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Uniaxial Compressive Strength Prediction for ConstructionConcrete using MLP

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Abstract: Accurate prediction of the uniaxial compressive strength (UCS) of concrete is crucial for ensuring the safety, durability, and performance of structures in construction. This study presents a predictive model using a multilayer perceptron (MLP), to estimate UCS based on key input parameters such as water-cement ratio, aggregate size, curing time, water and cement content. The MLP model was trained and validated using a dataset comprising 120 cubic laboratory-tested concrete samples (15cm × 15cm × 15cm) with varying compositions for normal construction materials. Performance of the model was evaluated using statistical metrics (split into training and testing sets as 70%-30%), showing that the MLP-based approach provides accurate and reliable predictions compared to traditional regression models. The proposed method offers a practical, efficient tool for geotechnical engineers to assess concrete strength, potentially reducing the need for extensive experimental testing and enhancing quality control in concrete production.

Keywords:Construction materials, Multilayer perceptron, Artificial intelligence, Concrete, MLP.

I. INTRODUCTION

Concrete is a cornerstone of modern construction, valued for its durability, flexibility, and ease of use (Azarafza et al., 2017). One of the most crucial aspects of concrete's performance is its uniaxial compressive strength (UCS), which indicates how much load it can bear before failing. This property is vital for designing safe and reliable structures, from buildings to bridges (Azadi et al., 2022). Understanding the UCS of concrete is fundamental for ensuring the safety and reliability of construction projects (Bewick et al., 2015). UCS measures the maximum load concrete can endure before failing, which is critical for designing structures that can withstand everyday stresses and extreme conditions (Kumar et al., 2022). For instance, buildings and bridges need to support significant loads from occupants, vehicles, and environmental forces. By accurately knowing UCS, engineers can design structures that meet safety standards and avoid potential failures (Mansouri et al., 2022). Moreover, UCS plays a key role in determining the suitability of concrete for different applications (Azarafza et al., 2017). Various construction projects have specific requirements based on load-bearing needs, environmental conditions, and durability expectations (Naseri et al., 2020). Knowing the UCS of concrete also aids in quality control and cost management. During construction, it’s important to verify that the concrete mix meets the specified strength requirements (Torres et al., 2017). Accurate UCS measurements can prevent issues related to under-strength concrete, which could lead to costly repairs or structural failures. Additionally, by optimizing concrete mixes based on UCS predictions, it’s possible to reduce material waste and control costs more effectively, making construction projects more efficient and economically viable (Zhu et al., 2022). Traditionally, UCS is determined through laboratory tests, which can be both costly and time-consuming. To address these challenges, there is growing interest in using data-driven methods, such as machine learning, to predict UCS more efficiently (Zhang et al., 2021).

Machine learning, and particularly artificial neural networks (ANNs), have emerged as powerful tools for tackling complex problems (Mansouri et al., 2022). Among these, the multilayer perceptron (MLP) stands out for its ability to handle nonlinear relationships and learn from complex datasets (McElroy et al., 2021). The MLP, with its multiple layers of interconnected nodes, can process various inputs to predict outcomes, making it well-suited for predicting UCS based on factors like water-cement ratio, aggregate size, and curing time (Abdelhedi et al., 2020).The challenge with predicting UCS lies in the complex interactions between different mix components and environmental conditions. Traditional models often struggle with these complexities, leading to less accurate predictions (Sebastiá et al., 2003). MLPs, however, excel at modeling these intricate relationships because they can learn from data and adapt to various patterns (Zhao et al., 2022). This study explores how MLPs can be used to predict UCS more accurately, potentially overcoming the limitations of traditional methods.

Although machine learning has shown promise in predicting concrete properties, most studies have been limited in scope, focusing on smaller datasets or fewer variables (Kumar et al., 2022). This research aims to extend the application of MLPs by using a broader dataset that includes a wide range of concrete mixes. By doing so, the study seeks to determine whether MLPs can reliably predict UCS across different concrete compositions and conditions.

