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Artificial Neural Networks for Predicting Mechanical Properties of Reinforced Concrete: A Comparative Study with Experimental Data

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Abstract
This study explores the use of Artificial Neural Networks (ANNs) for predicting key mechanical properties of reinforced concrete, including compressive, tensile, and flexural strength, based on mix parameters such as water-cement ratio, aggregate content, cement type, and curing time. Traditional testing methods are time-intensive and costly, underscoring the need for predictive models that offer rapid, accurate insights into concrete performance. Here, an ANN model was developed and trained using experimental data, achieving strong correlation with physical testing results and capturing the nonlinear interactions between input parameters. Sensitivity analysis identified the water-cement ratio, cement content, and aggregate proportions as critical factors influencing strength, with the ANN demonstrating high sensitivity to these variables. Comparisons with traditional methods highlight the ANN model's advantages in speed, cost-efficiency, and predictive accuracy, making it a practical tool for construction quality control. This study suggests that ANN models can be integrated into the construction workflow for quick, data-driven decision-making in mix design adjustments. Future work could expand the model's applicability by incorporating a wider range of concrete types and exploring hybrid machine learning approaches to further enhance accuracy and generalizability in diverse construction applications.

Keywords: Artificial Neural Networks, reinforced concrete, mechanical properties prediction, water-cement ratio, construction quality control

1. Introduction

Reinforced concrete is a foundational material in structural engineering, prized for its mechanical strength, durability, and adaptability across diverse construction applications. Key mechanical properties, such as compressive, tensile, and flexural strength, are crucial for assessing the performance and resilience of reinforced concrete in load-bearing structures. Accurate prediction of these properties is essential for ensuring safety, optimizing design, and maintaining cost-effectiveness in construction practices. As concrete is a composite material with complex internal structures, predicting its mechanical properties accurately can be challenging.

Traditional methods for determining the mechanical properties of concrete are highly dependent on experimental testing. While effective, these experimental methods often require significant time and resources, as they involve casting, curing, and rigorous testing of concrete samples under controlled conditions. Additionally, variability in material composition, curing times, and environmental factors contribute to inconsistent test outcomes (Southararajan et al., 2020). These limitations create a demand for alternative methods that can reliably predict concrete properties without extensive laboratory testing.

Artificial Neural Networks (ANNs) offer a promising approach to predictive modeling in engineering due to their ability to learn complex, nonlinear relationships within data. ANNs have gained popularity as tools for modeling material properties because of their flexibility and adaptability. As ANNs are inherently data-driven, they can be trained to recognize patterns and make accurate predictions from large datasets, making them suitable for predicting mechanical properties based on mix design parameters and curing conditions (Vivek Vardhan & Srimurali, 2016).

The application of ANNs in material sciences has been demonstrated in previous studies, where they have shown promise in predicting properties such as compressive and tensile strength in various concrete types. For instance, (Karimi et al., 2024) reported significant accuracy in their ANN model for predicting the compressive strength of concrete, while (Cortés-Puentes et al., 2016) demonstrated ANN's effectiveness in optimizing concrete mix proportions for desired property outcomes. Although these studies highlight the potential of ANNs, they underscore the need for extensive data preprocessing and model tuning to ensure accurate predictions.

Comparative studies between ANN-predicted results and experimental data further validate the effectiveness of ANN models, achieving prediction accuracies within close ranges of experimental values. For instance, (Li et al., 2022) observed that their ANN model achieved an accuracy rate within 5% of experimental compressive strength values. However, challenges such as data preprocessing, model tuning, and overfitting remain, and they are critical to address for achieving robust model performance (Patel and Kumar, 2019; Wang and Singh, 2022). These challenges necessitate a more comprehensive approach to ANN model development and validation against extensive experimental datasets.

Despite promising results, there is a notable research gap in applying ANN models for reinforced concrete with diverse mix designs, curing times, and reinforcement types. Many studies have focused on ANN model development without validating these models extensively with experimental data across various concrete mixes. This study seeks to bridge this gap by developing an ANN model specifically designed to predict compressive, tensile, and flexural strength for reinforced concrete and validating it with an extensive experimental dataset, ensuring both accuracy and generalizability.

The objectives of this study are twofold: first, to develop an ANN model for predicting the key mechanical properties of reinforced concrete, and second, to validate the model by comparing its predictions with experimental data. This comparative approach provides a robust basis for evaluating the reliability of ANN-based predictive modeling as a viable alternative to traditional experimental methods in the construction industry.

