Advances in Environmental Research, *Vol. 13, No. 1 (2024) 51-69*
https://doi.org/10.12989/aer.2024.13.1.051

Addressing environmental concerns in concrete design through artificial intelligence: A sustainable approach

Sina Aminbakhsh[1a], Ali Golsoorat Pahlaviani[*1] and Amin Tohidi[**2]

[1]Department of Civil Engineering, Central Tehran Branch, Islamic Azad University, Tehran 1955847781, Iran
[2]Department of Mining Engineering, Amirkabir University of Technology, Tehran 159163-4311, Iran

(Received January 14, 2024, Revised February 13, 2024, Accepted February 20, 2024)

Abstract. This paper addresses the urgent need for sustainable infrastructure by examining the application of artificial intelligence in concrete design, with a specific emphasis on predicting uniaxial compressive strength (UCS) to mitigate environmental impacts. Concrete, a fundamental construction material, is a major contributor to environmental degradation due to its substantial carbon footprint. The study focuses on harnessing the potential of Artificial Neural Networks (ANN) to forecast UCS in conventional construction concrete, which is extensively utilized in global construction practices. This emphasis stems from the recognition of the significant environmental consequences associated with these concrete types, affecting both carbon footprints and ecosystems. The research methodology involved analyzing a dataset comprising 300 cubic concrete specimens with dimensions of 15 cm × 15 cm × 15 cm, split into training and testing sets at a ratio of 70:30. Various machine learning classifiers, including Support Vector Machine and Decision Tree, were employed for comparison alongside the ANN model. Results demonstrated that the ANN-based predictive model outperformed alternative classifiers, achieving high accuracy rates and minimal error values, thereby affirming its reliability in estimating UCS values. These findings highlight the potential of integrating AI technologies to enhance sustainability in construction practices and mitigate environmental impacts associated with concrete usage. By adopting innovative approaches such as ANN prediction models, the construction industry can contribute significantly to environmental preservation and sustainable development efforts.

Keywords: artificial intelligence; concrete; construction management; environmental impact; sustainable structures

1. Introduction

Concrete is one of the most ubiquitous materials in modern construction, serving as the backbone for a wide range of structures, from buildings, retaining walls to bridges and dams (Azarafza *et al.* 2017, Azadi *et al.* 2022). However, its widespread use comes at a significant environmental cost. The production of traditional concrete involves high energy consumption and

*Corresponding author, Assistant Professor, E-mail: a.golsouratpahlaviyani@iauctb.ac.ir
**Corresponding author, Assistant Professor, E-mail: a.tohidi@aut.ac.ir
[a]Ph.D. Student, E-mail: sina.aminbakhsh@gmail.com

http://www.techno-press.org/?journal=aer&subpage=7 ISSN: 2234-1722 (Print), 2234-1730 (Online)

releases substantial amounts of carbon dioxide (CO_2) into the atmosphere, contributing to climate change and environmental degradation (Adesina 2020). As the global population grows and urbanization accelerates, the demand for concrete continues to rise, intensifying its environmental impacts. Consequently, there is an urgent need to develop more sustainable approaches to concrete design and construction (Habert *et al.* 2020).

In recent years, there has been growing interest in leveraging artificial intelligence (AI) technologies to address sustainability challenges in various industries, including construction (Nanehkaran *et al.* 2023). AI offers powerful tools for optimizing complex processes and decision-making, making it a promising avenue for improving the environmental performance of concrete (Polo-Mendoza *et al.* 2023). By harnessing AI algorithms, researchers and engineers can explore innovative strategies to reduce the environmental footprint of concrete while maintaining its structural integrity and functionality. For example, traditional concrete production is a significant contributor to greenhouse gas emissions due to the high energy consumption and CO_2 emissions from cement production to disposed the residual structured concrete. AI can help optimize various aspects of the concrete manufacturing process, such as the selection of raw materials, the design of concrete mixes, and the optimization of production processes. So, AI can analyze vast datasets to identify alternative, lower-carbon materials that can be used as substitutes for traditional cement or aggregates to construction stages. Additionally, AI can optimize the proportions of ingredients in concrete mixes to minimize cement content while maintaining desired strength and durability, thus reducing overall CO_2 emissions.

This paper seeks to investigate the potential of AI-based approaches for sustainable concrete design, focusing on environmental impact considerations (Onyelowe *et al.* 2022). The integration of AI into concrete design holds immense potential for revolutionizing traditional practices and promoting sustainability throughout the construction industry (Ligozat *et al.* 2022). Machine learning algorithms, for instance, can analyze vast datasets on material properties, construction techniques, and environmental factors to identify optimal solutions for concrete mixtures and structural configurations (Zhu *et al.* 2022). Additionally, optimization algorithms can streamline the design process by generating efficient solutions that minimize resource consumption and emissions. Through advanced computational modeling and simulation, AI enables engineers to explore a wide range of design alternatives and evaluate their environmental performance before implementation (De-Medeiros and Kripka 2014). Furthermore, AI-driven approaches offer opportunities for enhancing the durability and resilience of concrete structures, thereby extending their service life, and reducing the need for frequent repairs and replacements (Naseri *et al*. 2020). By incorporating predictive analytics and real-time monitoring systems, AI can facilitate proactive maintenance and risk management, ensuring the long-term sustainability of infrastructure assets. Moreover, AI technologies enable adaptive design strategies that can respond to changing environmental conditions and evolving performance requirements, fostering greater flexibility and resilience in construction projects (Mansouri *et al.* 2022).

The primary objective of this paper is to investigate the potential of AI and machine learning algorithms in mitigating the environmental impacts associated with concrete design and construction. Specifically, we aim to explore how AI algorithms can be applied to optimize concrete mixtures and structural designs, with a focus on reducing carbon emissions, minimizing resource consumption, and enhancing overall sustainability. By leveraging AI-driven approaches, we seek to develop innovative strategies for sustainable concrete production and infrastructure development, ultimately contributing to the global effort to address climate change and promote environmental stewardship in the construction industry. The main target for this article is considering uniaxial compressive strength (UCS) of concrete that used as ultimate engineering key element for variety of design and construction stages.

