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Prediction of slump value of concrete containing coconut shell aggregate using artificial neural networking

Ranjith Babu Baskaran*[1)]

[1)] *Department of Civil Engineering, PSNA College of Engineering and Technology, Dindigul, Tamil Nadu 624622, India*

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ABSTRACT

The use of Coconut Shell (CS) as a sustainable aggregate in concrete provides an effective alternative to conventional materials; however, it significantly influences workability characteristics. This study presents the development of an Artificial Neural Network (ANN) model for predicting the slump of Coconut Shell Aggregate (CSA) concrete. A dataset comprising 65 samples was compiled from published literature, considering cement, fine aggregate, coarse aggregate, CSA, water–cement ratio, and percentage replacement of CSA as input variables, with slump as the output parameter. The dataset was standardized and divided into training (80%) and testing (20%) subsets. A feedforward ANN model with a single hidden neuron and hyperbolic tangent activation function was implemented in Python using TensorFlow. The model was trained using the Adam optimizer with Mean Squared Error loss, and Early Stopping was employed to improve generalization and prevent overfitting. The model achieved a coefficient of determination of R2 = 0.7150 for training and R2 = 0.6046 for testing. The corresponding error values were Root Mean Square Error (RMSE) of 21.920 and 27.367, and Mean Squared Error (MAE) of 15.551 and 18.298 for training and testing, respectively. Validation using an independent mix resulted in a prediction error of 3.97%, indicating good predictive capability. Model interpretability was assessed using the Garson Algorithm, which identified fine aggregate (0.5879) as the most influential parameter, followed by cement (0.1645) and water-related parameter (0.1558), while other variables showed comparatively lower influence. Connection Weight analysis further confirmed these trends. The results demonstrate that the ANN model provides a reliable and interpretable tool for predicting workability in sustainable concrete systems.

1 Introduction

The slump test is one of the most common tests used to assess the workability of fresh concrete mixtures. It is conducted in both laboratories and at construction sites where concrete is placed. The test provides an indication of the consistency and fluidity of the concrete mix. In this test, fresh concrete is placed in a standard slump cone in three layers, and each layer is compacted with a tamping rod. After filling the cone, it is lifted vertically, and the concrete subsides or “slumps.” The difference between the original height of the cone and the height of the slumped concrete is measured in millimeters and is called the slump value of the concrete mix [1]. The slump value indicates the workability of the concrete mix. A higher slump value shows greater workability and ease of placement with less compaction effort. Therefore, a minimum slump value is recommended for placing concrete in structural elements such as beams, slabs, columns, and footings as per IS 456:2000 [2]. The Coconut Shell Aggregates (CSA) exhibit a highly porous structure and significantly higher water absorption capacity than conventional crushed stone aggregates. Due to this characteristic, a considerable amount of mixing water is absorbed by the Coconut Shell (CS) particles, reducing the free water available for cement hydration and lubrication within the concrete mix. Consequently, the workability of fresh concrete may decrease, leading to difficulties in mixing, transportation, placement, and compaction. Inadequate workability can also result in poor consolidation and the formation of voids within the hardened concrete. Therefore, workability evaluation and appropriate mix design adjustments, such as controlling the water-to-cement ratio or pre-soaking the CSA, are essential to ensure satisfactory fresh and hardened concrete performance when CSA are used as partial or full replacements for conventional coarse aggregates [3&4].

The construction industry is facing an increasing demand for natural aggregates, which occupy 70–80% of the total

* Corresponding author:
E-mail address: ranjithbabucivil@psnacet.edu.in

volume of a concrete mixture. Continuous extraction of natural aggregates from river deposits and rock quarries leads to resource depletion. In recent years, the use of alternative materials in concrete production has become a sustainable approach to concrete manufacturing [5&6]. In most reported studies, CS has been utilized as a replacement for conventional coarse aggregate, while natural fine aggregate is retained in the concrete mixture.

The CSA in concrete has been reported to achieve compressive strengths in the range of 19–20 MPa after 28 days of curing, making it suitable for several structural and non-structural applications. However, the mechanical performance of such concrete is strongly influenced by the replacement ratio and mix design parameters. The CS are primarily used as a partial replacement for coarse aggregates due to their lower density, higher porosity, and greater water absorption characteristics compared with natural aggregates. At moderate replacement levels, acceptable strength can be achieved without significant increases in cement content, whereas excessive replacement may result in strength reduction because of weaker aggregate–paste interaction and increased void content. Therefore, the selection of an appropriate replacement ratio is essential to balance strength, workability, and sustainability requirements. Furthermore, workability and compressive strength are closely related, as inadequate workability may lead to poor compaction and increased porosity, ultimately affecting the strength and durability of concrete. Consequently, accurate prediction of slump is important for optimizing fresh concrete performance and ensuring the desired mechanical properties of CSA concrete [5]. The CSA in concrete creates a better bonding with cement paste due to its rough surfaces [7].

