector regression is another approach that can be used. The development of ANN models may be attributed to the extensive efforts of previous researchers, who dedicated significant attention to their advancement. In this study, we use the concrete mix designs conducted in the laboratory for different on-site applications. The models have been developed to accommodate both sorts of mixtures, namely those including plasticizers and those without plasticizers. This report provides a comprehensive analysis and comparison of four distinct models. The optimal model has been chosen by considering its superior accuracy and minimal computing requirements, as determined by the outcomes of the four models. Each sample originally consisted of 24 features. The selection of the best-fitting models among the four methods used was based on the R squared value. The authors of the research conclude that decision tree regression is the most suitable method for estimating the necessary quantity of components, as shown by the R-squared values approaching 0.8 in the majority of the models. The Decision Tree Regression (DTR) model is shown to be more computationally efficient compared to ANN. This article strongly suggests that future research in mixed design should consider using the DTR model.

(Zhang, Huang, & Ma, 2021) examined the use of silica fume as a substitute for cement in concrete has many benefits, including the reduction of CO2 emissions associated with cement manufacturing, the repurposing of industrial waste materials, and enhancement of concrete's mechanical properties and resistance to deterioration. The process of optimizing the composition of silica fume concrete (SFC) necessitates balancing many goals, such as strength, cost, and embodied CO2 while taking into account numerous factors within a framework of extremely nonlinear limitations. The computing cost associated with gaining the Pareto front of this multi-objective optimization (MOO) issue is high. To tackle this matter, the current research endeavors to construct a MOO model by using ML methodologies alongside a novel meta-heuristic algorithm. Initially, the associations between components and SFC attributes are simulated on a dataset using a back propagation neural network model. Subsequently, a novel technique known as the Multi-goal Beetle Antennae Search technique (MOBAS) is devised. This algorithm is based on individual intelligence and aims to efficiently explore the search space for ideal combinations of Sustainable Fiber-Reinforced Concrete. The goal is to maximize the Unified Compressive Strength while simultaneously minimizing both cost and embodied CO2. These objectives are subject to predefined limitations. The findings suggest that the suggested MOBAS exhibits superior computing efficiency and sufficient accuracy when compared to algorithms that rely on swarm intelligence. The MOO model has a high level of accuracy in predicting UCS, as seen by its strong correlation coefficient of 0.9663 on the test set. The suggested model has effectively derived the Pareto front of optimum proportions for the SFC mixture in MOO issue. The suggested framework enhances the efficiency of SFC mixture optimization and enables informed decision-making before construction activities. (Nunez, Marani, & Nehdi, 2020) evaluated use of recycled aggregate concrete that serves as a means to address the issue of diminishing natural aggregates, reduce the environmental impact of the concrete building by minimizing carbon emissions, and prevent the accumulation of substantial quantities of construction and demolition trash in landfills. Nevertheless, the mixture optimization of recycled aggregate concrete presents challenges owing to the inherent difficulties arising from the diversity of recycled aggregates and the limited accuracy in calculating their compressive strength. Consequently, innovative and advanced methodologies are necessary to address these issues. The objective of this study is to construct advanced ML models to predict the compressive strength of recycled aggregate concrete and optimize its mixture design. The findings indicate that the implemented models, which include Gaussian processes, deep learning and gradient-boosting regression exhibited strong and reliable predictive capabilities. Notably, the gradient-boosting regression trees had the best level of accuracy in terms of prediction. In addition, a model combining particle swarm optimization and gradient boosting regression trees was created to optimize the mixture design of recycled aggregate concrete for different levels of compressive strength. The hybrid model successfully generated cost-effective RAC mixture designs that exhibited reduced environmental impact across several target compressive strength categories. The model has the potential to be used more extensively to attain sustainable concrete that incorporates an optimum amount of recycled aggregate, while also minimizing both cost and environmental impact.

