SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V10I12P101

Volume 10 Issue 12, 1-8, December 2023

Original Article

Comparative Study of Mathematical Models for the Strength of Bacterial Concrete Using Multiple Regression Analysis and Artificial Neural Network

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Received: 06 October 2023 Revised: 23 November 2023 Accepted: 08 December 2023 Published: 23 December 2023

Abstract - *This study advocates the adoption of Multiple Regression Analysis (MRA) and Artificial Neural Network (ANN) techniques for predicting concrete behaviour. It underscores these statistical prediction tools' expeditious and reliable nature, offering valuable insights for subsequent mass concreting endeavours through a swift assessment of concrete behaviour. The research endeavours to construct predictive models using a raw dataset curated from specific studies conducted by various researchers, employing Multiple Regression Analysis tools. In addition to MRA, the study incorporates Artificial Neural Network techniques to train the raw dataset. Subsequently, it utilizes various regression analyses to predict a new model derived from this updated dataset. The study's primary objective is to discern the combined influence of bacterial addition and concrete grade on the compressive strength of concrete. This holistic approach aims to advance our understanding of the intricate interactions among these variables, contributing to the enhancement of predictive models for concrete behaviour in the context of mass concreting projects. The study also contributes to exploring new dimensions in the research field of bacterial concrete.*

Keywords - *Artificial Neural Network, Bacillus subtilis, Bacterial concrete, Behavior prediction, Multiple Regression Analysis.*

1. Introduction

Concrete is a widely used construction material. However, cracks in concrete lead to durability issues. The micropores and cracks in concrete give way to the entry of water and other corrosive fluids, leading to the structure's deterioration. This degradation adversely impacts the durability of concrete, compromising the structures' overall serviceability [1]. Consequently, there has been a concerted effort to investigate and address the timely mitigation of cracks. Researchers have demonstrated interest in formulating intrinsic solutions to address the challenge of trials, particularly by incorporating self-healing materials during the concrete manufacturing process. One notably effective solution under scrutiny is self-healing bacterial concrete.

This method has garnered attention due to its biological basis, environment friendliness, cost-effectiveness and sustainability, presenting advantages over alternative approaches [2]. Bacterial concrete technology incorporates calcite bacterial precipitation activities into cementitious composites, significantly improving mechanical properties and enhancing structural durability. The mitigation of cracks is effectively carried out by introducing bacteria into the cementitious composites during the mixing process, primarily facilitated by bacterial precipitation mechanisms [3].

Producing calcium carbonate to self-heal surface cracks in concrete structures is mediated by biology in bacterially impregnated concrete. Spore-forming bacterial strains are incorporated into the concrete mix to effectuate this process. These bacterial strains used for this purpose include Bacillus subtilis, Bacillus sphaericus, Bacillus cohnii, Bacillus pseudofirmus, Bacillus megaterium, and Sporosarcina pasteurii. During preparation, these bacteria, nitrogen, phosphorus, and calcium nutrients are added to the concrete mixture. The long-term dormant latent self-healing agents come into action when they come into contact with water seeping through concrete cracks [4].

Upon activation, the bacteria metabolise the calcium compounds present in concrete, a process during which oxygen is consumed, transforming calcium compounds into insoluble calcite. The resultant calcite precipitates onto the fractured concrete surface, effectuating a sealing mechanism. Notably, this self-healing bacterial concrete paradigm extends the potential lifespan of concrete structures, providing an innovative and sustainable strategy for augmenting durability. The selection of bacterial strains is meticulously executed based on their compatibility with the concrete environment, resilience to adverse conditions such as elevated pH levels, and proficiency in precipitating minerals conducive to crack sealing. Integrating bacterial activity into the factual matrix signifies a pioneering and ecologically conscientious methodology for fortifying the resilience and lifespan of concrete infrastructures [5]. Implementing bacterial technology that imparts self-healing capabilities to cementitious materials reduces the associated costs and labour intensity of remediation endeavours, notably in the context of extensive concrete infrastructures like operational roads, tunnels, etc. This technology is envisioned to extend the life span of cementitious materials and structures, thereby reducing the carbon footprint of the cement [6].

