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Artificial Intelligence for Predicting the Concrete's UCS based on Experimental Data

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***Abstract*:** This study investigates the application of artificial intelligence in predicting the uniaxial compressive strength of concrete using experimental data. A multilayer perceptron (MLP) neural network was developed using TensorFlow and Keras in Python program. The dataset includes 150 concrete cube samples tested after 28-days of curing, divided into training (70%) and testing (30%) sets. The results show that the proposed model significantly improves prediction accuracy, achieving over 80% recall and maintaining consistent performance through 500 iterations, with an accuracy range of 80-85%. Comparative analysis with algorithms such as SVM, k-NN, RF, DT, and Adaboost indicates that the MLP model provides superior accuracy in predicting concrete strength. The confusion matrix reveals 91% accuracy and 99% precision. Evaluation using MSE, MAE, and RMSE metrics confirms that the MLP model has lower error rates than other algorithms, demonstrating its effectiveness in predicting uniaxial compressive strength.

Keywords: Artificial intelligence, Uniaxial compressive strength, Concrete prediction, MLP, Neural networks.

I. INTRODUCTION

CConcrete is a composite construction material made from cement, water, sand, and aggregate (Chen and Leung, 2014). Due to its high compressive strength, durability, and moldability, it is a popular material for various structures. Uniaxial compressive strength (UCS) is one of the most critical mechanical properties of concrete, indicating its ability to withstand compressive loads (Azarafza et al., 2017). This strength depends on several factors, including the type and quality of the concrete's components, the water-to-cement ratio, mixing methods, curing process, and environmental conditions (Chen and Leung, 2014). While the compressive test is a common method to determine this property, it can be costly, time-consuming, and prone to human and laboratory errors (Ding et al., 2011). In recent years, artificial intelligence (AI) has emerged as a powerful tool for predicting concrete's UCS (Zhang et al., 2020). AI techniques can analyze experimental data and establish relationships between UCS and its influencing factors, enabling accurate predictions without the need for traditional testing (Ngo et al., 2021).

Indeed concrete is one of the most widely used construction materials, made from a mixture of water, cement, and aggregates (Barzegar et al., 2016). It exists in two states as fresh and hardened (Ai et al., 2021). As it transitions from fresh to hardened, its behavior changes from plastic to elastic. This transformation occurs through a chemical reaction called hydration, during which water becomes part of the cured concrete (Nguyen et al., 2020). Over time, concrete's strength stabilizes, increasing as long as it is not exposed to damaging factors. The quality of concrete in structures depends on its properties in both the fresh and hardened states. UCS, the most important property of concrete, indicates its ability to withstand loads and serves as a key criterion for evaluating concrete quality (Zhang et al., 2020). While UCS is often assumed to be the focus, concrete can also experience tensile, flexural, shear, and torsional stresses. Among these, compressive, tensile, and flexural strengths are the most significant. Recent AI advancements have made it a powerful tool in optimizing and predicting various concrete properties, including mechanical strength, thermal quality, and durability (Nunez et al., 2021).

AI in concrete technology offers an innovative and advanced approach to making this engineering field more sustainable (Zhang et al., 2020). AI algorithms and techniques are used to optimize the formulation of concrete materials and predict its engineering and mechanical behavior. This optimization involves precise combinations of ingredients like cement, sand, aggregates, and additives, leading to increased strength, reduced weight, and improved mechanical properties. AI can also predict the behavior of concrete, particularly its strength, allowing for significant performance assessments. Moreover, AI helps predict concrete's mechanical behavior under various conditions, providing crucial information for engineers during the design process, and enabling better adaptation of concrete to environmental conditions. AI can also play a major role in automating concrete production processes, reducing errors, improving efficiency, and minimizing material waste (Zhang et al., 2020).