(Naseri, Jahanbakhsh, & Hosseini, 2020) stated that concrete is well recognized as the predominant material used in the building industry, but it is also acknowledged as a significant environmental pollutant. This recognition stems from the considerable sustainability issues it presents, particularly concerning resource depletion, energy usage, and greenhouse gas emissions. Hence, it is essential to concentrate on mitigating the environmental consequences associated with concrete to enhance its overall sustainability. The primary objective of this research was to examine the formulation of environmentally sustainable concrete mixes to promote the development of eco-friendly construction materials. Therefore, sustainability standards include considerations such as compressive strength, cost, environmental implications, and energy and resource use. To include these requirements, six distinct objective functions are formulated and implemented, to identify the most effective and sustainable objective function for estimating the composition of sustainable concrete. In the final analysis, the comparative evaluation of the calculated mixes is conducted concerning the sustainability index as delineated in prior scholarly investigations. The findings suggest that the water cycle algorithm exhibits the highest level of accuracy among the models considered, as shown by an MAE of 2.86 MPa. Moreover, the use of the quadratic distance as a metric for measuring the deviation from the ideal level proves to be the most efficient and sustainable goal function. Further, augmentation of cement and super-plasticizer content in the mixture design leads to a decline in the sustainability score. In due course, a total of 16 combination proportions that adhere to sustainable principles are formulated. These mixes are then evaluated and compared based on their sustainability indices to identify the most sustainable, economically viable, environmentally friendly, and least resource-intensive options.

Research Methodology

The basic goal of concrete mix design is to establish the right proportion and quantity of elements. Use a composition that optimizes concrete performance. The main parameters of concrete performance are compressive strength and durability. The strength and durability of concrete must be considered while mixing it. Durability is crucial in adverse environments [22-25]. After significant industry investigation, a few methods have emerged as the most often utilized ways for designing concrete mixes in European corporate engineering practice. These methods are the Bukowski method, the Eyman and Klaus method, and the Paszkowski methods. Finally, a mathematical formula that allows estimating the compressive strength of concrete is presented. The developed formula will evaluate the compressive strength of concrete based on four input variables, the amount of cement, water, fine, and coarse aggregate. In this study, all the mathematical calculations are derived from a formula that is “Three-Equation Method” or Bolomey method, which is a mixed experimental-analytical approach. It means that collected laboratory data should confirm that mathematical approach. Volume of required components is calculated by analytical measures and validate the results by destructive laboratory testing. In this method, we use a simple calculation that accounts for strength, consistency, and tightness to determine the kilograms per cubic meter of aggregate, cement, and water.

Equation (1) is used to determine compressive strength using Bolomey formula, which express the experimentally determined dependance of the compressive strength of hardened concrete of the grade of cement used, aggregate type, and cement paste water-cement ratio characterizing the cement paste. In this method, the concrete grade is assumed as input data.

$$f_{cm} = A_{1,2}\left(\frac{C}{W} \pm 0,5\right)[MPa] \qquad (1)$$

Where, f_{cm} is a medium compressive strength of concrete, expressed in kilograms. The value $A_{1,2}$ means coefficients, depending on the grade of cement and the type of aggregate; C is the amount of cement per m3 of concrete, expressed in kilograms; and W corresponds to the amount of water per m3 of concrete, expressed in kilograms.

A second consistency equation (2) which is included in the water demand formula necessary to make a concrete mix with the required consistency.

$$W = C.w_c + K.w_k[dm^3] \qquad (2)$$

Where K is the amount of aggregate per m^3 of concrete, expressed in kilograms; w_c is the cement water demand index in cubic decimeter (dm^3) per kilogram; and w_k is the aggregate water demand index in dm^3 per kilogram.

The simple volume formula incorporates Equation (3), which signifies that a watertight concrete mixture is achieved when the combined volume of the separate components is equivalent to the volume of the concrete mixture.

$$\frac{C}{\rho_c} + \frac{K}{\rho_k} + W = 1000[dm^3], \qquad (3)$$

ρc is the cement density in kilograms per dm3, and ρk is the aggregate density in kilograms per dm3.