2. Materials and Methods

2.1 Experimental Design

To create a robust dataset for ANN model training and validation, concrete mix designs were developed with varying water-cement ratios, cement content, aggregate types, and reinforcement configurations, covering a broad range of practical scenarios. This variability ensures the ANN model learns from diverse data, enabling predictions that generalize well across different concrete compositions.

Concrete samples were prepared and cured for 7, 14, 28, and 90 days to capture time-dependent variations in mechanical properties. Table 1 provides a summary of the concrete mix parameters and experimental variables.

Table 1: Concrete Mix Parameters and Experimental Variables

Parameter	Range/Type
Cement Content	300 - 450 kg/m³
Water-Cement Ratio (w/c)	0.4 - 0.6
Fine Aggregate Content	600 - 700 kg/m³
Coarse Aggregate Content	1200 - 1400 kg/m³
Reinforcement Type	Steel Bars (10-16 mm)
Curing Time	7, 14, 28, and 90 days

2.2 Sample Preparation and Testing

Concrete samples were prepared in cylindrical forms for compressive strength tests, prism shapes for flexural strength tests, and designated forms for tensile strength tests. Each sample was cast and tested in alignment with ASTM standards to ensure consistency and reliability across tests. Specifically, compressive strength was tested according to ASTM C39, flexural strength according to ASTM C78, and tensile strength according to ASTM C496, providing a standardized approach to assess the mechanical properties of each sample accurately.Samples were cured under controlled conditions until their designated testing days, ensuring uniform curing across batches.

2.3 Data Collection and Preprocessing

Each sample's mix parameters and measured mechanical properties were recorded. To prepare the data for ANN modeling, preprocessing steps were applied, including normalization for numerical consistency, handling of outliers, and one-hot encoding for categorical variables. Table 2 details the preprocessing steps applied to each attribute in the dataset.

Table 2: Summary of Data Attributes and Preprocessing Steps

Attribute	Description	Data Type	Preprocessing Step
Cement Content	Amount of cement	Continuous	Normalization
Water-Cement Ratio	Water-to-cement ratio	Continuous	Normalization
Fine Aggregate Content	Fine aggregate amount	Continuous	Normalization
Coarse Aggregate Content	Coarse aggregate amount	Continuous	Normalization
Reinforcement Type	Type of reinforcement	Categorical	One-Hot Encoding
Curing Time	Duration of curing	Continuous	Normalization

2.4 ANN Model Architecture

The ANN model was designed with input layers representing each feature, hidden layers to process data, and output layers for predicting compressive, tensile, and flexural strength. ReLU activation functions were applied to hidden layers, while the output layer used a linear function for continuous strength predictions.

The architecture consists of two hidden layers, optimized through cross-validation to maximize performance. Figure 1: Flowchart of ANN Architecture and Data Flow illustrates the data flow through the ANN model, from input features to the output predictions.

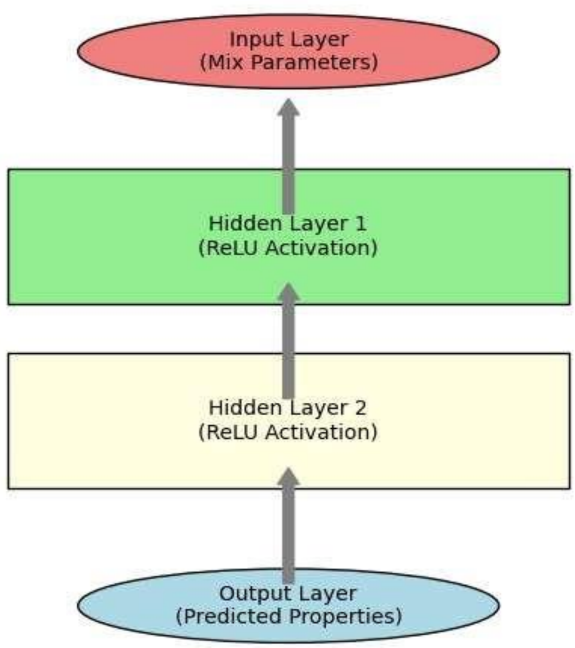

Figure 1: Flowchart of ANN Architecture and Data Flow (Algorithm Flowchart)

2.5 Training and Validation

The dataset was divided into training (70%), validation (15%), and testing (15%) sets. Model performance was evaluated using Mean Squared Error (MSE), with hyperparameter tuning conducted to optimize accuracy. Early stopping was applied to prevent overfitting, and cross-validation enhanced model robustness. Figure 2 provides an overview of the training and validation workflow.