One of the advantages of MLPs is their ability to improve prediction accuracy as more data becomes available. This is particularly useful in construction, where material properties can vary widely (Lavercombe et al., 2021). With an MLP model, predictions can be refined and updated continuously, helping engineers make better decisions and reduce reliance on experimental testing (Naseri et al., 2020).Furthermore, integrating MLP models into the construction process aligns with the industry's shift towards more data-driven and automated approaches. By leveraging real-time data from construction sites, MLP models can provide instant predictions, allowing for quicker adjustments and better-quality control. This not only helps in optimizing concrete mix designs but also reduces material waste and costs (Huang et al., 2014). Despite their potential, there are challenges in developing and applying MLP models for UCS prediction (Salahudeen et al., 2020). One major challenge is obtaining high-quality, diverse datasets that accurately represent real-world conditions. Additionally, ensuring that the model can generalize across different regions and construction practices is crucial. Collaboration between researchers and industry professionals is essential to overcome these obstacles and create robust, reliable models (Zhao et al., 2022).

In this study, we propose an MLP-based model for predicting UCS using a comprehensive dataset of concrete samples with various mix designs. We evaluate the model's performance against traditional regression methods to determine its accuracy and reliability. The results indicate that the MLP model provides more precise UCS predictions, offering a valuable tool for improving concrete design and quality control. So, using MLP models for UCS prediction represents a significant advancement over traditional methods. By harnessing the power of machine learning, this approach promises to make concrete design more efficient, cost-effective, and adaptable. The following sections will delve into the details of the MLP model development, dataset, methodology, and results, highlighting how this innovative approach can benefit the construction industry.

II. Uniaxial Compressive Strength

The UCS is a key engineering property that measures concrete's ability to withstand axial compression loads (Torabi-Kaveh et al., 2015). This property is essential for the design and analysis of concrete structures, helping engineers ensure that the concrete used in construction meets or exceeds the required strength specifications (Xuan et al., 2012). By evaluating UCS, engineers can assess how concrete will perform under regular and extreme loads, which is vital for maintaining the safety and reliability of structures (Suthar, 2020). This test also plays a role in improving concrete mix designs, leading to the development of stronger, more resilient, and sustainable building materials (Sun et al., 2019).The importance of UCS testing goes beyond just assessing strength; it also provides valuable insights into the material's overall behavior under stress, which is crucial for enhancing the durability and integrity of concrete structures (Naseri et al., 2020). Engineers and researchers rely on UCS data to make informed decisions during the construction and design phases, ensuring that structures can handle the demands of their environment and usage (Zhang et al., 2021). The test is especially useful for refining concrete formulations to meet specific project requirements, ultimately improving the performance and lifespan of the built environment (Bewick et al., 2015).

The UCS test itself involves applying a uniaxial compressive load to a cylindrical or cubical concrete specimen until it fails (Kumar et al., 2022). This test is typically conducted in controlled laboratory or field settings to ensure accurate and reliable results. The dimensions and preparation of the concrete sample are critical, as they significantly impact the outcome. Standardized procedures, such as those outlined by ASTM C109/C109M (2020) and ASTM C39/C39M (2021), are followed to maintain consistency and comparability across different studies and projects. Figure 1 provides an illustration of the UCS test setup, commonly used in concrete testing with geotechnical laboratory worldwide. ASTM C109/C109M (2020) and ASTM C39/C39M (2021) are both standards used for testing the compressive strength of concrete, but they differ in the type of specimens they use and their specific applications. ASTM C109/C109M focuses on testing mortar cubes, typically made from cement and sand, which are smaller and easier to handle. This standard is mainly used for quality control of cementitious materials like mortar in laboratory conditions. In contrast, ASTM C39/C39M is designed for testing larger concrete cylinders, which more accurately represent the compressive strength of full-scale concrete structures. This standard is crucial for assessing the actual performance of concrete mixes used in construction projects.One of the key differences between these two standards lies in the size and shape of the test specimens. The choice between cube and cylinder samples affects the UCS results. Generally, concrete tested using cylindrical specimens tends to produce lower strength values compared to cubic specimens, even when tested under the same conditions (Xuan et al., 2012). This difference is due to the geometry of the specimens; cubes are more resistant to lateral expansion under compression, which can lead to slightly higher recorded strength values. Cylindrical specimens, being taller and narrower, simulate more realistic loading conditions for concrete used in vertical elements like columns. The differences in specimen shape and size must be considered when comparing results from different test methods.

