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Predicting the Compressive Strength of Concrete Utilizing Machine Learning Techniques and Conventional Techniques

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ABSTRACT

In civil engineering, accurately determining the compressive strength of concrete is a crucial aspect of designing buildings. Precisely predicting this strength can lead to significant time and cost savings by quickly generating essential design data and reducing the need for trial mixes, thus minimizing material waste. This research employed two different types of soft computing approaches, specifically artificial neural network (ANN) and Random Forest (RF), to efficiently project the compressive strength (CS) of concrete to forecast the compressive strength of concrete reliably. The variables considered include age, cement content, fly ash, Blast Furnace Slag, water content, superplasticizer content, coarse aggregate, and fine aggregate. This study highlights the vast potential of cutting-edge machine learning models as a superior option for precisely predicting the compressive strength of concrete based on the concrete's components. The statistical analysis results show that all of the machine learning models displayed outstanding predictive abilities, as demonstrated by their high coefficient of determination (R^2) values of 99.5% and 95.3%, along with low Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Error values of 1.177, 3.069, 0.387, 2.657, Additionally, the compelling findings suggest that the proposed models based on the RF and ANN techniques significantly outperformed those proposed using conventional approaches.

التنبؤ بقوة الضغط للخرسانة باستخدام تقنيات تعلم الآلة والتقنيات التقليدية

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الكلمات المفتاحية:
قوة الضغط
الشبكة العصبية الاصطناعية
الغابة العشوائية
التعلم الآلي
التقنيات التقليدية

الملخص

في الهندسة المدنية، يعد التحديد الدقيق لقوة ضغط الخرسانة جانبًا حاسمًا في تصميم المباني. يمكن أن يؤدي التنبؤ الدقيق بهذه القوة إلى توفير كبير في الوقت والتكلفة من خلال إنشاء بيانات التصميم الأساسية بسرعة وتقليل الحاجة إلى الخلطات التجريبية، وبالتالي تقليل هدر المواد. استخدم هذا البحث نوعين مختلفين من أساليب الحوسبة الناعمة، وتحديدًا الشبكة العصبية الاصطناعية (ANN) والغابة العشوائية (RF)، لتقدير قوة الضغط (CS) للخرسانة بكفاءة للتنبؤ بقوة الضغط للخرسانة بشكل موثوق. تشمل المتغيرات التي تم أخذها في الاعتبار العمر، ومحتوى الأسمنت، والرماد المتطاير، وخبث الفرن العالي، ومحتوى الماء، ومحتوى الملدن الفائق، والركام الخشن، والركام الناعم. تسلط هذه الدراسة الضوء على الإمكانات الهائلة لنماذج التعلم الآلي المتطورة كخيار متميز للتنبؤ بدقة بقوة ضغط الخرسانة بناءً على مكونات الخرسانة. تظهر نتائج التحليل الإحصائي أن جميع نماذج التعلم الآلي أظهرت قدرات تنبؤية متميزة، كما يتضح من قيم معامل التحديد العالية (R^2) البالغة 99.5% و95.3% إلى جانب انخفاض المتوسط المطلق. خطأ (MAE)، خطأ جذر متوسط تربيعي (RMSE)، وقيم متوسط خطأ مربع 1.177, 3.069, 0.387, 2.657 بالإضافة إلى ذلك، تشير

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النتائج المقنعة إلى أن النماذج المقترحة القائمة على تقنيات الغابة العشوائية والشبكة العصبية الاصطناعية تفوقت بشكل كبير على تلك المقترحة باستخدام الأساليب التقليدية.

1. Introduction

Concrete is the most used construction material worldwide due to its advantages over other materials, such as integrity, durability, modularity, and cost-effectiveness [1]. Usually, standard concrete is made up of three primary elements: Portland cement, coarse and fine aggregates, water, as well as different admixtures and additives that improve its characteristics, longevity, and workability during mixing, casting, and curing procedures. These extra substances may involve chemical additives such as superplasticizers, air-entraining agents, and set-retarding agents, which alter the flow, strength development, and setting time of the concrete mix. Furthermore, mineral and pozzolanic additives like fly ash, silica fume, and slag can enhance the concrete's strength, reduce permeability, and improve its resistance to chemical attack and cracking [2].