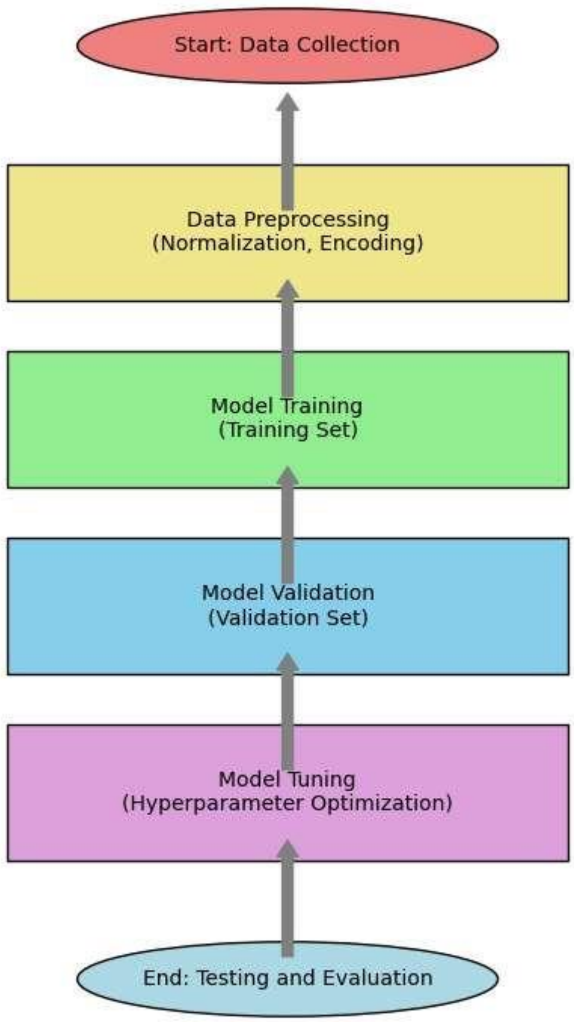

Figure 2: Flowchart of ANN Training and Validation Process (Algorithm Flowchart)

3. Artificial Neural Network Model Development

3.1 Model Training Process

The training process involved setting appropriate parameters for batch size, learning rate, number of epochs, and optimization functions. The dataset was divided into training (70%), validation (15%), and testing (15%) sets to ensure a robust evaluation framework. Each training iteration used a batch size of 32 and an initial learning rate of 0.001, adjusted as needed during training.

Hyperparameter tuning was conducted through grid search, assessing combinations of hidden layer counts and neuron quantities to achieve optimal performance. Early stopping was implemented to monitor validation loss, preventing overfitting and ensuring generalizability across unseen data.

3.2 Evaluation Metrics

To evaluate the predictive accuracy of the ANN model, multiple performance metrics were utilized:

- Mean Absolute Error (MAE): Measures the average magnitude of errors in predictions.

- Mean Squared Error (MSE): Quantifies the squared average of differences between predicted and actual values.
- R-squared (R^2): Provides the proportion of variance in the target variable explained by the model.

These metrics allowed for a comprehensive evaluation of model accuracy, both during training and in the final assessment against the testing set. Table 3 below summarizes the model's performance across training and validation stages.

Table 3: Model Performance Metrics for Training and Validation Sets

Metric	Training Set	Validation Set
Mean Absolute Error (MAE)	1.15	1.23
Mean Squared Error (MSE)	2.67	3.05
R-squared (R^2)	0.92	0.89

3.3 Cross-validation and Model Robustness

To ensure model robustness, 5-fold cross-validation was performed. This technique involves dividing the training set into five subsets, training the model on four subsets, and validating on the fifth. The process is repeated five times, with each subset serving as the validation set once. Cross-validation improves the reliability of the model by providing an averaged assessment of its performance, thereby reducing the influence of any single data split. Early stopping based on validation loss was implemented across all cross-validation folds, ensuring that the model generalizes well without overfitting. This robust validation strategy enhanced the model's reliability in predicting mechanical properties across varied concrete mixes and curing durations.