The use of CS in concrete improves thermal insulation and reduces the density of concrete, leading to more sustainable and energy-efficient construction. Therefore, the utilization of CSA in concrete represents a sustainable approach by converting agricultural waste into a useful construction material while also conserving natural resources [8&9].

In recent years, machine learning techniques have gained significant attention in civil engineering for predicting the properties of concrete, including compressive strength, slump, and durability. Traditional experimental methods used to determine these properties are often time-consuming, labor-intensive, and costly. Machine learning models provide an efficient alternative by establishing relationships between input parameters and concrete properties based on available datasets. These models can analyze complex nonlinear interactions among materials in concrete mixtures and generating accurate predictions with reduced experimental effort, thereby improving the efficiency of concrete mix design and material optimization [10 &11]. Among various machine learning techniques, Artificial Neural Networks (ANN) are one of the most widely used methods. They are structured like the human brain and consist of interconnected neurons organized into input, hidden, and output layers. The network learns patterns within the given dataset through a training process and can identify the relationship between the input and output variables. [12].

The ANN models have been widely applied in concrete technology due to their ability to capture complex nonlinear relationships among mixture constituents and fresh concrete properties. Several studies have demonstrated that ANN-based models can accurately predict workability characteristics, particularly the slump value of concrete mixtures, using input parameters such as cement content, water-to-cement ratio, aggregate proportions, admixture dosage, and supplementary cementitious materials [13–16]. The capability of ANN models to learn from experimental datasets makes them a reliable tool for predicting concrete workability and reducing the need for extensive laboratory testing.

Therefore, the ANN models can effectively predict workability characteristics, particularly the slump value of concrete mixtures. Therefore, the application of machine learning techniques offers an efficient and reliable approach for enhancing the optimization and sustainability of concrete mix design having the CSA.

The replacement of conventional coarse aggregate with CSA was considered, while the natural fine aggregate remained unchanged. The primary objective of incorporating CSA is to reduce the consumption of natural coarse aggregate and promote the utilization of agricultural waste materials, thereby enhancing the sustainability of concrete production. Furthermore, the selected replacement levels are intended to ensure that the concrete possesses adequate workability for practical applications in structural members such as beams, slabs, columns, and foundations [17-26].

The present study is to develop and validate an artificial neural network model for predicting the slump of CSA concrete using datasets compiled from published experimental investigations (Literature Review) and validated through independent experimental testing.

2 Materials and data compilation

2.1 Data sources

The experimental data were collected from previously published studies, and these data are summarized and presented in Table 1. The dataset variables cement, fine aggregate, coarse aggregate, coconut shell aggregate (CSA), water–cement (w/c) ratio, slump, and percentage of CSA replacement were used.

Datasets 1–20 were obtained from Reference 17; datasets 21–23 were sourced from Reference 18; datasets 24–29 were taken from Reference 19; and dataset 30 was collected from Reference 20. Furthermore, datasets 31–37 were obtained from Reference 21; datasets 38–41 were sourced from Reference 22; datasets 42–46 were taken from Reference 23; datasets 47–51 were obtained from Reference 24, data sets 52-57 from Reference 25, datasets 58–61 were obtained from Reference 26 and datasets 62–65 were obtained from Reference 27.

The dataset was divided into two phases: training (80% of the total dataset) and testing (20% of the total dataset).

The statistical summary of the dataset indicates a wide variation in mix proportions and workability characteristics. Cement content ranges from 300 to 510 kg/m³, while fine aggregate varies between 531 and 981 kg/m³. The coarse aggregate and CSA contents exhibit significant variability due to different replacement levels, ranging from 0 to 1263 kg/m³ and 0 to 1176 kg/m³, respectively. The water–cement ratio ranges from 0.38 to 0.72, reflecting variations in mix consistency.

The slump values vary from 0 to 150 mm, indicating a broad spectrum of workability conditions. The percentage replacement of CSA ranges from 0% to 100%, ensuring that the dataset captures both conventional and fully replaced mixes. This variability enhances the robustness of the ANN model by enabling it to learn diverse material behavior patterns.