Probabilistic models and constitutive equations are formulated to reduce the extensive requirements of experimental procedures in concrete mix design. A predictive tool is developed to anticipate outcomes and identify potential anomalies, serving essential purposes: ensuring the design strength, expediting the quality control process, and optimizing economic efficiency within the system. The utilization of regression analysis as a conventional model generation method has been documented by Chopra and Sharma [5]. Multiple Regression Analysis is a quicker and simpler prediction method used to forecast results like the compressive strength of concrete by implementing linear or nonlinear approaches. This statistical methodology scrutinizes the correlation between the parameters influencing the study's outcome and the actual study outcome [8, 9].

The compressive strength of concrete holds paramount significance as a criterion for defining its characteristics. Ensuring the conformity of the produced concrete to standard requirements is crucial when considering large-scale concrete production. Prediction models serve the purpose of forecasting strength, contributing to concrete quality assurance. A comprehensive understanding of the strength of bacterial concrete is essential for progress in this field [10]. Artificial Neural Networks (ANN) represent an application of Artificial Intelligence that has garnered extensive utilization across various domains within science and engineering [11]. This technology enhances the correlation between inputs and outputs, obviating the necessity for fixed equations. ANN demonstrates adaptability in scenarios involving novel data through its capacity for continuous retraining with new information. The application of ANN has notably emerged as a promising technique for predicting concrete properties and finds diverse applications within structural engineering [12].

Researchers have used several statistical indicators to assess various properties of concrete. The current investigation is centred on formulating a predictive model for the compressive strength of bacterial concrete integrating Bacillus subtilis species. Establishing such a system requires meticulous experimentation and iterative refinement to achieve optimal outcomes. This effort is expected to significantly advance self-healing research by formulating a comprehensive guideline for optimizing parameters that influence concrete strength. This contribution is poised to enhance the understanding and application of self-healing mechanisms in concrete, thereby facilitating the development of more robust and resilient concrete structures. This study's methodologies involve statistical tools such as Multiple Regression Analysis (MRA) and Artificial Neural Network (ANN) techniques. These tools are employed to discern the correlation between concrete grades, the presence of bacteria, and the compressive strength of concrete. This is achieved by fitting a linear equation to the observed data. Specifically, an Artificial Neural Network (ANN) is employed to train the dataset to generate the desired output, while Multiple Regression Analysis (MRA) is utilized to construct the predictive Model.

2. Data

The data utilized in this study is sourced from investigations involving both conventional concrete and bacterial concrete, with concrete compositions comprising well-graded M.Sand, 53 Grade OPC cement, and 20 mm and downsize coarse aggregates. A notable focus of prior research has been assessing the strength of bacterial concrete, with Bacillus species frequently employed in these studies due to its resilience and endurance in challenging environmental conditions. This research explicitly investigates the mechanical properties of concrete impregnated with Bacillus subtilis, a species renowned for its durability. The curing period for the concrete specimens is standardized at 28 days.

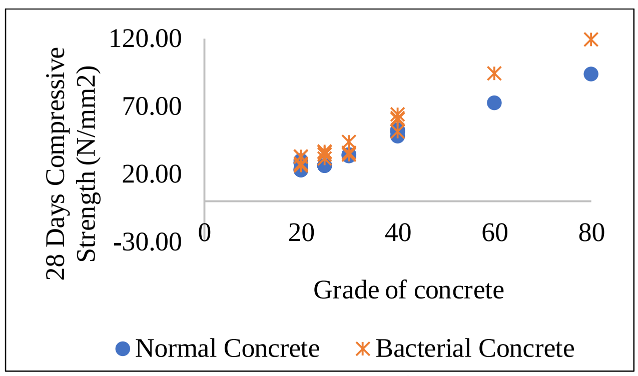


Fig. 1 28 days compressive strength (N/mm^2) for different grades of conventional and bacterial concrete derived from literature

The dataset under consideration is derived from a compilation of experiments conducted by diverse researchers, as documented in reputable publications authored by Reddy et al. (2010) [13], Bashir et al. (2016) [14], Rao et al. (2017) [15], Siva Rama et al. (2020) [16], Durga et al. (2020) [17], and Pachaivannan et al. (2020) [18]. This raw data compilation encompasses variables such as the grade of concrete and the presence of bacteria, which are treated as independent variables. The dependent variable in this dataset is the compressive strength of the concrete at 28 days, forming the basis for a comprehensive exploration into the mechanical attributes of Bacillus subtilis-infused concrete. Figure 1 shows the graphical representation of this data, plotting 28 days of compressive strength (N/mm^2) for different grades of conventional and bacterial concrete.