Machine learning Technique

Artificial Neural Network (ANN)

Artificial neural networks (ANNs) refer to computational models of the nervous system that draw inspiration from the behavioral characteristics shown by live animals. The system comprises interconnected nodes designed to emulate the functioning of the human brain. The categorization or grouping of transactions has been accomplished via the use of ANNs that have undergone training utilizing various learning methodologies such as supervised, unsupervised, and semi-supervised methods [26]. In contrast to real neurons, the neurons in artificial neural networks have a limited number of connections. Weight values that are connected to single nodes (b) are referred to as biases and weight values are displayed in the ANN design, which is seen in Fig1. Gupta et al. (2006) used ANN is an attempt to obtain more accurate concrete strength prediction based on parameters like concrete mix design, size and shape of specimen, curing technique and period, environmental conditions, etc. Kewalramani et a. (2006) used ANN for prediction of compressive strength of concrete based on weight and UPV for two different concrete mixes involving specimens of two different sizes and shapes as a result of need for rapid test method for predicting long-term compressive strength of concrete.

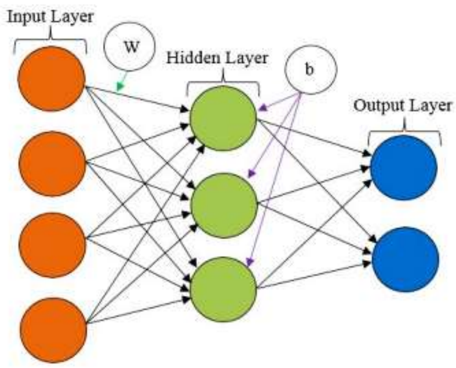

Fig. 1 The basic architecture of ANN [29].

This present work focuses on mix design of concrete using machine learning. The goal is to create an Artificial Neural Network (ANN) that can predict the compressive strength of a concrete mixture using a wide variety of experimentally proven formulae. Designing a concrete mix consists of selecting components and their amount to be achieve specific parameter of the concrete. One of the most significant parameters for concrete performance is the compressive strength, which defines the class of concrete. Poor durability may contribute to lowering the service quality of building in time. With a wrong manufacturing process, for example, poor concrete care can cause excessive cracks and reduce concrete tightness. The issue of machine learning applications, more precisely ANN, to predict the strength of concrete is present in the scientific discourse and is continuously evolving, making this topic very progressive. Based on a large number of tested concrete mix recipes, we would like to build an ANN will be able to estimate the compressive strength of the concrete mix. The ANN estimate the strength of the concrete based on the amount of the four main components of a concrete mix, more precisely cement, fine aggregate, coarse aggregate, and water. The constructed ANN was turned into source code and reduced into a single equation. The equation presented above establishes the relationship between the twenty-eight-day compressive strength of concrete and its four corresponding factors. The equation can be used in the calculation of compressive strength in concrete, hence functioning as a valuable instrument for verifying the adequacy of a concrete mix recipe. Fig2. illustrates the implementation of this strategy in the process of designing concrete mixes, emphasizing the need to adopt this approach.

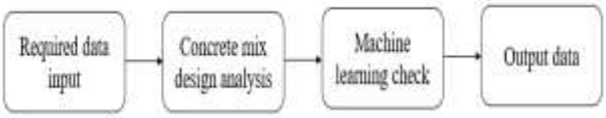

Fig. 2 Flowchart of Proposed methodology

Database of concrete mix recipes

In the scope of our research, we aimed to train the neural network to recognize the associations between the amounts of various components in a concrete mixture and the resultant compressive strength of the concrete. This was achieved via the utilization of a substantial dataset including many instances. The database was meticulously curated, including a vast array of records sourced from diverse sources such as literature, corporations, organizations, and labs. The concrete mix recipes used in our investigation were specifically formulated to cater to the varying dimensions, functions, and intended applications of concrete buildings. Hence, it is plausible that variations may exist among them, the origins of which are outside our predictive capabilities. The dataset has a maximum aggregate size of 20 mm. Portland cement was used to make the specimens. After extensive expert discussions, four critical elements that affect concrete compressive strength were included. Table 1 lists input parameters.