By adjusting the proportions of its components and introducing these additional materials, the properties of standard concrete can be customized to meet specific design criteria, making it a versatile and widely utilized construction material for various applications, from residential structures to infrastructure projects. compressive strength (CS) is a key parameter in reinforced concrete design. However, destructive compression tests can introduce non-linear factors. Since compressive strength is measured on the 28th day, this process requires time, planning, and financial resources. [3-5]. Predicting concrete's mechanical characteristics, including CS, is a significant and crucial endeavour to understand better how concrete structures behave under external loads and to develop design methods. Moreover, this valuable forecast not only aids in planning operations like prestressing and framework removal but also assists in optimizing and streamlining construction processes. By accurately predicting the mechanical properties of concrete, engineers and designers can ensure the structural integrity, durability, and performance of various concrete structures, leading to safer and more efficient construction practices. With the ability to estimate compressive strength, professionals can make informed decisions about materials and construction techniques, enhancing construction projects' overall efficiency and success. This intricate and intricate process of forecasting the mechanical characteristics of concrete unquestionably holds immense value in the construction industry. It plays a paramount role in shaping the future of infrastructure development. [6-8].

Nowadays, numerous machine learning (ML) are used for concrete compressive strength prediction, among which are Artificial Neural Network, Random Forest, and Support Vector Machine models. Technology are increasingly adopted in civil engineering for research, construction, control, and maintenance purposes. ML allows engineers to use algorithms and computational power to analyze and comprehend concrete behaviour deeply. By training machine learning models with extensive concrete-related data, patterns and correlations that may not be easily detected by humans can be identified. This enables more accurate predictions of concrete strength, leading to optimized construction processes, improved resource allocation, and enhanced structural designs [9-11]. The study objective to existing a highly practical, efficient, and reliable approach for accurately forecasting the CS of concrete. This will be achieved by using traditional and ML approaches. The proposed approach will be tested and validated using real data from existing projects. The ML approach will be trained and optimized to achieve the best performance. Finally, the results will be compared and evaluated.

2. Machine Learning Algorithms

In this comprehensive and in-depth study, two diverse and advanced machine learning models analyze the results rigorously. These models' intricate and profound nature will be thoroughly explored and elucidated in subsequent sections, providing a comprehensive understanding of their methodologies, functionalities, and outcomes.

- **Artificial Neural Networks (ANNs)**

Artificial neural networks (ANNs) are widely used in computer science to predict the compressive strength of various types of concrete mixtures, whether traditional or non-traditional. ANNs simulate the functioning of the human brain's biological neural network, a complex system. In computer science, an ANN is described as a highly adaptable and flexible learning model that can learn from input data to predict an output by dynamically adjusting the weight of each processing component or neuron through a rigorous and iterative training process [12,13]. Figure 1 displays a diagram of the ANNs algorithm.

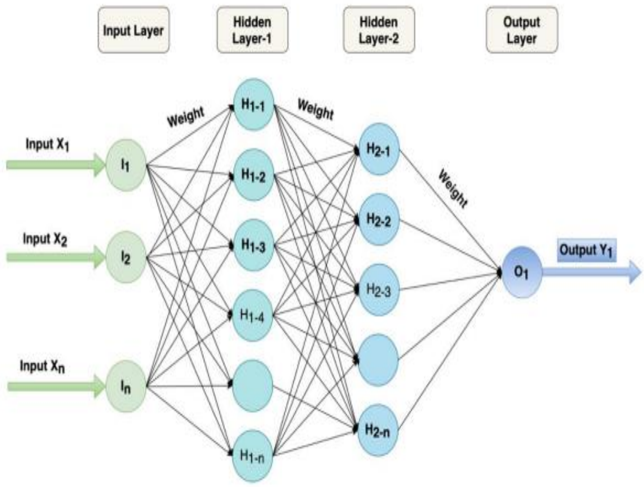

Fig 1 displays a diagram of the ANNs algorithm.

- **Random Forest (RF)**

The Random Forest algorithm, originally introduced by Leo Breiman and Adele Cutler in 2001 [14], is a highly effective and widely used supervised machine-learning model that builds upon the Decision Tree model. In the Random Forest regression model, predictions are generated by taking the average of the predictions from multiple trees. The Random Forest algorithm is known for its ability to handle large datasets and high-dimensional feature spaces and its resistance to overfitting.