3. Modelling Techniques

The analytical framework for this study uses two different tools: Artificial Neural Networks (ANNs) and Multiple Regression Analysis (MRA). By using a statistical lens to investigate the relationships between several independent variables and a dependent variable, Multiple Regression Analysis sheds light on the complex interactions between various factors. In addition, Artificial Neural Networks - which draw inspiration from the structure of the human brain - allow for modelling relationships in a more sophisticated and adaptive way. They are especially well-suited for capturing nonlinear patterns and dependencies found in data. When these tools are used, the analytical approach becomes more robust and can handle both linear and nonlinear aspects of the phenomena under investigation.

3.1. Multiple Regression Analysis (MRA)

Multiple Regression Analysis is a powerful statistical method employed in research across various disciplines to investigate the complex relationships among numerous independent and dependent variables. This analytical approach extends the principles of simple linear regression to accommodate scenarios where the outcome variable is influenced by more than one predictor, expressed as in Equation 1 [12, 19].

$$p = c + \sum_{i=1}^{n} c_i x_i \tag{1}$$

Where, p – dependent variable, n – number of independent variables, c – constant (y-intercept), c_i – coefficients of the corresponding independent variable and x_i – independent variables. Given the multidimensional nature of real-world phenomena, the main objective of multiple regression is to identify the degree to which two or more independent variables influence a dependent variable. The researchers use this method to identify patterns, assess the relative importance of predictors, and make predictions or infer causal relationships within a complex system.

3.2. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are a paradigm shift in computational modelling that mimics the human brain's complex data processing and learning abilities by modelling its complex neural architecture. ANNs, a subset of machine learning and computational neuroscience, have become well-known in various fields due to their ability to recognize patterns, anticipate outcomes, and carry out complex decision-making tasks. This introduction aims to clarify the theoretical underpinnings, architectural elements, and practical uses of Artificial Neural Networks (ANNs), highlighting the importance of ANNs in artificial intelligence and data-driven problem-solving. An Artificial Neural Network consists of interconnected nodes, or neurons, arranged into layers that work together to process and change input data into output [20].

The innate power of Artificial Neural Networks (ANNs) resides in their capacity to self-adapt and learn from data, optimizing performance by varying the weights of connections between neurons. Because of this feature, ANNs are especially good at identifying complex patterns, identifying nonlinear relationships, and extrapolating from training data to generate predictions for new inputs.

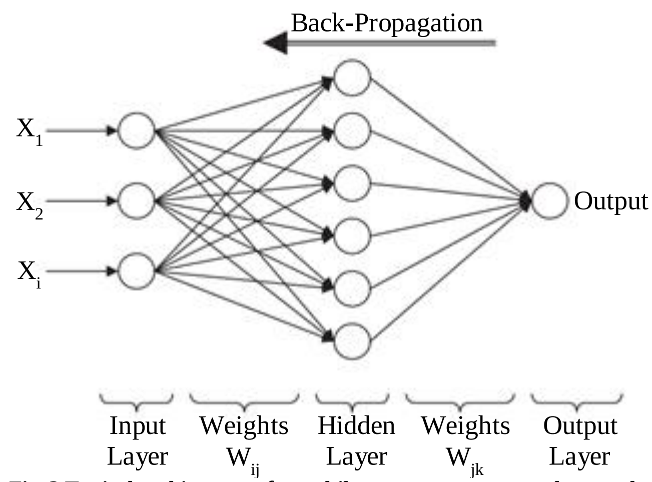


Fig. 2 Typical architecture of a multilayer perceptron neural network [12]

The typical architecture of ANN is shown in Figure 2, as depicted by Atici (2011) [12]. As a Processing Element (PE), every neuron receives inputs and uses a transfer function to produce an output signal. The weightings assigned to each connection reflect the influence of input sets or previous process elements in the hidden layers on the current processing element. The training process results in the initial random selection of the connection weightings and bias values, which are then fixed.