The novelty of this paper lays in its interdisciplinary approach to addressing sustainability challenges in concrete design through the integration of AI technologies that used to predict the UCS values for concrete. While previous research has explored various aspects of sustainable construction and AI applications separately (Huang *et al*. 2021; Lavercombe *et al*. 2021; Khan *et al*. 2021; Shahrokhishahraki *et al*. 2024), this paper seeks to bridge the gap between these fields by examining the synergies between AI and concrete engineering key properties as UCS. By harnessing AI algorithms for material optimization, structural analysis, and predictive modeling, we aim to pioneer eco-friendly methodologies for environmentally conscious concrete design that considers the full lifecycle impacts of construction projects. Additionally, this paper contributes to advancing the state-of-the-art in sustainable infrastructure by proposing an AI-driven solutions as machine learning-based predictive model for UCS that have the potential to revolutionize traditional practices and shape the future of construction towards a more sustainable and resilient built environment.

2. Engineering and environmental aspect of UCS

Uniaxial Compressive Strength (UCS) is a key mechanical/engineering property used to evaluate the ability of concrete to withstand axial loading, particularly compression which used the design and analysis of concrete structures. Engineers use this information to ensure that the concrete used in construction meets or exceeds the required strength specifications (Xuan *et al.* 2012). Additionally, the UCS test aids in understanding the material's behavior under extreme loading conditions, contributing to the ongoing improvement of concrete mixtures and the development of more resilient and sustainable construction materials (Sun *et al*. 2019, Zhang *et al.* 2021). So, it can be resulted that the UCS test is fundamental in assessing the structural integrity and durability of concrete structures, helping engineers and researchers make informed decisions in construction and design (Bewick *et al*. 2015). The UCS test involves subjecting a cylindrical or cubical concrete specimen to a uniaxial compressive load until failure occurs. The test is typically conducted in a controlled laboratory or field environments, ensuring precise conditions for accurate measurements. The concrete sample's dimensions and preparation are crucial factors, as they directly influence the test results. Standardized testing procedures, often following guidelines from organizations like ASTM C109/C109M (2020), ASTM C31/C31M (2019), ASTM C39/C39M (2021), are employed to ensure consistency and comparability across different studies and projects. Fig. 1 is provided a scheme of UCS test that usually performed on concrete specimens. During the UCS test, a hydraulic or servo-controlled testing machine applies a gradually increasing axial force to the concrete specimen. The load and corresponding deformation are continuously monitored until the specimen reaches failure, typically characterized by the development of cracks and the ultimate collapse of the sample. The maximum compressive stress endured by the concrete before failure is then recorded as the UCS value.

Considering the environmental aspects of UCS tests is key in the context of sustainability and responsible construction practices. One key environmental consideration is the reduction of the number and time of tests conducted. Each test requires resources, energy, and materials, contributing to the environmental footprint. By strategically selecting samples, optimizing testing frequency, and relying on new methods, engineers can minimize the number of UCS tests without

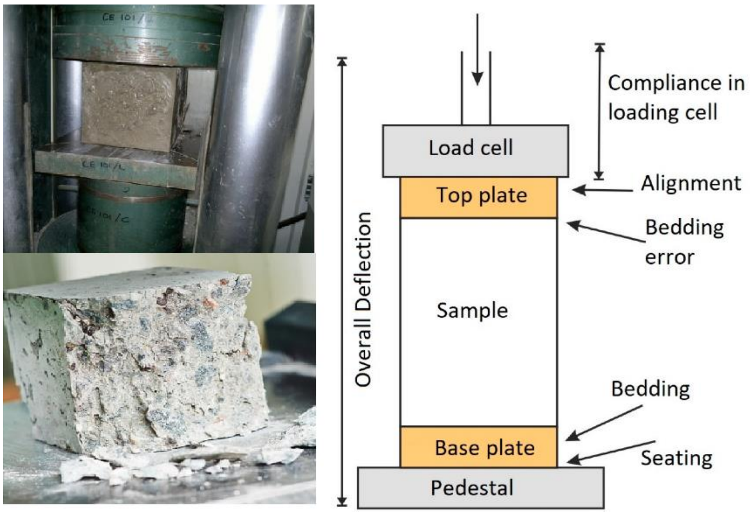

Fig. 1 The scheme and view of UCS test device (Cemiloglu *et al.* 2023)

compromising the reliability of results. Also, the ability to accurately forecast UCS through AI models enables construction managers to make informed decisions swiftly. By leveraging AI for UCS prediction, construction projects can be executed with greater efficiency, meeting deadlines more reliably and ultimately reducing overall project durations. This not only enhances project profitability but also improves stakeholder satisfaction by delivering projects on time or even ahead of schedule. This approach not only conserves resources but also reduces the associated environmental impact.

UCS tests can be inherently costly due to the specialized equipment and skilled personnel required for their execution. The environmental impact of costly tests is twofold. Firstly, the financial investment in testing contributes to increased resource consumption, including energy and materials used in equipment manufacturing and maintenance. Secondly, the economic cost may lead to a higher demand for construction materials, potentially accelerating the extraction and processing of natural resources. By exploring cost-effective alternatives, such as non-destructive testing methods or innovative technologies, engineers can mitigate the environmental consequences associated with the financial aspects of UCS testing. Additionally, the disposal of concrete samples after testing is an often-overlooked environmental aspect. In such cases, provide more eco-friendly methods can help to reduce the environmental impact of concrete testing with relying on UCS. In this regard, we provide a machine learning-based approach to predict the UCS values based on available materials as input which leads to reduce the dominant environmental footprint for extensive testing.