Table1. Experimental data collected from the literatures

Sample No.	Cement (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	Coconut Shell Aggregate (CSA) (kg/m^3)	water/ cement ratio	Percentage (%) of Replacement of CSA	Slump (mm)	28^{th} Day Cubical Compressive Strength (MPa)
1.	300	981	0	402	0.72	100	10	4.95
2.	400	820	0	336	0.55	100	25	9.81
3.	425	820	0	336	0.50	100	15	13.24
4.	450	824	0	338	0.45	100	25	13.49
5.	480	658	0	360	0.51	100	110	10.30
6.	480	802	0	331	0.42	100	65	15.20
7.	480	730	0	360	0.42	100	50	16.19
8.	480	768	0	384	0.44	100	50	16.68
9.	480	768	0	384	0.42	100	5	17.66
10.	480	768	0	336	0.42	100	30	18.15
11.	510	750	0	332	0.42	100	5	26.70
12.	510	928	0	281	0.38	100	0	23.40
13.	510	887	0	281	0.42	100	5	16.72
14.	510	801	0	281	0.48	100	140	13.38
15.	510	867	0	306	0.38	100	0	19.50
16.	510	816	0	306	0.42	100	0	16.16
17.	510	734	0	306	0.48	100	40	13.38
18.	510	806	0	332	0.38	100	0	27.20
19.	510	750	0	332	0.42	100	5	26.70
20.	510	673	0	332	0.48	100	150	14.50
21.	450	531	1238	0	0.40	0	60.5	46.7
22.	450	531	1176	62	0.40	5	50	29.6
23.	450	531	1114	124	0.40	10	25	7.4
24.	403	672	1260	0	0.48	0	72	27.58
25.	403	672	1134	126	0.48	10	66	23.46
26.	403	672	1008	252	0.48	20	60	20.95
27.	403	672	882	378	0.48	30	52	18.94
28.	403	672	756	504	0.48	40	46	17.06
29.	403	672	630	630	0.48	50	37	15.48
30.	340	690	952	21	0.57	5	83	38
31.	395	607.43	1213.82	0	0.50	0	85	25.65
32.	395	607.43	1153.13	60.69	0.50	5	79	25.20
33.	395	607.43	1092.43	121.382	0.50	10	73	24.25
34.	395	607.43	1031.74	182.07	0.50	15	67	22.92
35.	395	607.43	971.05	242.76	0.50	20	61	20.19
36.	395	607.43	910.36	303.45	0.50	25	57	19.52
37.	395	607.43	849.68	364.15	0.50	30	55	17.28
38.	300	750	1170	0	0.60	0	25	22.33
39.	300	750	1053	117	0.60	10	23	13.62
40.	300	750	994.5	175.5	0.60	15	22	9.38
41.	300	750	936	234	0.60	20	20	7.15
42.	403	672	1260	0	0.50	0	85	20.27
43.	403	672	1228.5	31.5	0.50	2.5	61	19.71
44.	403	672	1197	63	0.50	5.0	67	19.53
45.	403	672	1165.5	94.5	0.50	7.5	73	19.08
46.	403	672	1134	126	0.50	10	79	18.91
47.	383	536.2	957.50	0	0.5	0	75	34.66
48.	383	536.2	838.77	118.73	0.5	10	61	25.61
49.	383	536.2	612.80	256.61	0.5	21	55	19.74
50.	383	536.2	287.25	356.19	0.5	29	52	17.78
51.	383	536.2	229.80	383	0.5	31	50	16.52
52.	384.35	580.4	0	1176.1	0.5	0	26	30.64
53.	384.35	580.4	940.88	235.22	0.5	20	26	22.33
54.	384.35	580.4	705.66	470.44	0.5	40	27	18
55.	384.35	580.4	407.44	705.66	0.5	60	28	13.56
56.	384.35	580.4	235.22	940.88	0.5	80	29	11.42
57.	384.35	580.4	0	1176.1	0.5	100	31	8.33
58.	405	667	1263	0	0.44	0	40	34.10

59.	405	667	1136.7	126.3	0.44	10	30	28.53
60.	405	667	1010.4	252.6	0.44	20	35	22.32
61.	405	667	884.1	378.9	0.44	30	42	20.12
62.	419	976	958	0	0.55	0	115	25.8
63.	419	976	919.7	38.3	0.55	4	116	20.91
64.	419	976	881.4	76.6	0.55	8	113	14.65
65.	419	976	843.0	114.9	0.55	12	110	9.40
Min	**300**	**531**	**0**	**0**	**0.38**	**0**	**0**	**4.95**
Max	**510**	**981**	**1263**	**1176**	**0.72**	**100**	**150**	**46.70**

2.2 Input variables

Six input parameters were considered for the development of the predictive model, selected based on their known influence on concrete workability:

Cement content (kg/m³): Represents the binding material governing paste volume and consistency.