Ultimately, AI enhances concrete's resistance to environmental factors such as heat, moisture, and weather changes, improving the durability of structures and reducing future maintenance needs. The necessity of utilizing AI for predicting the UCS of concrete is critical for two main reasons (Nguyen et al., 2020). First, AI tools can analyze complex and large datasets to identify patterns in concrete's mechanical behavior, helping to predict its USC with greater accuracy. This information is vital for engineers and structural designers in material selection and design processes. AI enables engineers to consider various factors affecting concrete's UCS, such as material composition, water-to-cement ratio, and environmental conditions. These predictions guide engineers toward conducting fewer tests and optimizing costs for evaluating UCS. Given the complexity and variability of factors influencing concrete's UCS, the use of AI not only enhances the speed and accuracy of data but also offers better solutions for optimizing materials and concrete production processes (Nunez et al., 2021).

This study focuses on predicting the USC of concrete using experimental data. Traditional methods, such as compressive strength tests, can be expensive, time-consuming, and subject to human error. To address this, a neural network model called a multilayer perceptron (MLP) was created using TensorFlow and Keras in Python program. This model is designed to learn from the data and capture the complex relationships between various factors that influence concrete strength. By doing so, the model can provide accurate predictions without the need for repeated physical testing. The goal of this research is to make the process of evaluating concrete's strength more efficient, reliable, and cost-effective, ultimately contributing to improvements in construction and civil engineering practices.

II. CONCRETE'S UNIAXIAL STRENGTH

The UCS measures how much pressure concrete can withstand when subjected to a load in one direction (Nunez et al., 2021). Essentially, it tells us how much weight concrete can bear before it starts to crack or break (Lu and Zhao, 2010). Since concrete is great at handling compressive forces, UCS is one of its most important properties in construction (Zhang et al., 2019). UCS is determined through a simple test where a concrete sample, usually a cylinder or cube, is compressed until it fails (Zárate et al., 2022). The amount of pressure applied to the sample is recorded, and the UCS is calculated by dividing the load by the sample's surface area. This gives a measure of the concrete's strength in megapascals (MPa) or pounds per square inch, psi (Zhang et al., 2019).

In designing concrete structures, UCS plays a central role (Van Mier, 1998). Engineers rely on it to ensure that the concrete in columns, beams, and foundations can safely carry the loads they are meant to support (Ouyang et al., 2022). By knowing the UCS, engineers can figure out the right thickness, size, and reinforcement required for different parts of a structure. It helps guide the design process and material selection to ensure the building's strength and safety (Silva et al., 2015). UCS is crucial for a structure's stability. Concrete is often subjected to a variety of stresses, including the building's own weight, environmental forces, and dynamic loads like wind or earthquakes (Ouyang et al., 2022). A high UCS is ensures that the concrete can handle these forces without cracking or collapsing, thus maintaining the stability and integrity of the structures (Nunez et al., 2021).

The UCS of concrete directly affects how durable a structure will be over time (Lim et al., 2016). Concrete with higher UCS is better equipped to resist damage from weather, freeze-thaw cycles, and chemical exposure. This means that structures made with stronger concrete will last longer and require fewer repairs, making them more cost-effective in the long run, particularly for bridges, buildings, and infrastructure meant to last decades (Chandwani et al., 2014). Optimizing UCS helps engineers balance performance with cost. By understanding the exact strength of the concrete, designers can avoid using too much material. Stronger concrete allows for thinner walls or smaller columns while still maintaining safety, which can reduce construction costs (Nunez et al., 2021). By using less material, labor and transportation costs can also be reduced, leading to more efficient designs (Ouyang et al., 2022).

The UCS of concrete is heavily influenced by its mix design—the proportions of cement, water, aggregates, and any additives (Nunez et al., 2021). A key factor is the water-to-cement ratio: too much water weakens the concrete, while too little makes it difficult to work with. The quality of the aggregates, the type of cement, and the use of chemical additives also play a role (Talaat et al., 2021). Careful management of these variables ensures the concrete achieves the desired strength. UCS can be affected by environmental conditions during the curing process, such as temperature and humidity (Mendis, 2003). Curing, which involves keeping the concrete moist for a set period, is critical for the concrete to reach its full strength (Xiao et al., 2012). If the concrete dries too quickly or is exposed to extreme heat or cold, its UCS may be compromised. These factors must be monitored during construction to ensure the concrete gains the required strength (Mendis, 2003).