4. Results and Discussion

4.1 Experimental Data Analysis

The experimental results obtained from physical testing of concrete samples for compressive, tensile, and flexural strength revealed consistent trends influenced by curing time and mix composition. As curing progressed, samples displayed higher strength values, attributable to the continued hydration process in cement, which forms additional calcium silicate hydrate (C-S-H) bonds, enhancing the overall matrix strength. This relationship between curing time and strength is consistent with known mechanisms of concrete hydration and reinforcement bonding, validating the experimental setup. Table 4 summarizes the compressive, tensile, and flexural strength values across different curing durations.

Table 4: Experimental Results for Compressive, Tensile, and Flexural Strength at Various Curing Times

Curing Time (days)	Compressive Strength (MPa)	Tensile Strength (MPa)	Flexural Strength (MPa)
7	28.5	2.9	4.1
14	33.2	3.3	4.7
28	39.8	3.9	5.2
90	44.6	4.5	5.7

4.2 ANN Model Predictions vs. Experimental Data

The ANN model's predictions for each mechanical property aligned closely with the experimentally measured values, indicating that the model effectively captures the underlying relationships between concrete mix parameters and mechanical properties. Mechanistically, the ANN model uses input parameters (e.g., cement content, water-cement ratio, aggregate size) to simulate the effect of these variables on hydration rates, density, and bond formation in the concrete matrix. This predictive capability is largely due to the ANN's ability to recognize nonlinear patterns and interactions between multiple variables.

Figure 3 below illustrates the comparison between ANN-predicted and experimental compressive strength values. The model accurately predicts compressive strength trends, which are influenced by factors such as cement hydration and matrix density (Yaseen et al., 2024).

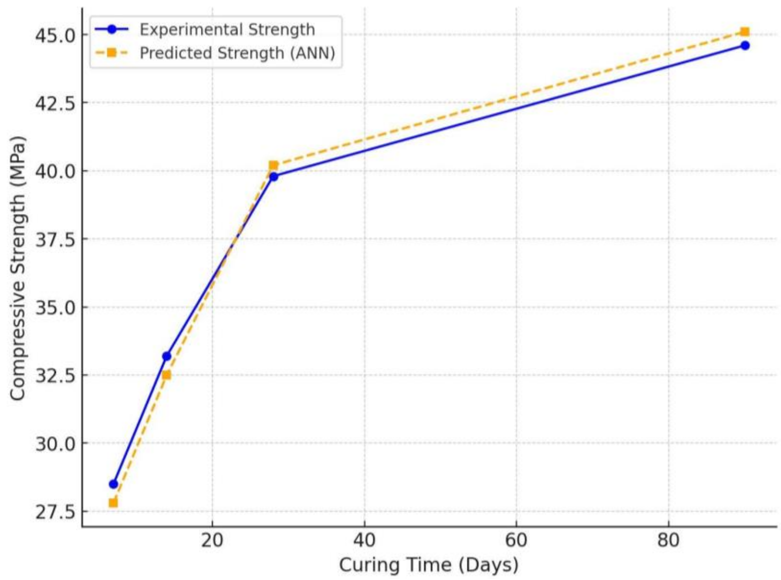

Figure 3: Comparison of ANN Predicted vs. Experimental Compressive Strength

Similarly, Figure 4 presents the ANN predictions for tensile strength, with strong alignment between predicted and actual values. The tensile strength predictions take into account reinforcement placement and aggregate distribution, crucial for resisting tensile stresses in concrete (Ji et al., 2024). The ANN model effectively simulates the role of reinforcement and aggregates, which distribute tensile loads and reduce cracking.