3. Methods and materials

3.1 Analysis method

The current investigation endeavors to leverage the capabilities of Artificial Neural Networks (ANN) for the prediction of UCS in conventional construction concrete, widely employed in

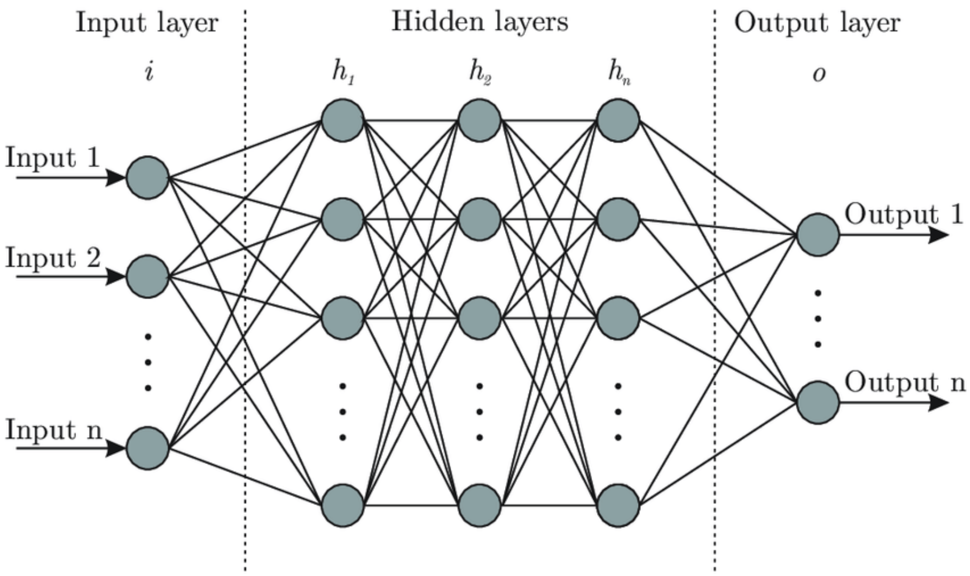

Fig. 2 An overall architecture of the ANN network (Bre *et al*. 2017)

global construction practices. This particular focus arises from recognition of the significant environmental implications associated with these concrete types, impacting both carbon footprints and ecosystems. By delving into the prediction of UCS values, we aim to enhance our understanding of the performance of standard construction concrete, fostering a more informed approach to its environmental repercussions. ANNs are computational models inspired by the structure and functioning of the human brain. They belong to the broader field of machine learning and are particularly well-suited for tasks involving pattern recognition, classification, regression, and decision-making (McElroy *et al*. 2021). ANNs consist of interconnected nodes, also known as neurons or artificial neurons, organized into layers. These layers typically include an input layer, one or more hidden layers, and an output layer (Zhao *et al*. 2022). Fig. 2 illustrates an ANN network architecture that mainly used to identify the various of layers. With respect to the Fig. 2, it can be stated that ANN comprise interconnected nodes, or neurons, organized into layers, including input, hidden, and output layers. Neurons process input signals using weighted connections and apply activation functions to introduce non-linearity. During training, ANN adjusts weights and biases through backpropagation, minimizing the difference between predicted and actual outputs. These networks excel in tasks such as pattern recognition and regression, owing to their ability to learn complex relationships from data.

3.2 Input data and resource

In the pursuit of analyzing and constructing a machine learning-driven predictive model for regular construction concrete, the foundation lies in assembling a comprehensive database of materials and resources. This database serves as the bedrock of the analytical process, drawing upon a multitude of sources, including extensive literature reviews and research conducted by various scholars in the field. Over a meticulous three-month period, a dataset comprising 300 distinct samples was meticulously curated. These samples are comprising cubic concrete

Table 1 The input-output parameters related to provide dataset for the analysis

I/O	Element	Unit	Max	Min	Average	Standard Deviation
Input	Water	Kg/m^3	230	120	175	3.425
	Cement	Kg/m^3	644	198	415	9.162
	Water-Cement ratio	-	0.60	0.35	0.47	0.072
	Coarse particles	Kg/m^3	744	310	521	6.251
	Fine particles	Kg/m^3	255	63	159	4.454
	Aggregate substitution rate	-	0.72	0.22	0.47	0.247
	Fine aggregate replacement	-	0.35	0.00	0.175	0.166
	Superplasticizer	Kg/m^3	2.00	0.00	1.00	0.050
Output	UCS	MPa	45.12	10.26	27.65	15.11

Table 2 The screen analysis results for majority of the concrete samples (mean values)

Sieve size (mm)	Passing particles (%)		Used limits (%)
	Upper limit	Lower limit	
25	100	100	100
19	100	90	90
9.5	60	10	45
4.75	20	0	10
0.075	10	0	5

specimens mirroring the dimensions of 15 cm × 15 cm × 15 cm, were meticulously chosen as standardized laboratory-scale representations. The meticulous selection of these samples was aimed at constructing a unified dataset conducive to the development of an effective predictive model for concrete UCS prediction. Tables 1 and 2 presents comprehensive details on the input and output variables encompassed within the dataset utilized for the development of the ANN-based model. It is imperative to highlight that our analysis predominantly centers around conventional construction concrete formulations, typically reliant on Type 2 Portland cements. This focus underscores our commitment to assessing and enhancing the predictability and efficacy of concrete compositions commonly utilized in construction applications. Type 2 Portland cement (Ingram and Daugherty 1991) is a specific formulation within the Portland cement family, which is one of the most widely used types of cement in construction (Tsivilis *et al*. 2002, Torres *et al*. 2017, Shaker *et al*. 2018, Tee and Mostofizadeh 2021).