It's important to consider UCS early in the design phase because it influences key decisions like material selection, reinforcement, and construction methods (Chandwani et al., 2014). Accurately predicting UCS allows engineers to design structures that are both safe and cost-effective (Wang et al., 2016). Failing to account for UCS could lead to structural weaknesses, higher costs due to over-engineering, or even failures in extreme cases (Zheng et al., 2022). Addressing UCS early helps ensure that the design aligns with the performance expectations of the structure (Lu & Zhao, 2010). Recent advances in technology have made it easier to predict UCS more accurately (Nguyen et al., 2020). By using large datasets and advanced software, engineers can analyze patterns in concrete behavior and predict its strength without extensive physical testing. These tools can also help fine-tune the mix design, allowing for faster and more precise adjustments in the field. This makes construction more efficient and leads to stronger, longer-lasting structures (Nunez et al., 2021).

III. MATERIALS AND METHODS

AI has emerged as a powerful tool for estimating the UCS of concrete. Traditional methods for determining UCS, like lab testing, are time-consuming and can be costly. AI, on the other hand, allows engineers to predict concrete strength using existing data with greater speed and accuracy (Zhao et al., 2022). By analyzing large sets of input variables, such as the mix proportions, curing conditions, and environmental factors, AI models can offer predictions that guide the design and quality control of concrete (Sun et al., 2022). Among AI techniques, machine learning (ML) models are particularly useful for predicting UCS. Algorithms like neural networks, decision trees, and support vector machines can be trained on historical data from concrete testing. These models learn from patterns within the data and can then predict the UCS for new concrete mixes based on input features (Khursheed et al., 2021). This ability to generalize from past results allows engineers to fine-tune concrete compositions without needing to run extensive physical tests, saving both time and resources (Ebdali et al., 2020). The accuracy of AI predictions for UCS largely depends on the quality and amount of data available. Inputs typically include material properties, such as the water-to-cement ratio, type of aggregates, and chemical additives, as well as external factors like curing time and temperature. The more comprehensive and precise the data, the better AI models can predict how these variables will impact concrete strength (Torkan et al., 2021). This highlights the need for thorough data collection and consistent record-keeping in the construction industry to maximize the benefits of AI in UCS estimation. In predicting the UCS of concrete, a MLP neural network was employed to model the complex relationships between concrete mix parameters and strength outcomes (Abdelhedi et al., 2020). MLP is a type of artificial neural network that mimics the way human brains process information, making it ideal for non-linear and multi-dimensional problems like UCS prediction. The MLP model was implemented using Python, with TensorFlow and Keras libraries, which provide robust frameworks for developing and fine-tuning machine learning models.

An MLP is a type of artificial neural network designed to process complex data by simulating how human neurons operate. It consists of three main types of layers: an input layer, hidden layers, and an output layer. Figure 1 is provided a schematic of MLP architecture. The input layer receives raw data, which is then passed through multiple hidden layers where complex patterns and relationships are learned. Each neuron in a layer is connected to neurons in the next layer, and these connections have adjustable weights and biases that are optimized during training (Lee & Choeh, 2014). MLPs are highly effective for tasks that require learning non-linear relationships, making them ideal for applications such as pattern recognition, classification, and prediction (Fiesler & Beale, 1996).

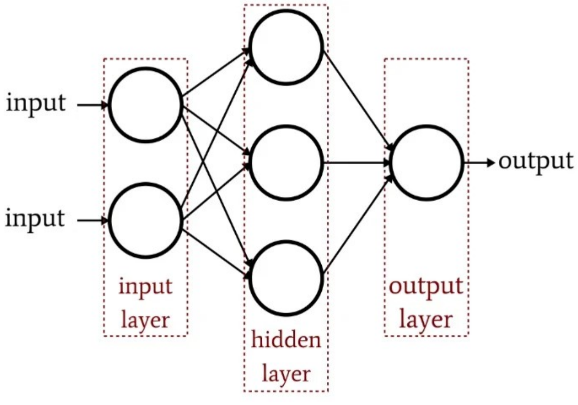
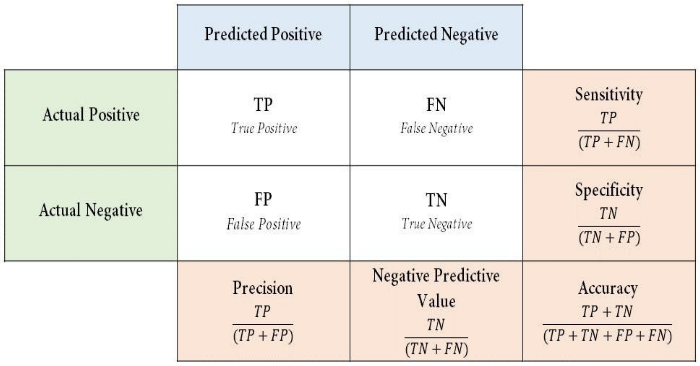