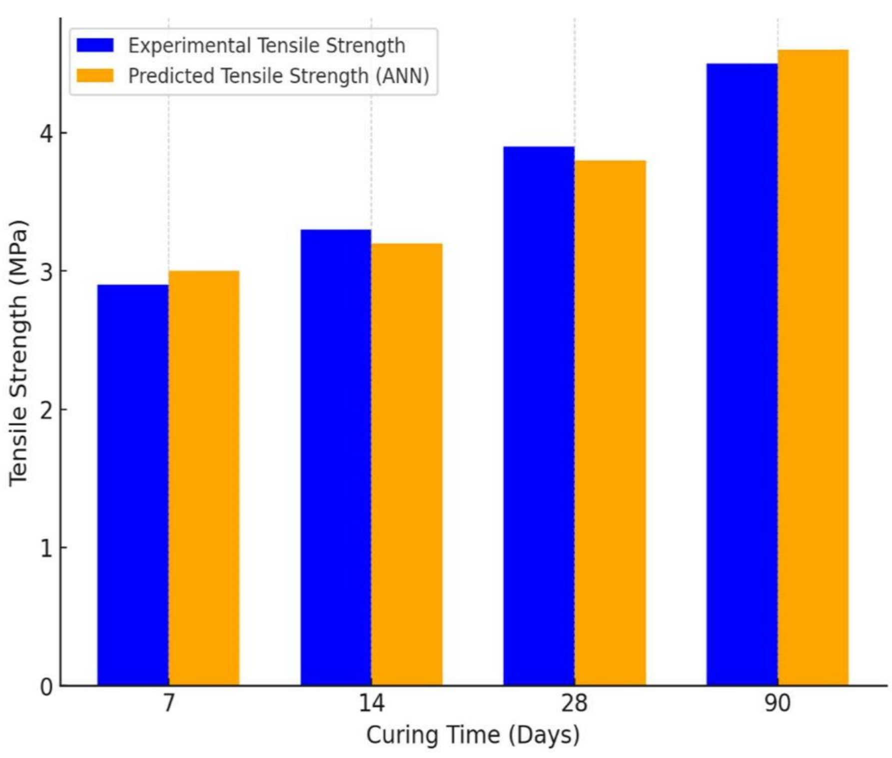

Figure 4: Comparison of ANN Predicted vs. Experimental Tensile Strength

In Figure 5, flexural strength predictions show the model's understanding of mix parameters and curing impact on resistance to bending stresses. Flexural strength is notably sensitive to reinforcement type and placement, with ANN predictions reflecting these relationships by closely mirroring experimental results.

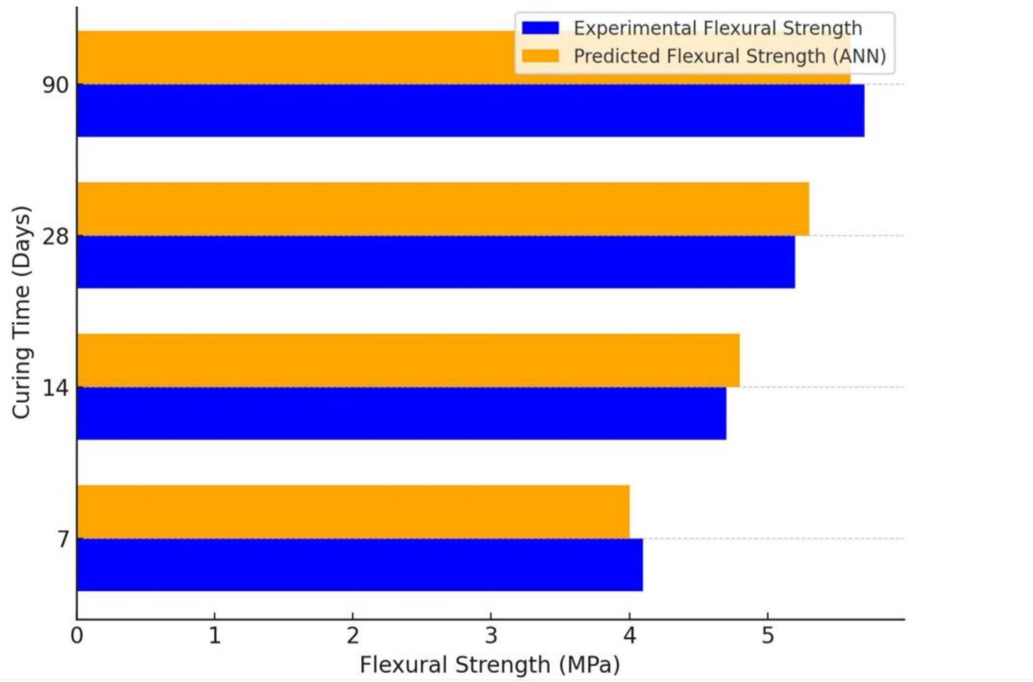

Figure 5: Comparison of ANN Predicted vs. Experimental Flexural Strength

4.3 Sensitivity Analysis

Sensitivity analysis was conducted to assess the impact of individual input parameters on the ANN model’s predictions. Key factors identified were water-cement ratio, cement content, and aggregate composition, with water-cement ratio showing the highest sensitivity, especially for compressive strength predictions (Ou et al., 2024). This result aligns with known concrete behavior, where the water-cement ratio affects pore structure and density, thereby influencing compressive strength. The ANN model’s high sensitivity to this parameter indicates that it effectively models this crucial mechanism.