The efficiency of the learning process depends on the choice of a suitable network configuration, which includes factors like the quantity of hidden layers and the neurons that make them up. When determining the connections between network inputs and outputs, hidden layer neurons are essential. The neural network undergoes distinct phases, commonly denoted as 'training,' 'validation,' and 'testing.' During the training phase, the network is exposed to training data, and adjustments are made based on obtained errors.

Sample data encompassing inputs and desired outputs are processed to optimize the network's production, minimizing deviations. The validation phase evaluates network generalization, and the training process is halted when generalization ceases to improve, providing an independent measure of network performance. This process continues during and after training [22]. The adopted ANN model is depicted in Figure 3.

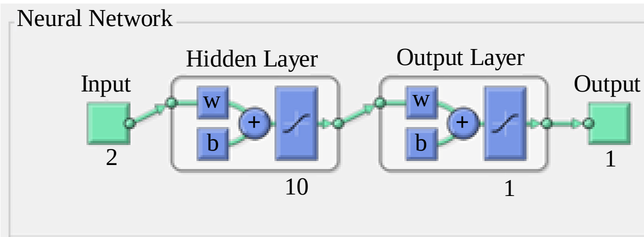


Fig. 3 ANN model adopted

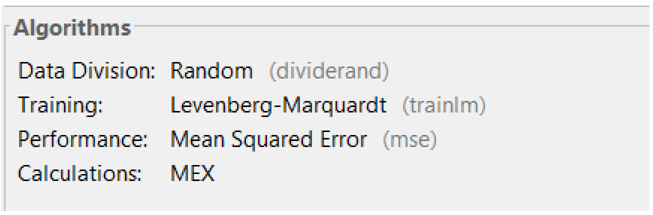


Fig. 4 Algorithm used in ANN model

In this investigation, Artificial Neural Network (ANN) is the computational tool of choice, employing a two-layer feed-forward network trained through the back-propagation training algorithm and the Levenberg–Marquardt optimization algorithm. When the trust-region algorithm fails to yield a satisfactory fit or adequately constrain coefficients, recourse to the Levenberg–Marquardt algorithm is recommended (Levenberg, 1944; Marquardt, 1963) [11, 23]. The back-propagation algorithm, a prevalent approach for training multilayer perceptrons, is employed as a gradient descent technique.

This involves iteratively adjusting the weights to minimize errors for specific training patterns [23], as illustrated in Figure 4. Multiple Regression Analysis (MRA) utilises the ANN response to construct a predictive model for response values in novel datasets. MRA simultaneously formulates a model for prediction using raw data. A separate test dataset is employed for validation purposes to ascertain the robustness of the Model. This methodological integration aims to leverage the complementary strengths of ANN and MRA, enhancing the modelling approach's predictive accuracy and generalization capabilities.

4. Results and Discussion

For the dependent variable, 28 days Compressive Strength, the independent variables considered for statistical analysis include grade of concrete and bacterial concentration. The independent variable grade of concrete was adopted in the study since it holds the proportion of concrete constituents & water-cement ratio adopted for the mix. Bacterial concentration was considered an independent variable due to its varying effect on the compressive strength of concrete with variation in bacterial concentration. The models suggest predicting 28 days of concrete strength at an earlier stage.

Table 1. Summary statics for the model 1 of Multiple Regression Analysis

Model No.	**Model 1**		
Dependent Variable	**28 Days Average Compressive Strength**		
Independent Variable	**Constant**	**Grade of Concrete**	**Bacterial Concentration**
Coefficient	-5.2763	1.3685	7.7560
p Value	0.0115	0.0000	0.0000
R Value	0.9772		
R^2 Value	0.9549		
Standard Error	4.8069		
F Value	370.2577		
Significance F	0.0000		

Multiple Regression Analysis was carried out for the raw dataset and is considered model 1. The parameters available for model 1 and the summarized results of the Multiple Regression Analysis of model 1 are shown in Table 1. The variable to be predicted is given against the Dependent variable in Table 1. The independent variables affecting the dependent variable and the constant derived are listed under Independent variables in Table 1. The raw dataset underwent training and validation employing the Artificial Neural Network (ANN) technique. The zenith of validation performance, as depicted in Figure 5, was realized at epoch 6, with an optimal value of 6.0134.