Fig. 1 A topical MLP architecture (Delashmit & Manry, 2005)

The architecture of an MLP typically involves several hidden layers, each containing multiple neurons. The complexity of the model increases with the number of hidden layers and neurons. Neurons in these layers use activation functions like ReLU (Rectified Linear Unit) or sigmoid to introduce non-linearity into the model, allowing it to capture more complex relationships in the data. The training process involves backpropagation, where the model calculates the error between predicted and actual outputs, and then adjusts the weights and biases accordingly to minimize this error. This iterative process continues through multiple epochs until the model's predictions reach an acceptable level of accuracy (Fiesler & Beale, 1996).

In the context of predicting the UCS of concrete, MLP models are particularly valuable due to the complex and non-linear relationships between the mix proportions, curing conditions, and other factors that influence concrete strength (Zheng et al., 2022). By feeding the MLP with relevant data points such as water-to-cement ratio, aggregate type, and curing time, the network learns to predict UCS values based on patterns in the historical data (Lu & Zhao, 2010). This approach eliminates the need for time-consuming physical testing, enabling engineers to make informed predictions about concrete performance more efficiently (Silva et al., 2015). The dataset used in this study consisted of 150 concrete cube samples, which were tested for UCS after 28 days of curing. These samples were divided into two subsets: 70% for training the MLP model and 30% for testing its predictive capability. During training, the model learned from the input features of the dataset—such as the concrete mix proportions, curing conditions, and environmental factors—and built relationships between these inputs and the UCS outcomes.

The MLP model was developed with multiple layers: an input layer to receive the dataset features, several hidden layers to process the data through activation functions, and an output layer that predicted the UCS. The MLP was trained through 500 iterations (or epochs) to optimize the weights and biases within the network, improving its ability to predict UCS accurately. During each iteration, the model adjusted itself based on the errors between its predictions and the actual UCS values, gradually refining its accuracy. To further assess the effectiveness of the MLP model, its performance was compared with several other machine learning algorithms, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forest (RF), Decision Trees (DT), and Adaboost which in terms of prediction, accuracy and recall (see Figure 2).



	Predicted Positive	Predicted Negative	
Actual Positive	TP *True Positive*	FN *False Negative*	Sensitivity $\frac{TP}{(TP+FN)}$
Actual Negative	FP *False Positive*	TN *True Negative*	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

Fig. 2 A confusion matrix structure (Mahesh, 2020)

IV. RESULTS AND DISCUSSION

A. Experimental Study

The UCS test is a critical method used to evaluate the strength of concrete by determining its ability to withstand compressive loads (Chen & Leung, 2014). According to C39/C39M, UCS testing is typically conducted on cylindrical or cubic samples of concrete (Figure 3). For cubic samples, a standard size of 15cm×15cm×15cm is often used to ensure consistency in the results (ASTM C109/C109M). These samples are cured for a 28-days period under controlled conditions before being tested to measure their maximum UCS. This test is essential for determining the concrete's quality and suitability for structural applications (Ebdali et al., 2020). Before conducting the UCS test, it is essential to properly prepare the cubic concrete samples. Concrete is mixed according to the desired proportions, poured into standard molds, and compacted to remove air voids (see Tables 1 and 2 as well as Figure 4). The samples are left to cure in the mold for 24 hours before being removed and placed in a curing chamber, where they are kept at controlled temperature/humidity levels for 28-days. Ensuring uniformity in sample preparation is lead to inconsistent test results.