3.3 Scaling and normalizing

Pre-processing feature values through scaling is a critical preparatory step in machine learning model development, standing as one of the cornerstone techniques in the field. The primary objective of feature scaling is to standardize the range of values across columns. For instance, while one column may contain values ranging from 0.00 to 1.00, another might encompass values spanning from 1.00 to 100.00. The disparate scales across features pose challenges when amalgamating them for modeling purposes, potentially compromising the effectiveness of the model. The efficacy of a machine learning model can often be discerned by its handling of this factor. Scaling methodologies typically encompass standardizing, normalizing, and scaling techniques. In this study, the dataset underwent scaling to normalize values within the range of 0 to 1, facilitating improved model performance and interpretability. In this regard, Min-Max scaling approach is considered for this study. Min-Max scaling (known as: Min-Max normalization), is a data preprocessing technique used to rescale numeric features to a fixed range, typically between 0 and 1. This method transforms the original data such that the minimum value of the feature is mapped to 0, and the maximum value is mapped to 1, with all other values linearly scaled accordingly within this range (De Schutter and van den Boom 2001). The formula for Min-Max Scaling is as follows:

$$(\overline{\mathrm{X}})_{\mathrm{MNS}} = \frac{\mathrm{X} - \mathrm{X}_{\mathrm{scaled}}}{\mathrm{X}_{\max} - \mathrm{X}_{\min}} \tag{1}$$

where, X is the original value of the feature, X_{scaled} is the rescaled value, X_{min} is the minimum value of the feature in the dataset. X_{max} is the maximum value of the feature in the dataset. Min-Max Scaling is particularly useful when the original data has varying ranges and scales across different features (Sharma 2022). By scaling all features to a common range, Min-Max Scaling ensures that they contribute equally during analysis and modeling, preventing features with larger magnitudes from dominating the learning process. This helps improve the stability and convergence of machine learning algorithms, especially those based on distance calculations or gradient descent optimization (Tang *et al*. 2022). In the context of ANN, Min-Max Scaling is commonly applied to the input features before training the model. ANN often requires input features to be on a similar scale to facilitate efficient learning and convergence. By scaling the input data using Min-Max Scaling, ANN can effectively learn the underlying patterns and relationships in the data, leading to improved performance and generalization ability.

3.4 Predictive model implementation

During the implementation stage of an ANN-based predictive model for UCS value prediction for construction concrete, the first crucial step involves initiating the project with a comprehensive review of available data sources and defining the project scope. This entails gathering datasets containing relevant features such as concrete mix proportions, curing conditions, aggregate properties, and corresponding UCS values which is provided in Table 1. Simultaneously, attention is directed towards understanding the specific requirements and objectives of the UCS prediction task, delineating key performance metrics, and establishing a roadmap for model development.

Flowchart of the roadmap for ANN-based model development is provided in Fig. 3. Upon data collection, preprocessing commences to ensure data quality and compatibility with the ANN model. This involves tasks like handling missing values, encoding categorical variables, and scaling numerical features using techniques such as Min-Max Scaling. Additionally, the dataset is partitioned into training, validation, and test sets, laying the groundwork for model training, validation, and evaluation phases. With the dataset prepared, the ANN model architecture is meticulously designed, considering factors such as the number of layers, neurons per layer, and activation functions as per exampled in Fig. 2. A feedforward neural network with several hidden

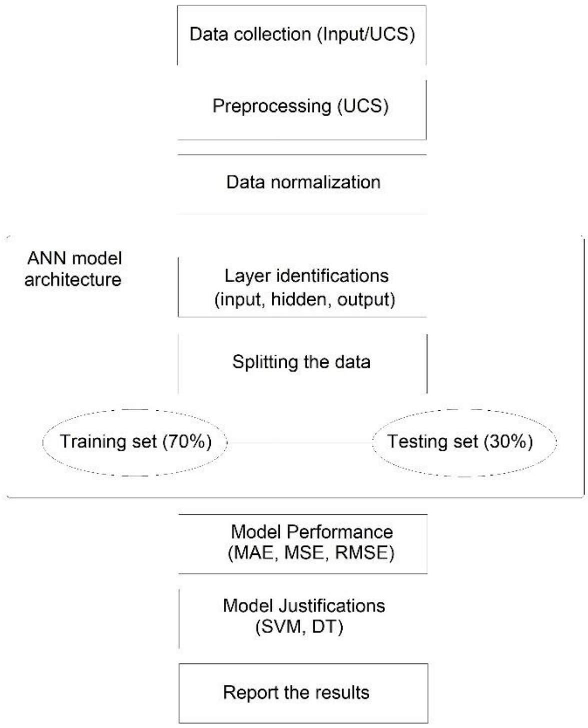

Fig. 3 Process flowchart that considered in this analysis

layers is chosen, alongside an appropriate activation function for each layer. This architecture is tailored to accommodate the nonlinear relationships inherent in UCS prediction tasks. Regarding mentioned basic, implementing ANN-based model for predicting UCS values of concrete in this study involves several key steps which provided as follow:

Data Collection and Preprocessing: Gather a dataset containing relevant input features and corresponding UCS values (see Table 1). Preprocess the data, which may include handling missing values, encoding categorical variables, and scaling numerical features using Min-Max Scaling normalization method.

Splitting the Data: The training set is used to train the model, the validation set is used to tune hyperparameters and monitor model performance during training, and the test set is used to evaluate the final model's performance. The presented study used 70% of primary dataset as training set and remained 30% of the primary dataset is considered for validation and testing sets. It should be noted that splitting data is provided fully randomly, and user hasn’t had any effect on the data divisions.

Model Architecture Design: Determine the ANN architecture, including the number of layers, number of neurons in each layer, and activation functions. For regression tasks like UCS prediction, a common choice is a feedforward neural network with three or more hidden layers and a linear activation function in the output layer (Benardos and Vosniakos 2007).