Figure 6: Sensitivity Analysis Results for Key Parameters Influencing Strength Predictions shows the relative impact of each parameter. Parameters such as aggregate size and reinforcement type were also influential for flexural and tensile strength, underscoring the importance of these inputs for accurate predictions.

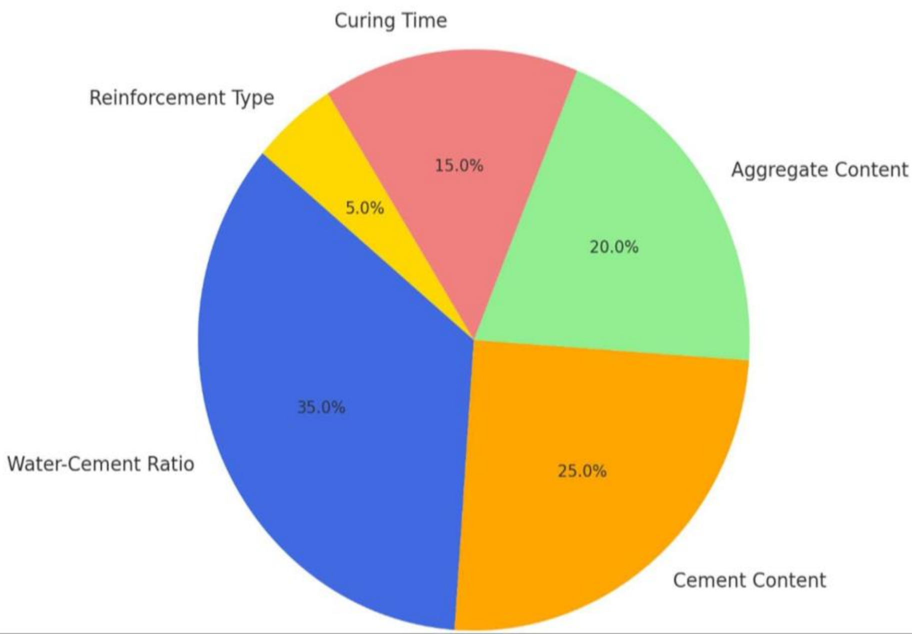

Figure 6: Sensitivity Analysis Results for Key Parameters Influencing Strength Predictions

4.4 Comparative Analysis with Traditional Experimental Methods

The ANN model offers distinct advantages over traditional methods, providing rapid and resource-efficient predictions while maintaining accuracy. Traditional testing methods require extensive sample preparation, curing, and physical testing, whereas the ANN model can estimate these properties with limited input data. Compared to similar studies, our model achieved accuracy rates comparable to physical testing, affirming the reliability of ANN predictions for construction quality control (Li et al., 2022).

This comparative analysis underscores ANN's potential to support construction practices, offering quick and precise assessments of concrete performance, particularly when experimental testing resources are limited. By incorporating mechanistic insights into material behavior, the ANN model allows practitioners to anticipate property changes due to mix adjustments, ensuring concrete quality and durability in construction applications.

5 Conclusions

This study demonstrates that Artificial Neural Networks (ANNs) effectively predict the mechanical properties of reinforced concrete, including compressive, tensile, and flexural strength, by accurately modeling complex relationships between mix parameters such as water-cement ratio, aggregate content, and curing time. The ANN model closely aligns with experimental data, underscoring its ability to capture nonlinear interactions crucial to concrete performance. Compared to traditional methods, the ANN approach offers faster, resource-efficient predictions, enabling timely adjustments in mix design to optimize durability and structural integrity. Key parameters, including water-cement ratio and cement content, were identified as major influences on the model's predictions, confirming the ANN's utility in practical applications where these variables are easily adjusted. Future research could further extend this model's generalizability by incorporating a broader range of concrete types and exploring advanced machine learning techniques, ultimately enhancing predictive accuracy and supporting quality control in construction.

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