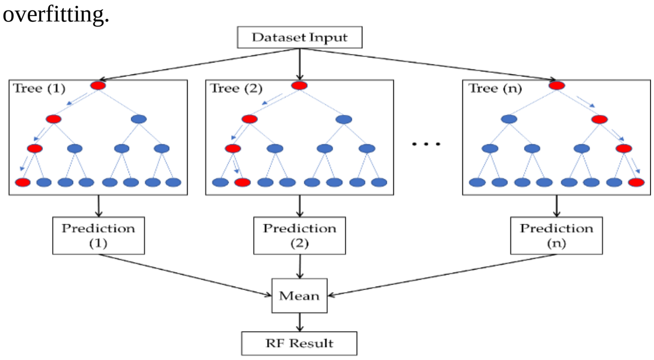

Fig 2 displays a diagram of the RF algorithm.

It can also handle numerical and categorical data, making it a versatile model. Its flexibility and robustness have made it a popular choice for various applications, including regression, classification, and feature selection. Overall, the Random Forest algorithm has proven to be a powerful tool in machine learning, showcasing its effectiveness and wide-ranging capabilities [15]. Figure 2 displays a diagram of the RF algorithm.

3. Methodology

In this study, 1030 data points collected were analyzed to create an accurate model for predicting compressive strength (CS) using conventional and ML techniques. Table (1) shows the descriptive statistics for 1030 data points. This data set was collected by Yeh [16].

Table (1) the descriptive statistics for data points

	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Std. Error	Statistic
Cement (kg in a m^3 mixture)	102.0	540.0	281.166	3.2563	104.507
Blast Furnace Slag	0.0	359.4	73.895	2.688	86.279

(kg in a m^3 mixture)					
Fly Ash (kg in a m^3 mixture)	0.0	200.1	54.187	1.994	63.997
Water (kg in a m^3 mixture)	121.8	247.0	181.566	0.665	21.356
Superplasticizer (kg in a m^3 mixture)	0.0	32.2	6.203	0.186	5.974
Coarse Aggregate (kg in a m^3 mixture)	801.0	1145.0	972.919	2.422	77.754
Fine Aggregate (kg in a m^3 mixture)	594.0	992.6	773.579	2.498	80.175
Age (day)	1	365	45.66	1.968	63.170
Concrete compressive strength (MPa, megapascals)	2.33	82.60	35.818	0.521	16.706

The dataset includes important variables such as age, cement (C), water (W), fly ash (FA), blast furnace slag (BFS), superplasticizer (SP), coarse aggregate (CA), and fine aggregate (S), all of which play a major role in determining the strength of concrete. Figure (3) depicts the methodological framework utilized in this study.

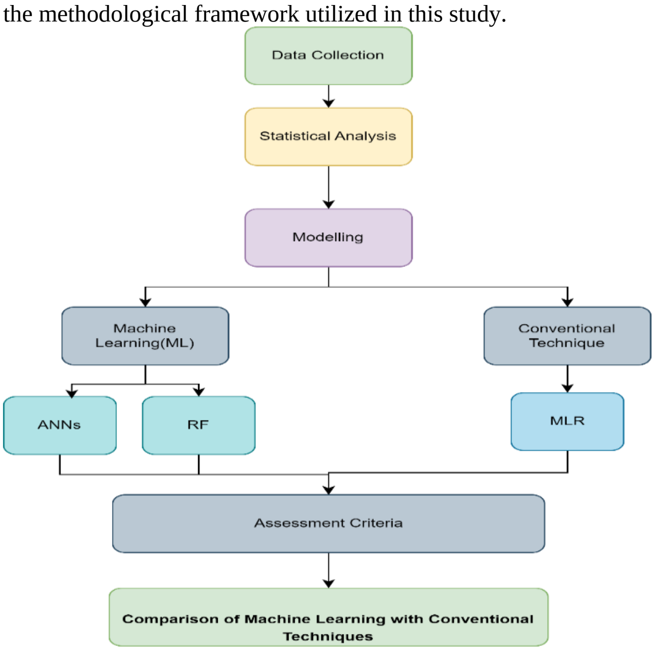

Fig 3. Methodology of the study.

4. Assessment criteria for models

Several metrics were used to evaluate the accuracy of analyzing and modelling intricate data patterns. These extensive measures were meticulously employed and deeply scrutinized to gauge the forecasting outcomes' precision, performance, and reliability. These meticulously chosen metrics played a vital role in examining the various aspects of the predictions [17]. Table 2 provides a mathematical demonstration of performance metrics.

Table 2 The mathematical demonstration of performance metrics.