Fine aggregate (kg/m³): Influences packing density and water demand, significantly affecting slump.

Coarse aggregate (kg/m³): Contributes to the overall skeleton of the mix and affects flow characteristics.

Coconut shell aggregate (CSA) (kg/m³): Acts as a lightweight alternative aggregate, altering absorption and surface texture properties.

Water–cement ratio: A critical parameter controlling the fluidity and consistency of concrete.

Percentage replacement of CSA (%): Indicates the proportion of coconut shell used in place of conventional coarse aggregate, directly impacting workability behavior.

These variables were selected to capture the combined effects of material composition and replacement strategy on the slump of concrete.

2.3 Output parameter

The output parameter considered in this study is the slump value (mm), which serves as a standard measure of concrete workability. Slump values were obtained from the compiled literature dataset, ensuring consistency in testing procedures. The slump parameter was chosen due to its practical significance in assessing the ease of mixing, placing, and compaction of concrete in engineering applications.

3 Artificial neural network model development

3.1 ANN architecture

A feedforward Artificial Neural Network (ANN) was developed to model the relationship between concrete mix constituents and slump. The network was implemented using the TensorFlow–Keras framework [28] in a sequential configuration. The input layer consists of six neurons corresponding to the selected variables: cement, fine aggregate, coarse aggregate, coconut shell aggregate (CSA), water–cement ratio, and percentage replacement of CSA.

The hidden layer comprises a single neuron with a hyperbolic tangent (*tanh*) activation function. The *tanh* function introduces nonlinearity and enables the network to capture complex interactions among the input variables. Although the architecture is relatively simple, it is adequate for capturing the underlying trends in the available dataset while minimizing the risk of overfitting.

The output layer contains a single neuron with a linear activation function, which produces the predicted slump value as a continuous output. The overall architecture can therefore be described as a 6–1–1 network structure. The ANN for CSA concrete slump prediction as shown in Figure 1.

3.2 Training strategy

Prior to training, the input and output data were standardized using the Standard Scaler method [29] to ensure zero mean and unit variance, thereby improving numerical stability and convergence of the model.

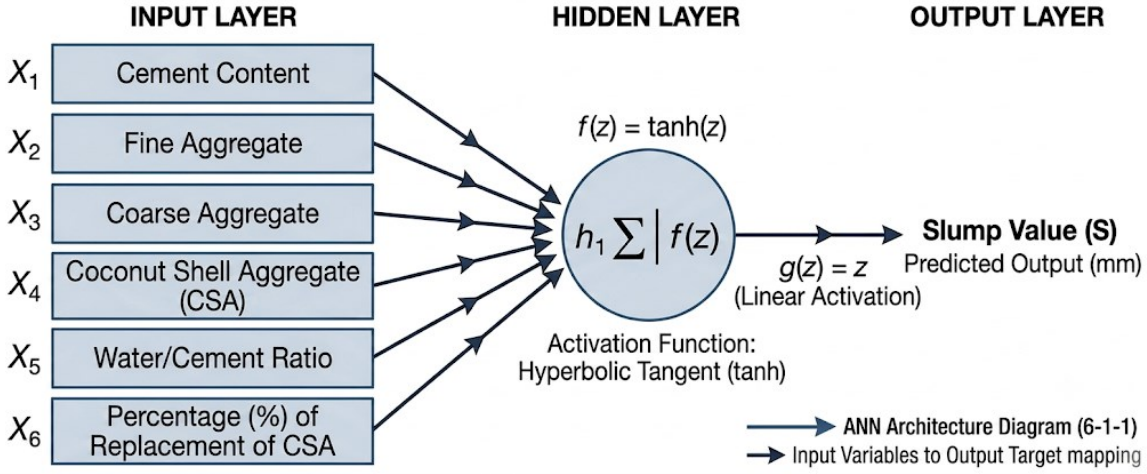


Figure 1. Schematic diagram of the 6–1–1 ANN for slump value forecasting

The ANN was trained using the Adam optimization algorithm [30] with a learning rate of 0.001. Adam combines the advantages of adaptive learning rates and momentum, making it suitable for nonlinear regression problems involving small to moderate datasets. The loss function employed was Mean Squared Error (MSE), which minimizes the squared differences between predicted and actual slump values.

To enhance model generalization and prevent overfitting, Early Stopping was implemented by monitoring the validation loss during training. The training process was terminated when no improvement in validation loss was observed for a predefined number of epochs, and the best-performing model weights were restored. This approach ensures that the model retains optimal predictive performance on unseen data.