The UCS test is performed by placing the cured concrete cube in a compression testing machine (see Figure 3), as specified by ASTM C39 and ASTM C109. The testing machine applies an increasing compressive load to the cube until failure occurs, meaning the point where the concrete can no longer withstand the pressure.

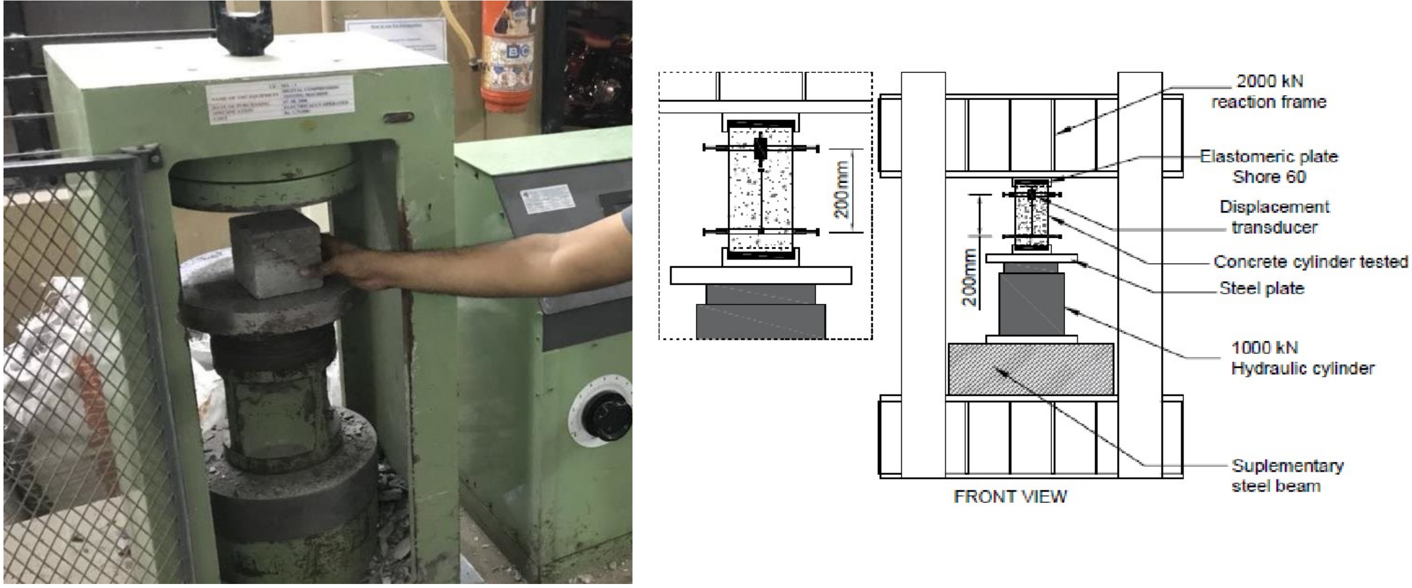


Fig. 3 A view of UCS test and schematic diagram of device (updated from Reinhardt, 1991)

Table 1 Physical and chemical properties of the cement used in this study

Physical properties			*Chemical properties*		
Parameters	Unit	Value	Parameters	Unit	Value
Fine particles	cm^2/g	3335	SiO_2	ww (%)	21.70
Particles remained on 90 µm sieve	%	3.85	Al_2O_3	ww (%)	5.25
Autoclave expansion potential	%	0.15	Fe_2O_3	ww (%)	3.46
Le Chatelier expansion potential	mm	1.12	CaO	ww (%)	65.5
Density	g/cm^3	3.16	MgO	ww (%)	2.22
Initial setting time	min	115	SO_3^{2-}	ww (%)	2.00
Final setting time	min	180	Na_2O	ww (%)	0.25
3-day uniaxial compressive strength	kg/cm^2	240	K_2O	ww (%)	0.63
7-day uniaxial compressive strength	kg/cm^2	350	Cl^-	ww (%)	0.01
28-day uniaxial compressive strength	kg/cm^2	468	Loss on Ignition (LOI)	ww (%)	1.35