Measure Models	Formula	Variables Description
Determination Coefficient	$R^2 = \frac{(\sum y_i - \hat{y}_i)^2}{(\sum y_i - \bar{y}_i)^2}$	ŷi represents the predicted values. ȳ represents the mean of the actual values. y = observed values, $\hat{y}$ = predicted values, n = number of observations, p = number of predictors .
Mean Absolute Error	MAE= $\left(\frac{1}{n}\right) * \sum\lvert y - \hat{y}\rvert$	
Root Mean Squared Error	RMSE= $\sqrt{\sum\left(\frac{(y-\hat{y}_i)^2}{(n-p)}\right)}$	

5. Research Analysis Approaches

5.1 Developing Conventional Techniques Models

In this study, the researchers extensively utilized multiple linear regression (MLR) techniques to forecast compressive strength (CS) accurately. The CS value, which directly corresponds to the concrete's strength, was considered the dependent variable in the analysis. On the other hand, the eight input parameters (age, cement (C), water (W), fly ash (FA), blast furnace slag (BFS), superplasticizer (SP), coarse aggregate (CA), and fine aggregate (S) were treated as independent variables to examine their impacts on the CS value.

Table 3 The CS model summary.

Model	Unstandardized Coefficients		Standardized Coefficients	Test(t)
	B	Beta		
Constant	-23.164		-	0.871
Age	0.114	0.432	0.432	21.046
Cement	0.120	0.749	0.749	14.110
Blast Furnace Slag	0.104	0.536	0.536	10.245
Fly Ash	0.088	0.337	0.337	6.988
Water	-0.150	-0.192	-0.192	-3.741
Superplasticizer	0.291	0.104	0.104	3.110
Coarse Aggregate	0.018	0.084	0.084	1.919
Fine Aggregate	0.020	0.097	0.097	1.883
R^2	61.5			
RMSE	10.354			
MAE	8.215			

The researchers used the comprehensive IBM SPSS Statistics package to conduct the analysis. The obtained dataset was then meticulously analyzed using MLR to explore and understand the correlation between the independent and dependent variables. Evaluating the correlation between these variables was based on robust statistical measures, including R^2, RMSE, and MAE values, providing essential insights into the relationship between the variables. A comprehensive summary of the MLR model and its findings can be found in Table (3) of this study. Equation (1) represents the derived MLR model, which symbolizes the mathematical relationship between the independent and dependent variables. The equation (1) presented demonstrates the regression models employed and showcases the correlation between the independent variables and the dependent variable, known as CS, as follows:

CS=-23.164+0.114*Age+0.120*Cement+0.104*Blast Furnace Slag+0.088* Fly Ash- 0.150*Water +0.291* Superplasticizer+0.018* Coarse Aggregate+0.020* Fine Aggregate (1)

Equation (1) displays the outcomes of the regression analysis for compressive strength (CS). Age, Blast Furnace Slag, Fly Ash, Superplasticizer, Coarse Aggregate, and Fine Aggregate exhibited positive associations with CS, while Water showed negative ones. Using statistical error measures such as (R^2), (MAE), and (RMSE), the precision of the regression model was affirmed. The examination unveiled a good coefficient of determination R^2, indicating that the independent variables fairly account for the variations in CS. Furthermore, the MAE and RMSE values signalled a satisfactory correspondence between the estimated and actual values. These results confirm the regression model's resilience and dependability in projecting compressive strength (CS) performance. Figure 4 displays a diagram of the RF algorithm.

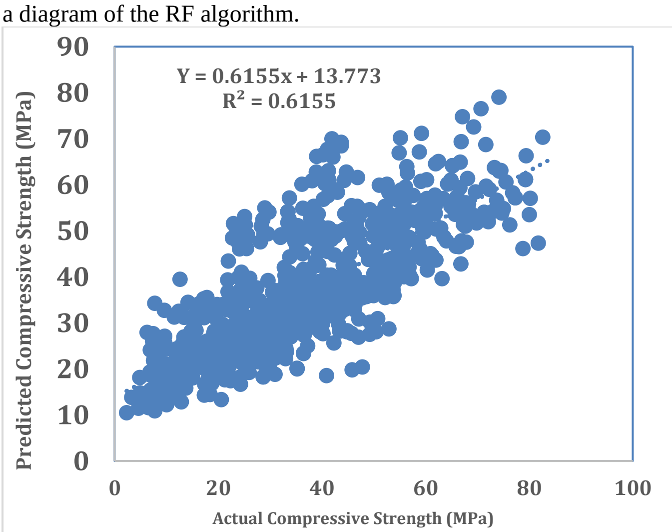

Fig 4. MLR prediction results for CS model.