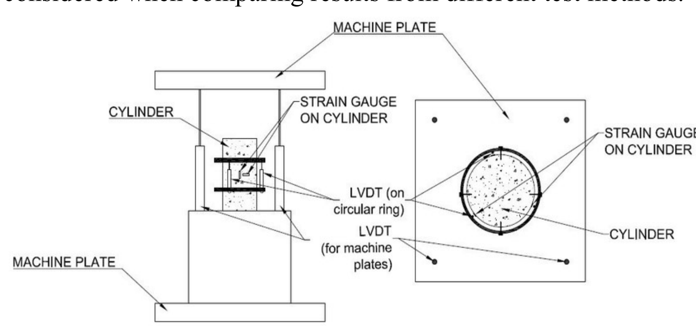

Fig. 1 A schematic of UCS testing for concrete (Mina et al., 2021)

There are specific advantages to using cubic samples for UCS testing, especially when conducting routine quality control in a laboratory setting (Sun et al., 2019). Cubes are easier to cast, handle, and store due to their smaller size and simple shape. They require less material, which can be a cost-effective solution for early-stage testing of cement or mortar mixtures. Additionally, the uniformity of the cubes reduces variability in results, making it easier to compare data across different batches of materials. This makes cubic samples an excellent choice for testing early-stage properties of concrete mixes before scaling up to larger specimens (Sabbağ & Uyanık, 2017). However, despite their advantages in a controlled laboratory environment, cubic samples do not always provide the most accurate representation of how concrete will behave in structural applications. Cylindrical specimens, as tested under ASTM C39/C39M, better mimic the real-world stresses that concrete will experience in actual construction. For this reason, while cubic samples are useful for initial testing and comparison, cylindrical samples are often preferred for final strength assessments when determining whether concrete meets the specifications required for structural safety (Kurtuluş et al., 2018).

III. Materials and Methods

This study aims to predict the UCS of concrete using a MLP model. The prediction is based on key input parameters such as water-cement ratio, aggregate size, curing time, water content, and cement content. To develop and validate the MLP model, a dataset consisting of 120 laboratory-tested concrete samples was used. The concrete samples were cast into 15 cm × 15 cm × 15 cm cubic molds, which is the standard size for UCS testing. All samples underwent a curing period of 28 days to simulate standard construction conditions.The dataset was constructed using concrete mix designs that represent normal construction materials. For each sample, five key input parameters were recorded:

- *Water-cement ratio*: A crucial factor that influences the workability and strength of concrete.
- *Aggregate size*: The maximum size of the coarse aggregates used in the concrete mix.
- *Curing time*: Fixed at 28 days for all samples, which is the standard period for measuring UCS in concrete.
- *Water content*: The amount of water in kilograms per cubic meter of concrete.
- *Cement content*: The amount of cement in kilograms per cubic meter of concrete.

These parameters varied across the 120 samples to cover a wide range of typical concrete compositions. The corresponding UCS values for each sample were determined experimentally by applying a uniaxial compressive load until failure. The UCS was recorded in megapascals (MPa). Table 1 provides statistical analysis results for input data of modeling were used in this study.It is important to emphasize that our analysis primarily focuses on standard construction-grade concrete formulations, which predominantly use Type 2 Portland cement. Additionally, all samples in the study contain a consistent 2% superplasticizer by weight to enhance workability.Type 2 Portland cement is specifically described by Ingram & Daugherty (1991).