Model Training: Train the ANN using the training data which concluded 70% of primary dataset. During training, the model adjusts its weights and biases to minimize the difference between predicted and actual UCS values. Choose an appropriate optimization algorithm (in this

Table 3 The predictive ANN-based model's hyperparameters

No.	Classifier	Hyperparameters
1	SVM	- C (Regularization parameter) - Kernel (Type of kernel function: linear, polynomial, radial, etc.) - Gamma (Kernel coefficient for 'rbf', 'poly', and 'sigmoid' kernels) - Class weights (Weights assigned to different classes)
2	DT	- Criterion (Function to measure the quality of a split: 'gini' or 'entropy') - Max depth (Maximum depth of the tree) - Min samples split (Minimum number of samples required to split an internal node) - Min samples leaf (Minimum number of samples required to be at a leaf node)
3	ANN	- Number of hidden layers - Activation function for each layer (e.g., 'relu', 'sigmoid') - Learning rate (Rate at which the model updates its parameters) - Batch size (Number of samples processed before updating the model's parameters) - Number of epochs (Number of times the entire dataset is passed forward) - Regularization techniques (e.g., L1/L2 regularization)

article is Adam) and a suitable loss function (in this article are mean absolute error, MAE, mean squared error, MSE and root mean squared error, RMSE) to guide the training process. Monitor the model's performance on the validation set and adjust hyperparameters as needed to prevent overfitting or underfitting.

Model Evaluation: Evaluate the trained model using the test set to assess its performance on unseen data. Calculate evaluation metrics included MAE, MSE, and RMSE for model performance analysis (Kumar *et al*. 2022). The coefficient of determination (R^2) is used to quantify the model's accuracy and reliability.

Hyperparameter Tuning and Optimization: Fine-tune the model's hyperparameters based on performance metrics obtained from the validation set. Experiment with different architectures, activation functions (in this article is RELU), learning rates, and regularization techniques to optimize the model's performance. Table 3 is providing the model's hyperparameters that used in this research. It should be noted that these hyperparameters can significantly influence the performance and behavior of each classifier and ANN model and are typically tuned during the model development process to optimize predictive accuracy and generalization ability.

Model Verification and Justification: To assess the performance of the provided model, it will undergo comparison with benchmark machine learning classifiers including Support Vector Machine (SVM), and Decision Tree (DT), classifiers. This comparative analysis aims to evaluate the effectiveness and robustness of the model against established methods in the field. By benchmarking against these classifiers, insights into the relative strengths and weaknesses of the provided model can be gleaned, aiding in the refinement and optimization of predictive performance.

3.5 Cross-validation

Ensuring the reliability and effectiveness of machine learning-based prediction models is paramount. Therefore, meticulous checks and controls are essential to validate their performance, accuracy, and overall reliability in real-world applications. In the case of the provided ANN-based predictive model for UCS prediction, rigorous validation mechanisms are employed. These include

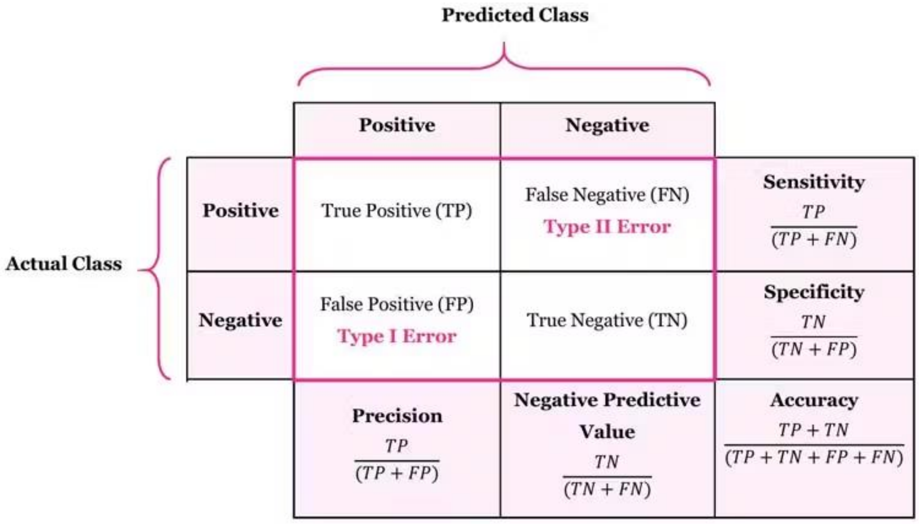

Fig. 4 The basic understanding of confusion matrix (Aggarwal 2018)

assessing the model's performance using tools such as the confusion matrix, evaluation metrics, and error analysis. Furthermore, comparative evaluations against benchmark classifiers are conducted to gauge the model's effectiveness relative to established standards. By subjecting the ANN model to such comprehensive scrutiny, its suitability for practical deployment and its comparative performance against other methodologies can be robustly evaluated, ensuring confidence in its predictive capabilities. The confusion matrix offers a comprehensive snapshot of an ANN model's performance by summarizing the number of correct and incorrect predictions across different classes. It provides valuable insights into the model's ability to accurately classify instances and detect potential misclassifications, thus serving as a fundamental tool for evaluating classification performance (Azarafza *et al*. 2022, Cemiloglu *et al*. 2023). Fig. 4 is providing a view illustration of confusion matrix and related formulations. On the other hand, using evaluation metrics (error tables), quantifies the variety of errors that recorded in during model implementation. The MAE, MSE and RMSE error metric was used to calculate the evaluation rates for both training and testing sets. Additionally, the R^2 that quantifies the proportion of variance in the target variable that is explained by an ANN model was used to provide a regression analysis. Ranging from 0 to 1, higher R^2 values indicate a better fit of the model to the data, suggesting that it can effectively capture and explain the variability in the target variable.