5.2 Developing Machine Learning (ML) Models

The study used two machine learning techniques, specifically artificial neural networks (ANNs) and random forest (RF), to predict the compressive strength (CS) of concrete mixtures based on eight parameters. The modelling results for both machine learning methods can be found in Table 4. Furthermore, for a more visual representation of the obtained results, Figures 5 and 6 exhibit the explicit prediction outputs for the concrete strength model using the ANNs and RF models, respectively. The results of this research's four ML techniques are presented in Table (4) and Figures (5) and (6). The ANNs) model achieved an R^2 score of 99.5%, RMSE of 1.177, and MAE of 0.387. The RF model scored R^2= 95.3%, RMSE = 3.609%, and MAE = 2.657 Consequently, the ANNs model was more accurate than the RF models.

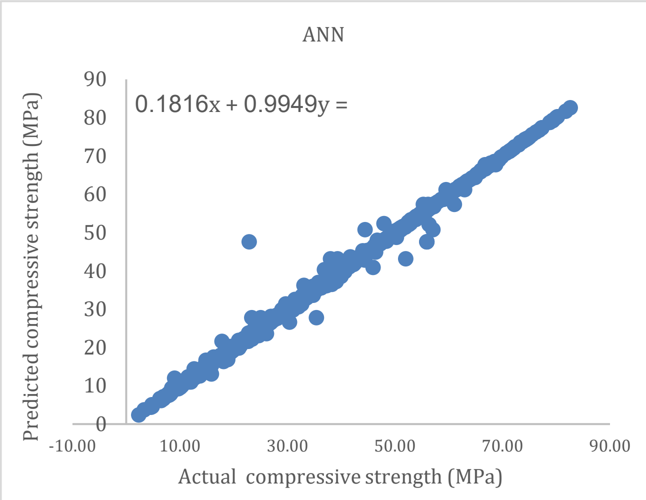

Table 4: Performance of CS models ML techniques

ML technique	Statistical Error Measures		
	R^2	RMSE	MAE
ANNs	99.5	1.177	0.387
RF	95.3	3.609	2.657

Fig 5. ANNs prediction results for CS model.

6. Comparison of Machine Learning with Conventional Techniques

Various measures, such as coefficient of determination ($R2$), root mean squared error (RMSE), and mean absolute error (MAE), were effectively utilized to comprehensively assess the efficiency and performance of machine learning approaches in comparison to traditional methods. Upon careful examination and analysis of the findings derived from both approaches, it was evident that all the implemented models showcased remarkable precision and accuracy in their predictions. A thorough comparison and evaluation of the outcomes between conventional techniques and the utilization of machine learning algorithms are extensively outlined in Table (5), with the visual aids of Figures (7) to (8) distinctly illustrating the profound disparities and variations observed between the application of machine learning and traditional methods.

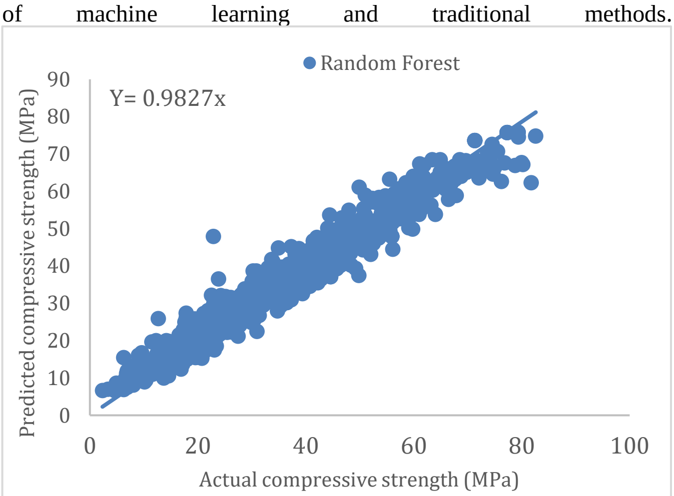

Fig 6. RF prediction results for CS model.

Table 5: Comparison of the ML and MLR techniques.