Table 2 Physical and chemical properties of the aggregates used in this study

Physical properties			*Chemical properties*		
Parameters	Unit	Value	Parameters	Unit	Value
Moisture content	%	2.59	SiO_2	ww (%)	21.4
Water absorption rate	%	14.84	Al_2O_3	ww (%)	4.83
Density	g/cm^3	75.3	Fe_2O_3	ww (%)	3.55
Bulk density	g/cm^3	83.0	CaO	ww (%)	64.5
Crushing index	%	16.16	MgO	ww (%)	1.75
Clay or fine particle content	%	0.75	SO_3^{2-}	ww (%)	2.93
			Na_2O	ww (%)	0.64
			K_2O	ww (%)	0.90
			Cl^-	ww (%)	-
			Loss on Ignition (LOI)	ww (%)	0.62

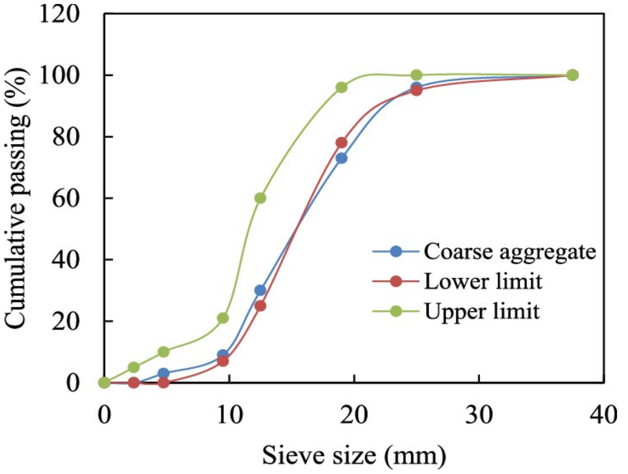


Fig. 4 Aggregate particle-size curve used in concrete testing

The load is applied at a controlled rate of 0.25 MPa per second to prevent sudden failure and ensure accurate results. The maximum load that the sample can bear before it cracks or fails is recorded. This value is then divided by the cross-sectional area of the cube (15cm×15cm) to calculate the UCS in MPa. The UCS results obtained from the test provide essential data for evaluating the structural integrity of concrete. A higher UCS indicates a stronger concrete capable of withstanding greater compressive forces, making it suitable for load-bearing structures like columns and beams. If the UCS falls below the required threshold, adjustments may be needed in the mix proportions or curing process. This experimental UCS data helps in ensuring the long-term durability and safety of concrete structures.

B. Model Implementation

As previously mentioned, after gathering the data and creating the initial database, this dataset was randomly divided into two groups: a training set and a testing set. The dataset, consisting of 70% training data and 30% testing data, was evaluated using performance metrics such as the confusion matrix, model error function, and comparative analysis approaches with common machine learning models. This section outlines the implementation process and the results obtained from the proposed MLP-based model, as well as validation through other machine learning models. During the implementation of the proposed model, the performance was initially measured by generating confusion matrices and comparing them with validation methods outlined in methodology section. The goal was to evaluate the accuracy and precision of the MLP-based evaluation matrix through machine learning. To achieve this, the model was implemented in comparison with the classification methods, and confusion matrices along with performance factors were generated.

The MLP model was first applied to the training dataset, which contains 150 results from concrete UCS tests conducted continuously over a 3-month period, prepared according to ASTM standards. The validation approaches include SVM, k-NN, DT, RF, and the AdaBoost algorithm. Figures 5 to 10 present the results from the proposed model, which were used to create the confusion matrix and evaluate the performance metrics.

With a thorough review of all obtained results. The comparisons revealed that the proposed model, which utilizes a MLP neural network, performed exceptionally well in assessing the UCS of the concrete samples analyzed. When the results of the MLP model were compared with those from other algorithms, such as AdaBoost, decision trees, random forests, k-nearest neighbors, and support vector machines, it was evident that the evaluation metrics indicated that the proposed method outperformed the other four classification algorithms. Therefore, it can be concluded that the model presented in this study achieved more accurate UCS predictions with lower error rates.