Table 1 Statistical analysis of input data used in this study

Parameters	Unit	Max	Min	Mean	St.Dv.
Input					
Water-cement ratio	-	0.65	0.23	0.44	0.31
Aggregate size	Kg/m^3	594	316	455	11.34
Water content	Kg/m^3	250	125	187	51.03
Cement content	Kg/m^3	377	198	285	7.39
Output					
UCS	MPa	42.7	16.3	29.5	10.7

The concrete cubes were prepared following standard mixing and casting procedures to ensure consistency. The materials used for the concrete mix included ordinary Portland cement (OPC), natural aggregates (both fine and coarse), and potable water. The water-cement ratios used in the mixes ranged from 0.2 to 0.7, representing common construction practices. The aggregate sizes varied between 10 mm and 25 mm, and the water and cement contents were adjusted accordingly for each mix.Once the concrete was mixed, it was poured into the cubic molds in three layers, each compacted to remove air bubbles. The molds were left undisturbed for 24 hours before being removed and transferred to a curing tank. The samples were submerged in water for 28 days to ensure proper hydration of the cement and to mimic typical field curing conditions. After 28 days, the samples were tested for their UCS using a hydraulic compression machine. The UCS values were calculated based on the load at failure and the surface area of the sample.

The MLP model was implemented using Python and the Scikit-learn library, which provides a range of tools for machine learning. An MLP consists of multiple layers of interconnected neurons (nodes), where each neuron applies a mathematical transformation to the input data. The model used in this study had three layers: an input layer, one hidden layer, and an output layer. The input layer received input parameters (water-cement ratio, aggregate size, water content, and cement content). The output layer provided the predicted UCS value.

The hidden layer contained 8 neurons, chosen based on trial and error to balance computational complexity and model performance. The activation function used for the hidden layer was the Rectified Linear Unit (ReLU), which is a common choice for neural networks because it helps the model learn nonlinear relationships. For the output layer, a linear activation function was applied to produce a continuous UCS value. The model was trained using the Adam optimization algorithm, which is well-suited for handling noisy data and adjusting learning rates dynamically during training.

Before training the MLP model, the data was preprocessed to ensure optimal performance. First, all input features were normalized to a range between 0 and 1. This step was crucial because it prevented certain features with larger scales from dominating the learning process. The dataset was then split into training and validation sets, with 70% of the data used for training and the remaining 30% reserved for validation. This split ensured that the model could learn from a majority of the data while still being tested on unseen examples.Additionally, a k-fold cross-validation technique was applied with k set to 5. This method divides the dataset into five subsets, trains the model on four of them, and tests it on the fifth. This process is repeated five times, and the average performance is reported.

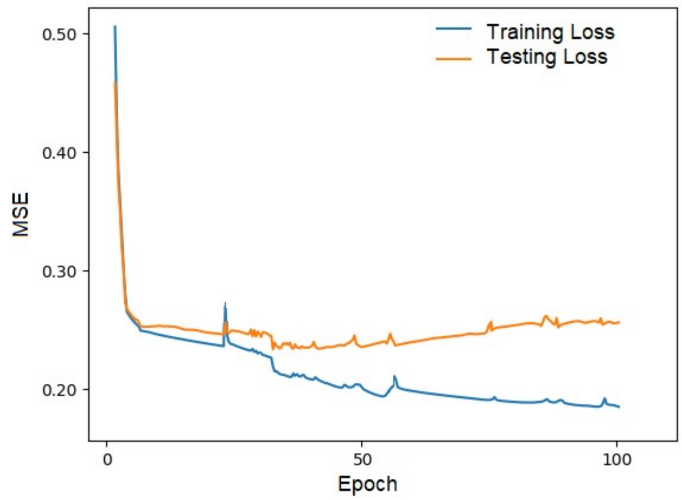

Fig. 2 The results of loss function estimated for model

The MLP model was trained on the training set for 100 epochs, meaning the model was exposed to the entire dataset 100 times. The loss function used was the mean squared error (MSE), which measures the average squared difference between the predicted and actual UCS values. The Adam optimizer was employed to minimize the loss function by adjusting the model's weights and biases. Figure 2 provides the results of loss function calculations for this modeling.During training, the model's performance was monitored on the validation set to ensure that it was not overfitting to the training data. The performance metrics used to evaluate the model included the mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). These metrics provide a comprehensive understanding of how well the model predicts UCS values.

To further improve the model's accuracy, hyperparameter tuning was conducted. The primary hyperparameters that were adjusted included the number of neurons in the hidden layer, the learning rate, and the batch size. A grid search approach was used to systematically test different combinations of these hyperparameters and identify the configuration that produced the best results. The final model was selected based on its performance on the validation set, with the goal of minimizing RMSE and maximizing R^2.