Technique	Statistical Error Measures		
	R^2	RMSE	MAE
MLR	61.5	10.354	8.215
ANNs	99.5	1.177	0.387
RF	95.3	3.609	2.657

The results obtained from implementing machine learning algorithms exceeded expectations, providing significant evidence of their superiority over conventional methods. (R^2) values registered were exceptionally high, indicating a strong correlation between the input variables and the predicted outcomes. Additionally, the (RMSE) values obtained were remarkably low, implying that the machine learning models accurately captured the underlying patterns and trends in the data. Moreover, the (MAE) values were impressively close to zero, further reinforcing the reliability and precision of the machine learning approaches. These results demonstrate the potential of machine learning to revolutionize various fields and industries by providing accurate and efficient predictions. The comprehensive evaluation and comparison of the outcomes between machine learning and traditional methods reveal distinct disparities and variations. While still valuable, the conventional techniques showcased limitations in terms of precision and accuracy. On the other hand, using machine learning algorithms presented significant improvements and advancements, allowing for more reliable and precise predictions. In Table (5), detailed insights regarding the efficiency and performance of both approaches are provided, allowing for a comprehensive understanding of the advantages offered by machine learning. The visual aids provided in Figures (7) to (8) further highlight these disparities, clearly depicting the profound impact of machine learning on the accuracy and precision of predictions

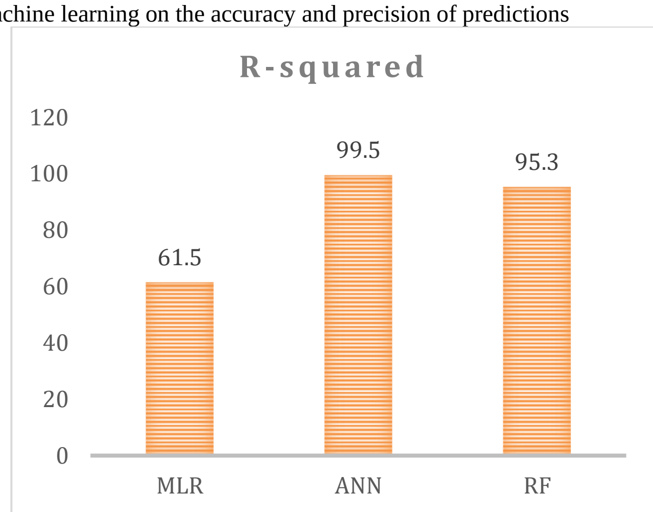

Fig 7. Comparison among the ML and MLR techniques (R-Squared)

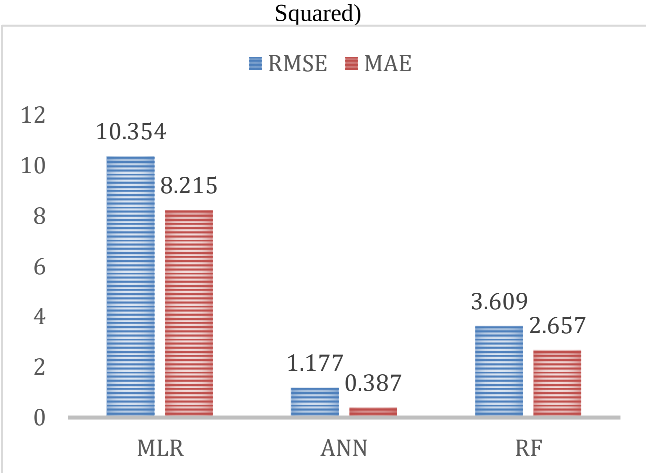

Fig 8. Comparison among the ML and MLR techniques (RMSE and MAE).

7. Conclusion

In this investigation, the forecast of the compressive strength CS relies on eight parameters created using the traditional technique (MLR) and two ML methods, ANNs and RF. Considering the study's results, the following conclusions can be inferred:

A grand total of 1030 data sets inclusive of varying mix proportion specifications, including the age, cement (C), water (W), fly ash (FA), blast furnace slag (BFS), superplasticizer (SP), coarse aggregate (CA), and fine aggregate (S), were utilized as input parameters.

2. Statistical methods like MLR, ANNs, and RF were applied to develop innovative prediction models for forecasting the Compressive strength of mixture concrete.

3. A comparison of MLR, ANNs, and RF models reveals that the ANNs model demonstrates superior accuracy in predicting compressive strength.

4. The performance criteria show that the ANNs model outperformed the other models developed in the current study.

5. The statistical measurements for the ANNs model on the test datasets were R^2 of 99.5%, RMSE of 1.177 MPa, and MAE of 0.387 MPa.

6. The research demonstrated that both approaches successfully predicted CS values, alleviating the requirement to analyze CS values and thus conserving time and resources.

8. Data availability

The data considered in this study was obtained from the published literature [13]

9.Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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