This particular 'epoch' marked the culmination of the model's proficiency throughout the neural network's training progression, as evaluated against a validation dataset. In this context, "performance" denotes the neural network's efficacy in accurately predicting or classifying data. The numerical representation "6.0134" corresponds to the specific performance metric, encompassing measures such as mean squared error or accuracy, attained by the model on the validation dataset at the specified epoch. A diminished metric value signifies an augmented model performance, indicating heightened accuracy or reduced error in the neural network's predictions concerning the validation data.

Figure 6 illustrates the processes of the Artificial Neural Network (ANN) in analyzing the raw data. The training graph reveals a diminishing training loss, indicating that the model effectively fits the training data. Concurrently, the validation plot demonstrates a consistently stable validation loss, signifying robust generalization capabilities. The correlation coefficient (R value) surpassing 0.98 for both training and validation showcases a positive inclination toward the efficacy of the ANN processes.

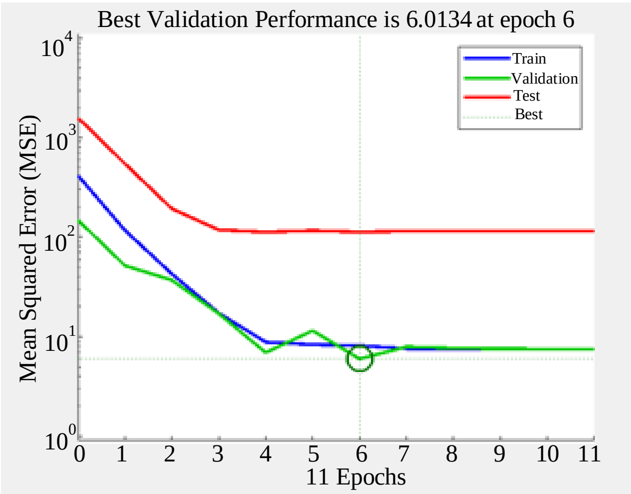


Fig. 5 ANN training progression

In the test graph, a little deviation from the training pattern is observed; however, the R value of 0.98987 denotes a good performance on new, unseen data. The graph exhibits only a slight variation from the training and validation performances, and the R value of 0.97668 provides an overarching assessment of the Model's good overall performance across diverse datasets.

This comprehensive evaluation, considering both individual and collective metrics, emphasizes the ANN's proficiency in handling the intricacies of the raw data and its effectiveness in generalization to new and diverse datasets. Multiple Regression Analysis was carried out for the ANN-trained dataset and is considered model 2. The parameters available for model 2 and the summarized results of the Multiple Regression Analysis of model 2 are shown in Table 2.

Table 2. Summary statics for the model 2 of Multiple Regression Analysis

Model No.	**Model 2**		
Dependent Variable	**28 days Average Compressive Strength**		
Independent Variable	**Constant**	**Grade of Concrete**	**Bacterial Concentration**
Coefficient	-1.8231	1.2446	7.6956
p Value	0.2632	0.0000	0.0000
R Value	0.9819		
R^2 Value	0.9640		
Standard Error	3.8959		
F Value	469.1893		
Significance F	0.0000		

The regression models derived from the analysis are expressed as linear equations (Equations 2 and 3). The equations predict the compressive strength of concrete.