IV. Results and Discussion

This study successfully utilized an MLP model to predict the UCS of concrete using key input parameters (Table 1). The model was trained on a dataset of 120 laboratory-tested concrete samples and validated using rigorous cross-validation techniques. The results indicate that MLPs can provide accurate predictions of UCS, offering a practical tool for engineers and researchers in the construction industry. With further refinement and access to larger datasets, this approach could significantly reduce the need for experimental UCS testing and streamline the concrete mix design process.The methodology section details the steps followed in processing the primary dataset. The data is divided into training and testing sets, with validation performed using several methods, including evaluation metrics, and error analysis to ensure the model's accuracy and reliability.

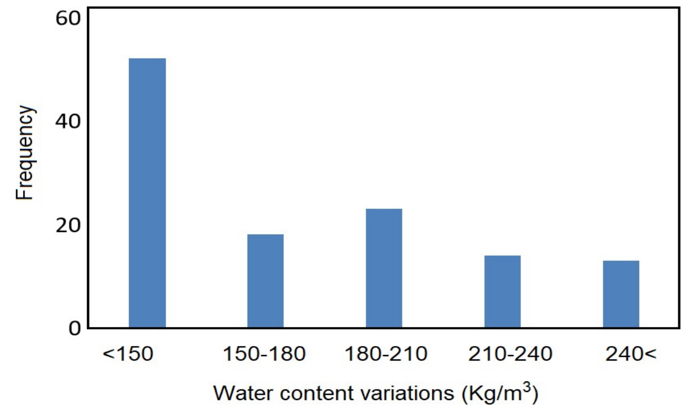

Fig. 3 The water content variations in studied samples

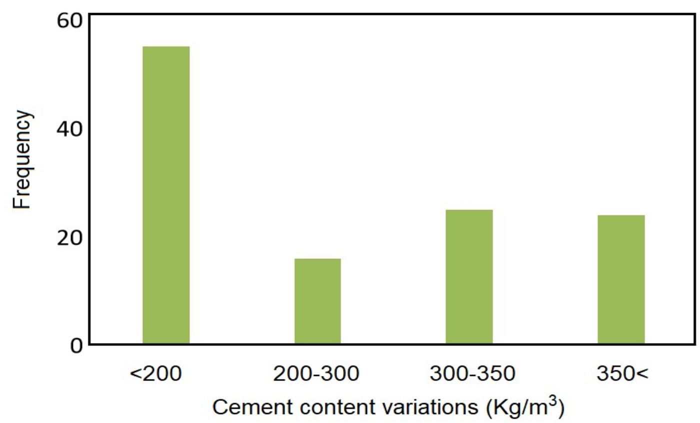

Fig. 4 The cement content variations in studied samples

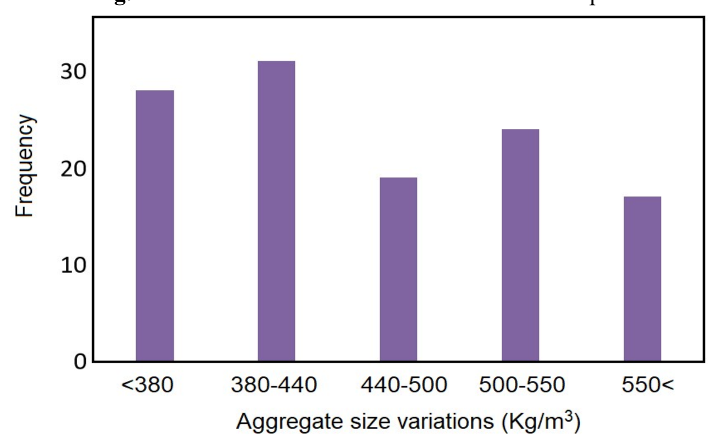

Fig. 5 The aggregate size variations in studied samples

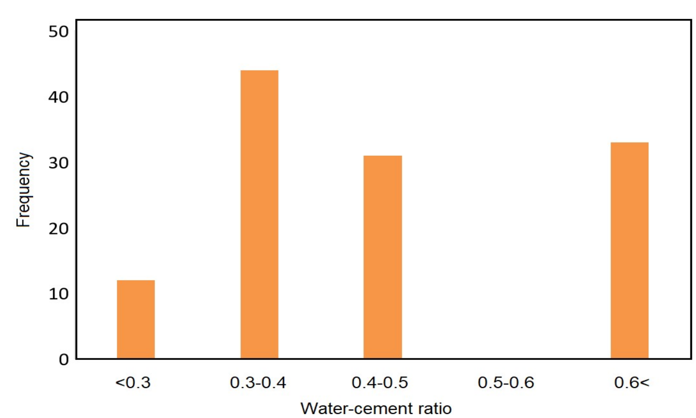

Fig. 6 The water-cement ratio variations in studied samples

Figures 3 to 6 illustrate the variations in input parameters across different concrete samples. By analyzing these variations in the composition of concrete mixes, we can gain deeper insights into how these factors influence the UCS and stiffness values of the specimens, which are directly linked to their compositional elements. This understanding is essential for optimizing the performance and durability of concrete structures. Figures 7 and 8 showcase the results of applying machine MLP model to predict UCS values based on the input parameters. Each model was trained and tested using the same dataset split, with 70% of the data used for training and 30% for testing. Furthermore, correlation regression analyses for the various models are illustrated in Figure 9, highlighting the relationships between predicted and actual UCS values.

After training and validation, the MLP model achieved a high level of accuracy in predicting UCS values.The R^2 value on the training set was 0.897 validation set was 0.833, indicating that the model explained 89% of the variance in UCS. This variation is provided in Fig. 9 for consideration. Based on analysis of statistical error indexes, errors were found to be within acceptable limits, suggesting that the model was able to make reliable predictions across a range of concrete compositions. Tables 2 and 3 are illustrated the estimated confusion matrix and statistical error indexes that provided for MLP model for both test and training sets.