In the pursuit of comparative justification within machine learning methodologies, benchmark classifiers serve as pivotal tools to assess the efficacy and accuracy of predictive models. In this study, to comprehensively understand the performance of the primary predictive model and ensure its reliability, a comparative analysis was conducted utilizing Support Vector Machine (SVM), and Decision Tree (DT) classifiers. Evaluation parameters such as accuracy, precision, recall, and F1-score were meticulously recorded for all predictive models, facilitating a thorough examination of their predictive capabilities. Notably, the primary dataset underwent a consistent partitioning into 70% training and 30% testing sets across all models, ensuring uniformity in modeling conditions. The results obtained from each model were systematically compared to derive meaningful insights and enable informed decision-making regarding the most effective modeling approach. So, each metric offers unique insights into different aspects of model performance, enabling researchers and practitioners to make informed decisions based on the specific requirements of the prediction task. By comparing the performance across these metrics, stakeholders can identify the most suitable modeling approach for their application, considering factors such as interpretability, computational efficiency, and predictive accuracy.

The selection of SVM, DT, and ANN for predicting UCS was driven by their distinct capabilities in handling regression and classification tasks, particularly in the context of concrete strength prediction. SVM is known for its effectiveness in high-dimensional spaces and its ability to handle non-linear relationships, which makes it suitable for complex datasets like those involving concrete properties. Decision Tree models, on the other hand, offer a transparent and interpretable decision-making process, which is valuable in understanding the factors influencing UCS. The simplicity of DT in handling both categorical and continuous variables also add to their appeal in this context. These classifiers were chosen to provide a comprehensive comparison across different machine learning paradigms—SVM for kernel-based learning, DT for rule-based learning, and ANN for deep learning. The inclusion of ANN was particularly motivated by its capability to model non-linear relationships more effectively than traditional machine learning models. ANN, with its multi-layered structure, excels at capturing intricate patterns in data, which is essential when dealing with the highly variable nature of concrete's compressive strength. The goal was to assess the performance of these diverse models under the same dataset and conditions to ensure a fair comparison. By including SVM and DT alongside ANN, the study aimed to evaluate not only the predictive power of these models but also their accuracy, reliability, and error rates. This comparison ultimately demonstrated that ANN outperformed the other models, achieving higher accuracy and lower error values, making it the most suitable for predicting UCS in concrete.

4. Results and discussion

Concrete is recognized for its environmental impact, posing risks like washout, cement dissolution, chemical hazards, and waste generation. To mitigate these concerns, innovative approaches are crucial in lessening concrete's ecological footprint. Thus, this paper aims to introduce an ANN predictive model to assess the UCS of traditional construction concrete. By exploring this model, we aim to enhance sustainability in diverse construction endeavors while safeguarding the environment and ecosystems. The methodology section outlines the process stages applied to the prepared primary dataset. The results are categorized into training and testing sets, and validation is conducted using various techniques, including confusion matrices, evaluation metrics, and error analysis. The validity of the ANN-based model was established by comparing its performance with well-known benchmark learning classifiers such as SVM, and DT.

The same dataset was utilized for all models to ensure consistent and reliable results for comparison and performance assessment. Figs. 5 to 7 present the outcomes of implementing various machine learning models on UCS data to predict values based on input parameters. These figures utilize the same training (70%) and testing (30%) portions of the primary dataset. Additionally, correlation regression was conducted for various models, as depicted in Fig. 8. As depicted in Figure 8, it is evident that the ANN-based model achieved the highest accuracy, with R^2 values of 0.98 in the training set and 0.97 in the testing set. This suggests that the ANN model can provide valid information regarding UCS. Additionally, Tables 4 and 5 presents the estimated

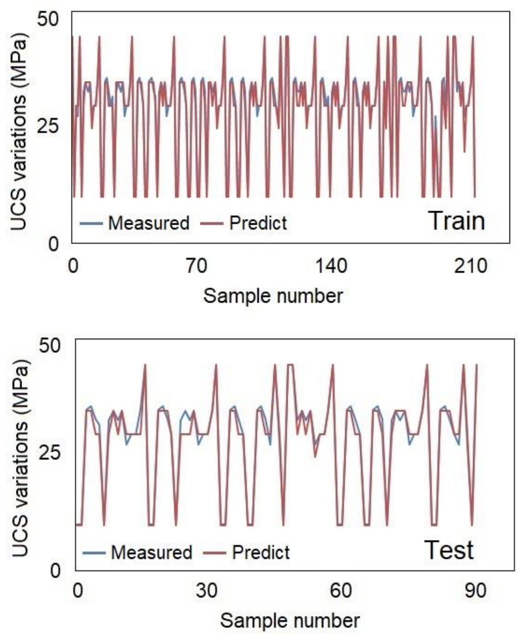

Fig. 5 The training and testing stages for implementation of ANN predictive model

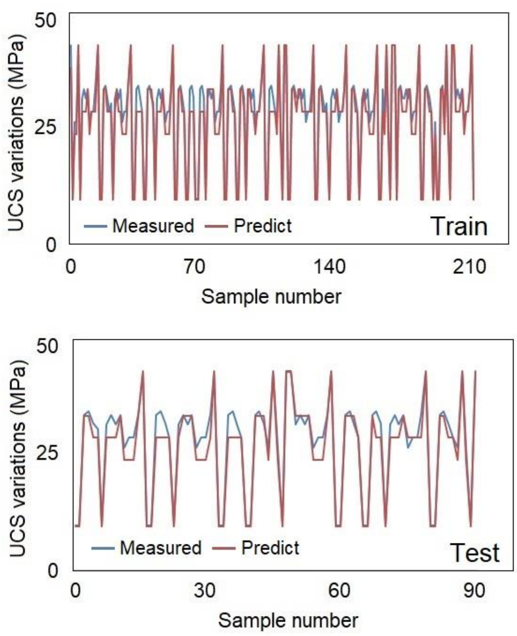

Fig. 6 The training and testing stages for implementation of SVM predictive model

confusion matrix and error rates for various predictive models, confirming the accuracy of the ANN predictive model. Based on estimated error table, it can be stated that ANN model reach to