$$p_1 = -5.2763 + 1.3685\,x_1 + 7.7560\,x_2 \qquad (2)$$

$$p_2 = -1.8231 + 1.2446\,x_1 + 7.6956\,x_2 \qquad (3)$$

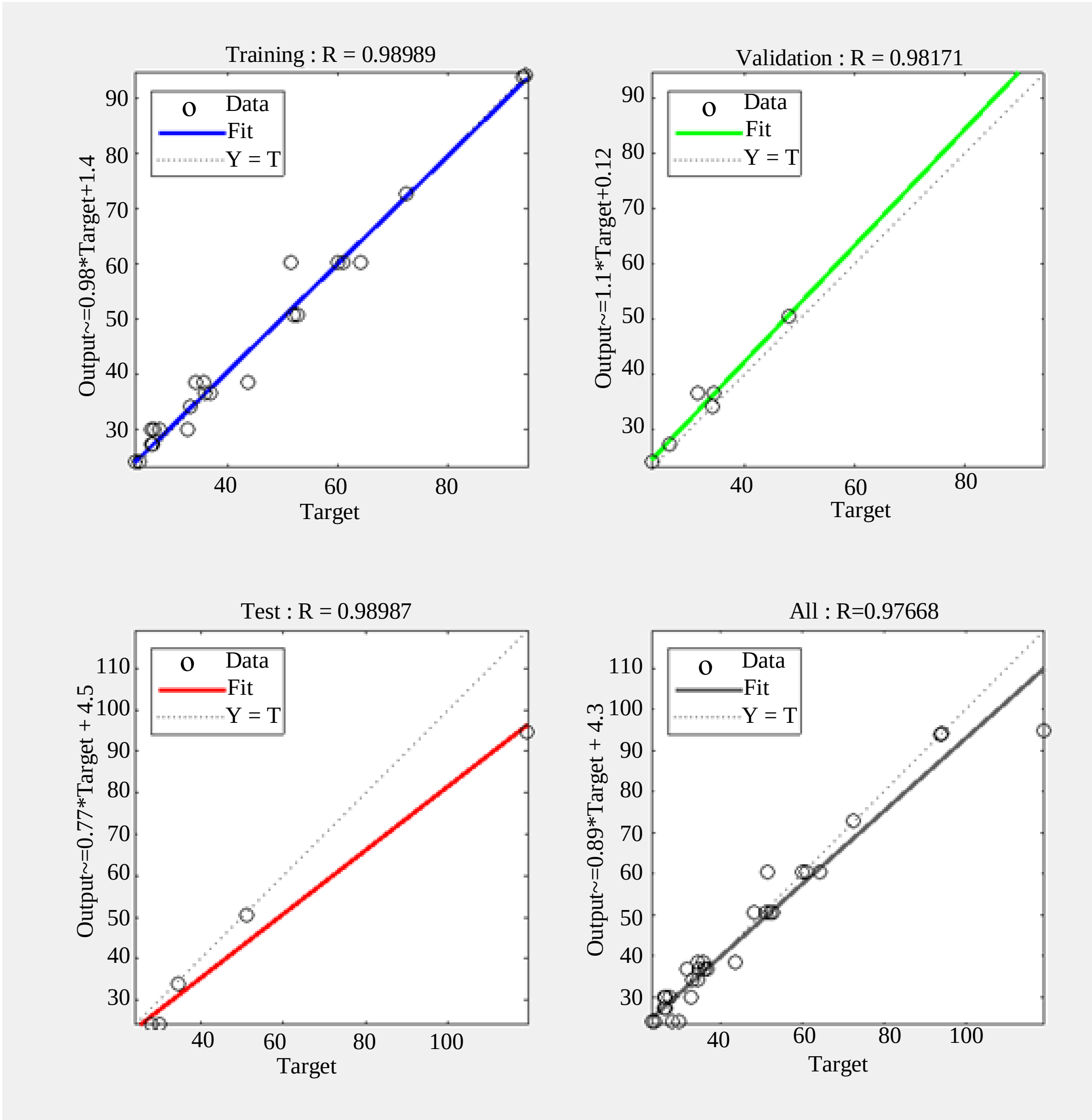
Where p_1 – 28 days average compressive strength in N/mm^2 as per model 1, p_2 – 28 days average compressive strength in N/mm^2 as per model 2, x_1 – Grade of concrete, x_2 – Bacterial concentration indicating '1' as present and '0' as not present. The coefficients derived from the Multiple Regression Analysis equations are crucial in elucidating the relationships between the Independent Variables (IV) and the Dependent Variable (DV). These coefficients, representing the weightage of each independent variable, signify the magnitude of their influence on the dependent variable.