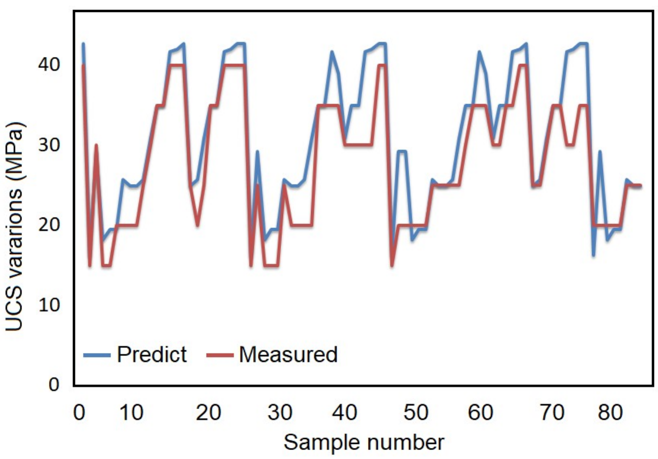

Fig. 7 The prediction process in training set based on MLP

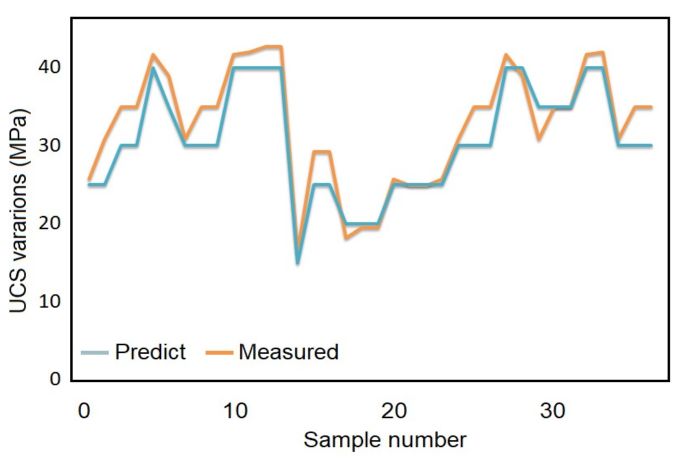

Fig. 8 The prediction process in testing set based on MLP

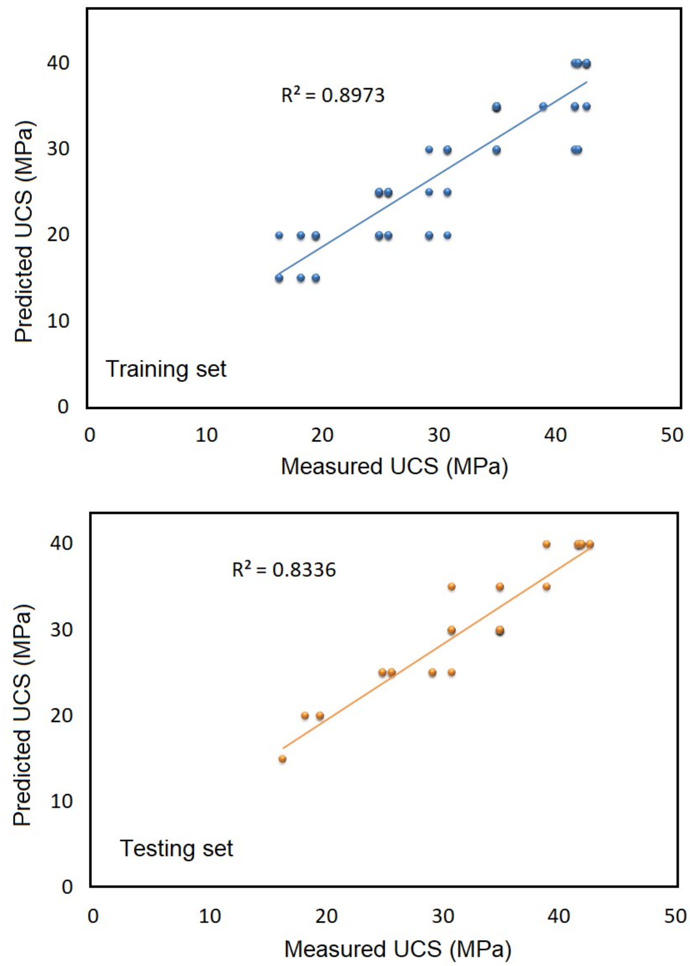

Fig. 9 The correlation analysis results for MLP model

Table 2 The results of performance analysis for MLP model

Analysis set	Assessment score (%)			Accuracy
	Precision	Recall	F1-score	
MLP train	89.90	86.78	89.90	89.59
MLP test	83.39	85.12	85.15	83.11

Table 3 Statistical indexes estimated for MLP model

Analysis set	MAE	MSE	RMSE	R^2
MLP train	0.25	0.23	0.23	0.85
MLP test	0.33	0.33	0.30	0.80

In accordance with theMLP model's ability to predict UCS based on input parameters such as water-cement ratio, aggregate size, and curing time demonstrates its potential as a valuable tool for construction professionals. By accurately predicting UCS, engineers can optimize concrete mix designs without relying solely on time-consuming experimental testing.

V. Conclusion

This study demonstrates the effectiveness of using a MLP model to accurately predict the UCS of concrete based on key input parameters such as water-cement ratio, aggregate size, curing time, and material content. The MLP model, trained on a dataset of 120 laboratory-tested concrete samples, performed exceptionally well, with an R^2 value of 0.897 for the training set and 0.833 for the validation set, indicating a high level of accuracy. The statistical error indexes further confirmed that the predictions were reliable and within acceptable limits.By leveraging this machine learning approach, engineers and researchers can streamline the concrete mix design process, reducing the need for extensive experimental testing. The model provides a practical tool for predicting UCS, which is critical for ensuring the safety, durability, and performance of concrete structures. With further refinement and access to larger datasets, this method holds the potential to significantly enhance quality control in concrete production and offer more efficient solutions for geotechnical engineering applications.

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Authors' contributions

Sina Aminbakhsh conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Amin Tohidi assisted in the development of the methodology and performed validation checks, provided supervision, conceptual guidance, and critical revision of the manuscript. All authors read and approved the final manuscript.

Conflict of interest

The authors have not disclosed any competing interests.

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