Table 1 Parameters adopted in dataset

Parameter	**Compressive strength after 28 days**	**Cement**	**Water**	**Sand 0-2mm**	**Aggregate above 2mm**
Codename Type	Cs_28 target	Cement input	Water input	Fine aggregate	Coarse aggregate input
Description	The compressive strength of	The weight of cement	The weight of water	The weight of sand	The weight of aggregate which have

concrete 28 days after hydration. Considered as full strength	added to the mixture	added to the mixture	added to the mixture	more than 2mm, added to the mixture

The parameters from Table 1 were categorized into two distinct groups: inputs and target variables. The inputs represent the characteristics of the input variables, while the target variables represent the characteristics of the output variables. Upon commencing the process of cement hydration, the strength of concrete gradually increases over some time until it reaches its maximum strength. It has collectively embraced the prevailing notion that concrete attains its intended compressive strength during twenty-eight days. Before the twenty-eighth day, the concrete exhibits a level of strength that is only partial, and hence cannot be regarded as attaining its maximum strength. In the context of our investigation, it was postulated that the concrete attained its ultimate strength due to the deliberate formulation of the combination to achieve such strength. All entries about concrete specimens of younger ages were eliminated from the database. The research does not account for some elements, such as the curing process, that may have an indirect impact on the achieved concrete strength. It was postulated that the quality control measures in place were enough for the production of concrete with optimal strength. Table 2 displays the lowest, maximum, and average values for each input variable.

Table 2 Ranges of input features of database input features

Input features	**Minimum (Kg/m^3)**	**Maximum (Kg/m^3)**	**Average (kg/m^3)**
Cement	86.0	540.0	278.0
Water	121.8	247.0	182.0
Fine aggregate (sand 0-2mm)	372.0	1329.0	768.5
Coarse aggregate (aggregate above 2mm)	597.0	1490.0	969.0

Result and discussion

The influence of various factors on the outcome has been evaluated and is shown in Fig3. The training input was selectively deleted and the output results were then evaluated. A contribution value of 1.0 or less indicates that the variable has a lesser level of influence on the outcomes. The study conducted revealed that the primary factor influencing the findings is cement, aligning with our initial hypothesis that the water-cement ratio significantly affects the strength of concrete.

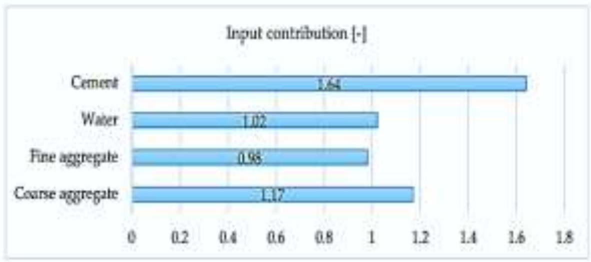

Fig. 3 Input Contribution

The robustness of the ANN model was shown to be poor when applied to recipes involving high-strength concrete, namely those with compressive strengths of 50MPa and higher. The limited quantity of recipes used to train the ANN for these specific ranges might perhaps account for this observation. The observed behavior of the ANN might potentially indicate the occurrence of under fitting. It is essential to acknowledge that the provided technique functions as a starting point for the broader use of machine learning in the domain of concrete mix design, and does not include all facets of this particular area of study. Specifically, the analysis fails to account for important factors like as durability and the technical process.