Table 4 The estimated confusion matrix for various predictive models

Methods	Dataset	Performance Criteria			Accuracy
		Precision	Recall	F1-score	
ANN	Train	0.97	0.95	0.97	0.98
	Test	0.93	0.93	0.95	
SVM	Train	0.95	0.90	0.90	0.95
	Test	0.95	0.95	0.90	
DT	Train	0.88	0.85	0.85	0.88
	Test	0.88	0.84	0.84	

Table 5 The estimated error rates for various predictive models

Methods	MAE	MSE	RMSE
ANN	0.2455	0.2530	0.2417
SVM	0.3425	0.3509	0.3540
DT	0.3912	0.4001	0.3856

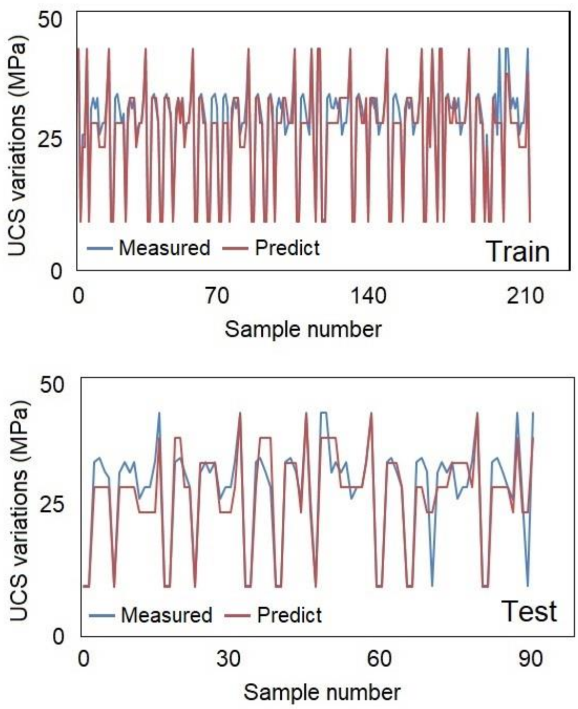

Fig. 7 The training and testing stages for implementation of DT predictive model

lowest error value with 0.2417 in training set. So, it can be used as UCS value predictive model with high reliability.

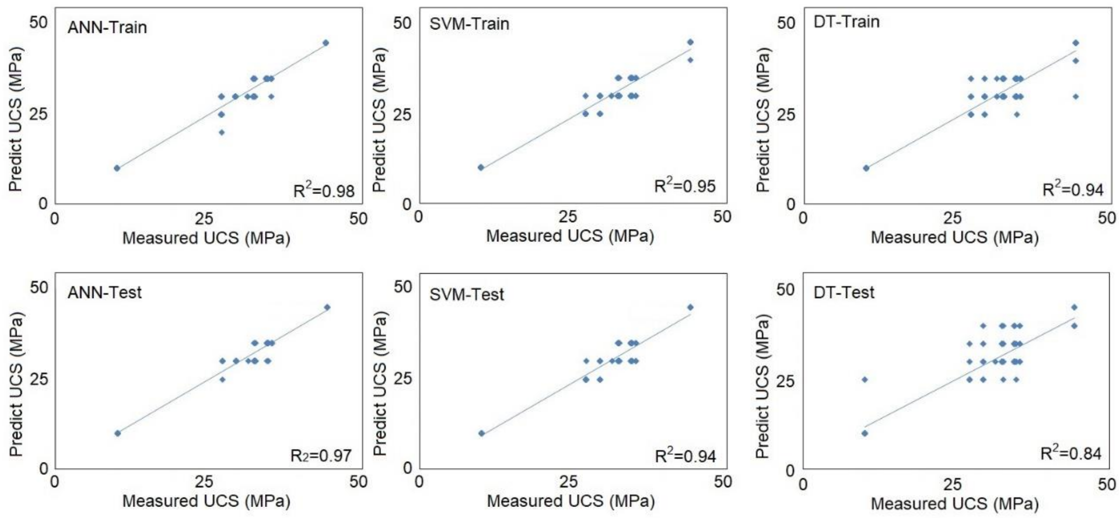

Fig. 8 The regression correlation between various models in both testing and training sets

It should be noted that the dataset used in the study, comprising 300 cubic concrete specimens with dimensions of 15 cm × 15 cm × 15 cm, was split into training and testing sets at a 70:30 ratio. This split ensured that 70% of the data was used for training the machine learning models, including the ANN, SVM, and DT, while the remaining 30% was reserved for testing the models' performance. The division aimed to ensure a robust model evaluation, where the training set allowed the models to learn patterns and relationships in the data, and the testing set assessed their generalization capabilities. This standard practice ensured that the models were evaluated on unseen data, providing a reliable measure of their predictive accuracy and error rates, which were validated through techniques like confusion matrices and regression analysis.

The ANN-based predictive model outperforms traditional methods of UCS estimation in terms of accuracy, efficiency, and ease of implementation. With R^2 values of 0.98 in the training set and 0.97 in the testing set, the ANN model demonstrates superior accuracy compared to traditional methods, which often rely on empirical formulas or extensive laboratory testing that can be time-consuming and less precise. The ANN model efficiently processes large datasets to predict UCS with minimal error (as low as 0.2417 in the training set), reducing the need for repeated physical testing. Additionally, once trained, the ANN model is relatively easy to implement in construction projects, providing quick and reliable UCS predictions based on input parameters, making it a more efficient and scalable tool than traditional, labor-intensive methods. It seems that, the ANN-based predictive model significantly surpasses traditional UCS estimation methods in accuracy, efficiency, and ease of implementation. It achieves high accuracy with R^2 values of 0.98 and 0.97 in the training and testing sets, respectively, indicating a robust prediction capability compared to traditional empirical methods that may offer less precision.