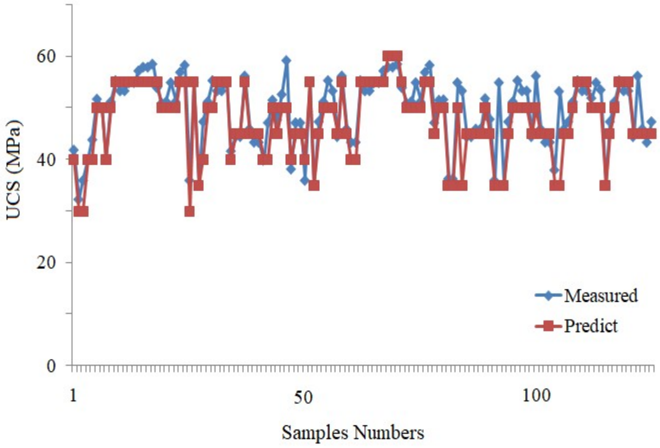


Fig. 5 MLP-model prediction results for UCS in the training set

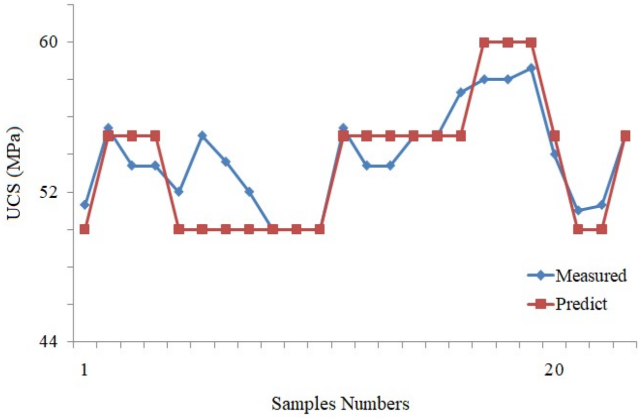


Fig. 6 MLP-model prediction results for UCS in the testing set

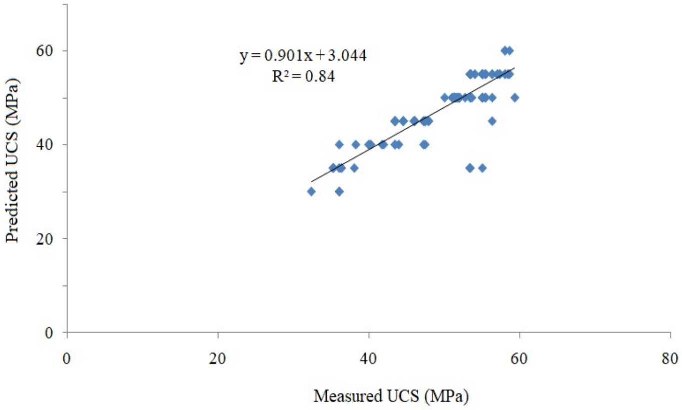


Fig. 7 Regression for Predicting UCS in the training set

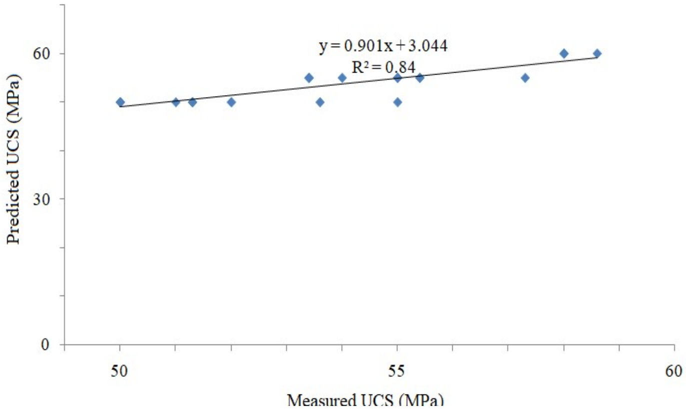


Fig. 8 Regression for Predicting UCS in the testing set

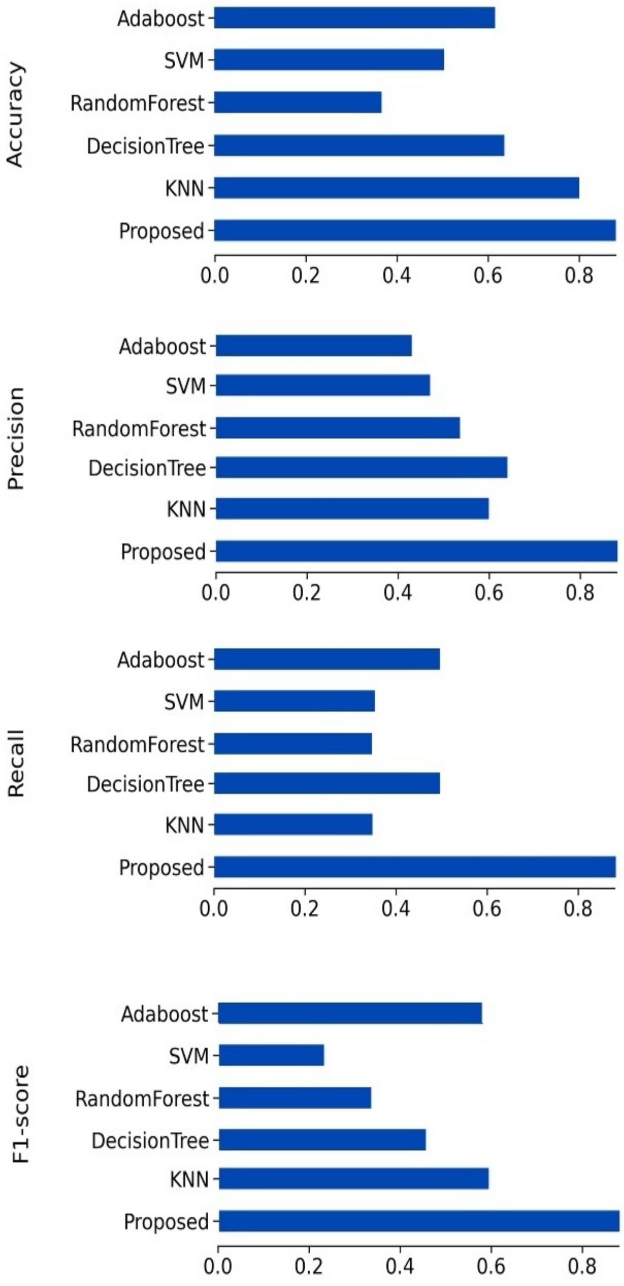


Fig. 9 Results of the performance matrix for various models

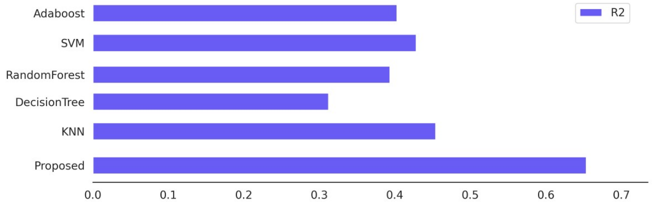


Fig. 10 Results of the R^2 for various models

V. CONCLUSION

In conclusion, this study highlights the effectiveness of using a MLP neural network for predicting the UCS of concrete. By analyzing a dataset of 150 concrete cube samples, the model achieved notable accuracy, showing over 80% recall and reliable performance throughout 500 iterations. The comparisons made with other machine learning algorithms, such as AdaBoost, decision trees, random forests, k-nearest neighbors, and support vector machines, further demonstrate the advantages of the MLP approach. The MLP model not only delivered better accuracy but also managed to reduce prediction errors significantly. The careful division of data into training and testing sets played a crucial role in ensuring the validity of the results. This research emphasizes the potential of artificial intelligence in improving predictive methods in civil engineering, especially regarding the properties of materials like concrete. Moreover, the study reveals the importance of incorporating advanced machine learning techniques in assessing construction materials. Such approaches can lead to more accurate evaluations and more efficient construction practices. The success of the MLP model indicates that similar methodologies could be beneficial for optimizing other concrete properties, ultimately enhancing material performance and contributing to better construction outcomes.

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AUTHORS' CONTRIBUTIONS

Hamed Mahmodi conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Karim Samadzamini 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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