The model is trained to design concrete mixes with specific properties, such as a compressive strength of 50 MPa as shown in Fig4. The designed data shows that the model is able to achieve this goal consistently. The uniform nature of the designed data also suggests that the model is not overfitting the training data. Overfitting occurs when a model learns the training data too well and is unable to generalize to new data. If the model were overfitting the training data, the designed data would be more variable. Overall, the uniform nature of the designed data is a positive sign. It indicates that the machine-learning model is able to design concrete mixes with specific properties consistently and accurately.

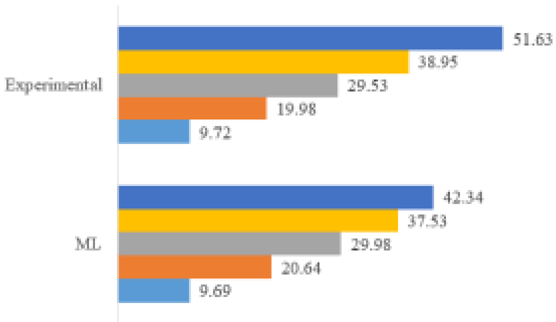

Fig. 4 Comparative analysis between experimental and ML obtained compressive strength

Conclusion and Future scope

Our project aims to examine the use of machine learning methods in concrete mix design to provide a useful engineering tool. This study employed the finest ANN architecture and a large library of concrete mix formulations. A laboratory destructive test is associated with each concrete mix recipe. During neural network building, the goal was to predict concrete compressive strength from a specific mix of components. The goal was to find the best ingredient ratio for compressive-strength concrete. This shows that the water-cement ratio is crucial to concrete compressive strength. The chosen ANN model has four input variables, four major components, six hidden neurons, and one target output. Converting artificial neural networks (ANNs) into formal mathematical equations has revolutionized machine learning in engineering. The method was reduced to one equation to compute concrete's compressive strength after 28 days. The previously created algorithm may help quickly evaluate concrete mix design. To obtain the required concrete grade, the technique evaluates the four key components of a concrete mixture: water, fine aggregate, coarse aggregate, and cement. It should be kept in mind that mathematical equations may have few boundary limitations and may not reflect all component interactions. Our objective is to enhance the process how admixtures impact concrete's long-term stability to improve the method's dependability.