The findings from this study have significant implications for advancing sustainability in construction practices and policies, particularly through the application of AI in optimizing concrete design. Concrete, as a fundamental material in construction, contributes heavily to environmental degradation due to its substantial carbon footprint and resource-intensive production processes. By demonstrating the effectiveness of ANN in predicting UCS of conventional construction concrete, this research opens the door to more efficient and environmentally friendly approaches. ANN models can reduce the reliance on trial-and-error methods traditionally used in concrete formulation, allowing for more precise designs that optimize material usage and minimize waste. This shift could directly contribute to reducing the carbon footprint associated with concrete production, as well as conserving raw materials, thus aligning with global sustainability goals. The implementation of ANN-based predictive models could also influence construction practices by promoting the adoption of data-driven approaches. Traditional construction practices often rely on conservative estimates and excessive use of materials to ensure structural integrity, leading to overconsumption of resources. By providing accurate predictions of UCS, the ANN model allows for optimized material mix designs, which ensure strength and durability while minimizing material overuse. This innovation could encourage the construction industry to adopt more efficient methods, leading to less material waste, lower emissions, and reduced environmental impact throughout the lifecycle of a construction project. Furthermore, it could aid in developing more resilient structures, potentially extending the lifespan of buildings and infrastructure, which contributes to long-term sustainability. From a policy perspective, these findings could inform regulations and guidelines aimed at promoting sustainable construction practices. Policymakers could incorporate AI-based models like ANN into building codes and standards, encouraging or even mandating their use to ensure more environmentally responsible construction practices. The high accuracy and reliability demonstrated by the ANN model in predicting UCS could serve as a benchmark for developing industry standards around concrete usage, ensuring that sustainability is integrated into the design phase of construction projects. This shift would not only reduce the environmental burden of new construction but also support broader goals of reducing greenhouse gas emissions in line with international climate agreements, such as the Paris Agreement. Overall, the integration of AI technologies like ANN into construction practices offers a pathway toward more sustainable infrastructure development. By leveraging accurate predictive models, the construction industry can optimize resource use, reduce waste, and lower carbon emissions, contributing significantly to environmental preservation. These findings highlight the potential for technological innovation to transform traditional practices and guide the industry toward more sustainable solutions, ultimately helping to mitigate the environmental impacts of construction on ecosystems and the planet as a whole.

One potential limitation of the research is the size of the dataset, which consists of 300 cubic concrete specimens. While this size is sufficient for demonstrating the effectiveness of the ANN model, a larger dataset could enhance the model's generalizability and robustness by capturing a wider range of variability in concrete properties. Additionally, the study focuses on conventional concrete types, which may limit the applicability of the findings to other types of concrete or construction materials. Although the ANN model outperformed traditional methods and other machine learning classifiers, its performance in different contexts or with alternative models could vary. Expanding the dataset and exploring a broader range of concrete types or additional machine learning techniques could address these limitations and provide more comprehensive insights.

Optimizing UCS predictions using ANN can lead to significant reductions in the carbon footprint of concrete-based construction practices. Concrete production, particularly the manufacturing of cement, is a major source of carbon dioxide emissions, contributing up to 8% of global CO_2 emissions. By accurately predicting the UCS through ANN models, construction professionals can optimize the concrete mix design, ensuring that the minimum necessary amount of cement is used without compromising structural integrity. This precision reduces material overuse, which not only decreases the amount of cement produced and used but also reduces the associated environmental impacts such as energy consumption, raw material extraction, and greenhouse gas emissions. This approach aligns with the industry's increasing focus on sustainability by minimizing waste and improving resource efficiency. Additionally, by adopting ANN-based UCS predictions, construction practices can incorporate alternative, eco-friendly materials like supplementary cementitious materials (SCMs), such as fly ash or slag, which are often underutilized due to uncertainty in their performance. ANN models can predict UCS with high accuracy even when these sustainable materials are included, enabling their broader use in concrete mixes. This reduces the reliance on traditional cement while maintaining the necessary strength and durability, further decreasing the carbon footprint. By implementing optimized UCS predictions in both small-scale and large-scale construction projects, significant reductions in emissions and resource use can be achieved across the construction sector, contributing to more sustainable infrastructure development globally.

5. Conclusions

In conclusion, this study addresses the critical environmental concerns associated with concrete usage in construction by introducing an innovative approach through an Artificial Neural Network (ANN) predictive model. By focusing on predicting the Unconfined Compressive Strength (UCS) of traditional construction concrete, this research not only aims to enhance the sustainability of construction practices but also underscores the importance of mitigating environmental impacts. Through meticulous methodology outlined in this paper, the ANN model was developed and rigorously tested alongside benchmark classifiers such as Support Vector Machines (SVM) and Decision Trees (DT). The results clearly demonstrate the superiority of the ANN model in accurately predicting UCS values, as evidenced by its high accuracy rates and lowest error values compared to alternative models. Figs. 5 to 7 are illustrate the outcomes of employing various machine learning techniques, showcasing the ANN model's remarkable performance. Moreover, the correlation regression analysis depicted in Figure 8 solidifies the reliability of the ANN model, revealing exceptionally high R^2 values in both training and testing sets. Furthermore, the estimated confusion matrix and error rates presented in Tables 5 and 6 reaffirm the effectiveness of the ANN predictive model, with notably low error values in the training set, indicating its robustness and reliability. In summary, the findings of this study endorse the ANN-based predictive model as a valuable tool for estimating UCS values in traditional construction concrete with high accuracy and reliability. By adopting such innovative approaches, we can not only optimize construction processes but also contribute significantly to environmental preservation and sustainable development in the construction industry. This research underscores the importance of embracing technological advancements to address environmental challenges while advancing construction practices towards a more sustainable future.

Acknowledgments

We would like to express our deepest gratitude to the editors and anonymous reviewers for their critical reviews and helpful comments.

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