The IV with the highest coefficient holds a predominant impact on the DV. Positive coefficients indicate a direct proportionality, while negative coefficients imply an inverse relationship. The constant term represents the y-intercept. Examining Equation 2, derived from Model 1, it can be inferred that the compressive strength, the dependent variable, is influenced 1.3685 times by the grade of concrete and 7.7560 times by the presence of bacteria. Notably, the presence of bacteria exerts the most substantial influence on compressive strength is a trend consistent with Equation 3.

The p-value serves as a critical indicator at a 95% confidence level. A p-value below 0.05 for an independent variable affirms its significant influence on the dependent variable. In Models 1 and 2, the independent variables, namely the grade of concrete and the presence of bacteria, exhibit p-values below 0.05, confirming their affirmative impact on compressive strength.

The correlation coefficient (R) ranges from -1 (indicating a perfect negative relationship) to 1 (indicating a perfect positive relationship). An R-value approaching 1, notably more significant than 0.8, denotes a robust positive relationship between the estimated and accurate models. Models 1 and 2 manifest R-values (0.9772 and 0.9819, respectively) close to 1, as indicated in Tables 1 and 2, signifying a robust positive relationship.

The determination coefficient (R^2) spans from 0 to 1, with a higher R^2 showing less error variance. R^2 values exceeding 0.5 are generally considered acceptable in scientific research. The models under consideration demonstrate appreciable R^2 values of 0.9549 for Model 1 and 0.9640 for Model, affirming their strong reliability.



*Statics summary: Min- 23.1200, Max- 94.2100, Mean- 43.3365, Median- 34.9950, Mode- 32.7400, Std- 20.4002, Range- 71.0900

Fig. 6 Comprehensive evaluation of model performance: training, validation, test, and overall

The Significance F value for Models 1 and 2 is less than 0.05. At a 95% confidence level, a Significance F value below 0.05 implies that the model is well-suited to fit the data. This statistical significance further supports the validity of the regression models. Upon applying additional known data to validate both models, model 1, subjected to analysis through Multiple Regression Analysis (MRA) utilizing raw data, demonstrated a percentage variation of 10.7% between the predicted and experimental outcomes.

In contrast, model 2, which underwent MRA with data trained using an Artificial Neural Network (ANN), exhibited a marginally higher percentage variation of 14.1% between the predicted and experimental outcomes. This observation underscores the significance of employing MRA and ANN tools in predicting concrete properties, highlighting these methodologies' complementary roles in enhancing predictive accuracy and understanding complex relationships within the data.

5. Conclusion

Applying Multiple Regression Analysis and Artificial Neural Network techniques in predicting concrete behaviour exemplifies the efficiency and reliability of statistical prediction tools. This approach offers a swift and dependable means for assessing concrete behavior, contributing valuable insights for subsequent research endeavors. Models derived from the raw and trained datasets exhibit R-values approaching '1,' indicating a robust affirmation of the derived output. The findings underscore the substantial influence of concrete grade on compressive strength. Additionally, the presence of bacteria is shown to positively impact the compressive strength of concrete, validating anticipated outcomes and contributing positively to research on bacterial concrete. Multiple Regression Analysis emerges as an effective tool for predicting concrete behaviours; however, it becomes imperative to cultivate a more extensive and diverse database for developing a regression model with broad applicability.

Multiple Regression Analysis proves advantageous due to its simplicity in calculation procedures, determination of regression constants, and estimating the significance of various independent variables, particularly in linear relationships. Moreover, the performance of Artificial Neural Network (ANN) trained models is noteworthy.

With its capacity to handle nonlinear functional relationships where classical methods may fall short, ANN demonstrates its suitability.

The study's potential for extension lies in the augmentation of the database with varied parameters, contributing to a more comprehensive understanding of bacterial concrete behavior. This avenue of research holds promise for advancing the knowledge and applicability of predictive models in the domain of definite behaviour prediction.

Author Contribution Statement

CM conceived and designed the study, collected and analyzed data, and wrote the manuscript. SV contributed to data analysis interpretation and critically revised the manuscript. All authors read and approved the final version of the manuscript.

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