References

1. Du, H., & Dai Pang, S. (2018). Value-added utilization of marine clay as cement replacement for sustainable concrete production. Journal of Cleaner Production, 198, 867-873.
2. 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, 107396.
3. 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.
4. 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), 127.
5. Alghamdi, S. J. (2022). Classifying High Strength Concrete Mix Design Methods Using Decision Trees. Materials, 15(5), 1950.
6. Moradi, N., Tavana, M. H., Habibi, M. R., Amiri, M., Moradi, M. J., & Farhangi, V. (2022). Predicting the compressive strength of concrete containing binary supplementary cementitious material using machine learning approach. Materials, 15(15), 5336.
7. DeRousseau, M. A., Kasprzyk, J. R., & Srubar Iii, W. V. (2018). Computational design optimization of concrete mixtures: A review. Cement and Concrete Research, 109, 42-53.
8. Xu, J., Zhou, L., He, G., Ji, X., Dai, Y., & Dang, Y. (2021). Comprehensive machine learning-based model for predicting compressive strength of ready-mix concrete. Materials, 14(5), 1068.
9. Khademi, A., Behfarnia, K., Kalman Šipoš, T., & Miličević, I. (2021). The use of machine learning models in estimating the compressive strength of recycled brick aggregate concrete. Computational Engineering and Physical Modeling, 4(4), 1-25.
10. Jagadesh, P., de Prado-Gil, J., Silva-Monteiro, N., & Martínez-García, R. (2023). Assessing the compressive strength of self-compacting concrete with recycled aggregates from mix ratio using machine learning approach. Journal of Materials Research and Technology, 24, 1483-1498.
11. Mahesh, B. (2020). Machine learning algorithms-a review. International Journal of Science and Research (IJSR).[Internet], 9(1), 381-386.
12. Tipu, R. K., Panchal, V. R., & Pandya, K. S. (2023). Multi-objective optimized high-strength concrete mix design using a hybrid machine learning and metaheuristic algorithm. Asian Journal of Civil Engineering, 24(3), 849-867.
13. Chen, H., Cao, Y., Liu, Y., Qin, Y., & Xia, L. (2023). Enhancing the durability of concrete in severely cold regions: Mix proportion optimization based on machine learning. Construction and Building Materials, 371, 130644.
14. Liu, K., Zheng, J., Dong, S., Xie, W., & Zhang, X. (2023). Mixture optimization of mechanical, economical, and environmental objectives for sustainable recycled aggregate concrete based on machine learning and metaheuristic algorithms. Journal of Building Engineering, 63, 105570.
15. Alghamdi, S. J. (2023). Determining the mix design method for normal strength concrete using machine learning. Journal of Umm Al-Qura University for Engineering and Architecture, 1-10.
16. Sadrossadat, E., Basarir, H., Karrech, A., & Elchalakani, M. (2022). Multi-objective mixture design and optimisation of steel fiber reinforced UHPC using machine learning algorithms and metaheuristics. Engineering with Computers, 38(Suppl 3), 2569-2582.
17. Liu, J., Liu, F., Zheng, C., Zhou, D., & Wang, L. (2022). Optimizing asphalt mix design through predicting the rut depth of asphalt pavement using machine learning. Construction and Building Materials, 356, 129211.
18. 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), 19-3
19. Zhang, J., Huang, Y., Ma, G., & Nener, B. (2021). Mixture optimization for environmental, economical and mechanical objectives in silica fume concrete: A novel frame-work based on machine learning and a new meta-heuristic algorithm. Resources, Conservation and Recycling, 167, 105395.

20. Nunez, I., Marani, A., & Nehdi, M. L. (2020). Mixture optimization of recycled aggregate concrete using hybrid machine learning model. Materials, 13(19), 4331.
21. 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, 120578.
22. Li, J., Wu, Z., Shi, C., Yuan, Q., & Zhang, Z. (2020). Durability of ultra-high performance concrete–A review. Construction and Building Materials, 255, 119296.
23. Qu, F., Li, W., Dong, W., Tam, V. W., & Yu, T. (2021). Durability deterioration of concrete under marine environment from material to structure: A critical review. Journal of Building Engineering, 35, 102074.
24. Schabowicz, K., Gorzelańczyk, T., & Szymków, M. (2019). Identification of the degree of degradation of fibre-cement boards exposed to fire by means of the acoustic emission method and artificial neural networks. Materials, 12(4), 656.
25. Godycki-Ćwirko, T., Nagrodzka-Godycka, K., & Wojdak, R. (2016). Reinforced concrete thin-wall dome after eighty years of operation in a marine climate environment. Structural Concrete, 17(5), 710-717.
26. Sahin, Y., & Duman, E. (2011, June). Detecting credit card fraud by ANN and logistic regression. In 2011 international symposium on innovations in intelligent systems and applications (pp. 315-319). IEEE.
27. Gupta, R., Kewalramani, M., & Goel, A. (2006). Prediction of concrete strength using Neural-Expert system. Journal of Materials in Civil Engineering, 18(3), 462–466.
28. Kewalramani, M., & Gupta, R. (2006). Concrete compressive strength prediction using ultrasonic pulse velocity through artificial neural networks. Automation in Construction, 15(3), 374–379.
29. Rahman, M. A., Muniyandi, R. C., Islam, K. T., & Rahman, M. M. (2019, October). Ovarian cancer classification accuracy analysis using 15-neuron artificial neural networks model. In 2019 IEEE Student Conference on Research and Development (SCOReD) (pp. 33-38). IEEE.