4 Model performance evaluation

4.1 Training and testing results

The predictive performance of the developed ANN model was evaluated using standard statistical indicators, namely the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics provide a comprehensive assessment of model accuracy by quantifying both the strength of correlation and the magnitude of prediction errors.

4.2 Validation with experimental data

To further assess the practical applicability of the developed model, validation was performed using an independent concrete mix not included in the training or testing datasets. The predicted slump value obtained from the ANN model was compared with the experimentally measured slump. The experimental mix proportions and the measured slump value is shown in the Table 2.

The percentage error was calculated using the following expression:

$$\%\, Error = \left(\frac{\left|S_{actual} - S_{predicted}\right|}{S_{actual}}\right) \times 100 \quad (1)$$

where S_{actual} and $S_{predicted}$ represent the measured and predicted slump values, respectively. The validation results indicated a prediction error of 3.97%, demonstrating good agreement between the experimental and predicted values. This low error confirms the reliability of the ANN model in estimating slump for new mix proportions.

5 Sensitivity and interpretability analysis

5.1 Garson algorithm

To address the interpretability of the developed ANN model, the relative importance of input variables was evaluated using the Garson Algorithm. This method quantifies the contribution of each input parameter by partitioning the connection weights between the input, hidden, and output layers [31]. The algorithm computes the relative importance based on the absolute values of the product of input–hidden and hidden–output weights, followed by normalization.

The relative importance I_i of the i^{th} input variable is expressed as:

$$I_i = \frac{\sum_{j=1}^{n_h}\left|w_{ij} * w_j\right|}{\sum_{i=1}^{n}\sum_{j=1}^{n_h}\left|w_{ij} * w_j\right|} \quad (2)$$

where w_{ij} represents the weight between the i^{th} input neuron and the j^{th} hidden neuron, w_j is the weight between the j^{th} hidden neuron and the output neuron, n_h is the number of input variables, and n_h is the number of hidden neurons.

5.2 Connection weight analysis

To further examine the influence of input variables, Connection Weight Analysis was performed. This method evaluates both the magnitude and direction (positive or negative) of the relationship between inputs and the output by computing the combined effect of weights across the network [31].

The connection weight for each input variable is determined using:

$$CWi = \sum_{j=1}^{n_h}\left(w_{ij} * w_j\right) \quad (3)$$

The resulting values were normalized to facilitate comparison across inputs. Positive values indicate a direct relationship with slump, whereas negative values represent an inverse relationship.

6 Results

6.1 Model performance metrics

The predictive performance of the developed model was assessed using the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) for both the training and testing datasets. For the training dataset, which comprised 80% of the total data, the model achieved an R^2 value of 0.7150, indicating that approximately 71.50% of the variation in the target variable was explained by the model. The corresponding RMSE and MAE values were 21.920 mm and 15.551 mm, respectively. For the testing dataset, representing the remaining 20% of the data, the model obtained an R^2 value of 0.6046, demonstrating a satisfactory predictive capability on unseen data. The RMSE and MAE values for the testing dataset were 27.367 mm and 18.298 mm, respectively. Although the testing performance showed a slight reduction compared to the training results, the model maintained reasonable prediction accuracy and generalization ability, indicating its suitability for estimating the response variable.

Table 2. Experimental mix proportion for concrete with CSA and its slump Value

Cement (kg/m^3)	Fine aggregate (kg/m^3)	Coarse aggregate (kg/m^3)	Coconut Shell aggregate (kg/m^3)	water/cement ratio	Slump (mm)
335	528	491	242	0.5	110

6.2 Experimental validation result

To evaluate the practical applicability and predictive capability of the developed model on independent data a validation mix was tested and its experimentally (Shown in Table 2) measured slump value was compared with the model prediction. As presented in the Table 3 the validation mix exhibited an actual slump (S_{actual}) of 110 mm, while the model predicted a slump ($S_{predicted}$) of 114.36 mm. The resulting absolute error between the predicted and actual values was only 4.36 mm, corresponding to a percentage error of 3.97%. This relatively low prediction error demonstrates the robustness and reliability of the developed model in estimating slump values for new concrete mixtures, confirming its suitability for practical applications and validating its generalization performance beyond the training and testing datasets.

6.3 Sensitivity analysis

6.3.1 Garson algorithm

The relative importance of the input variables influencing the slump value was evaluated using the Garson weight partitioning algorithm. The analysis revealed that fine aggregate was the most influential parameter, with a relative importance value of 0.5879, contributing 58.79% to the model output. Cement was identified as the second most significant factor, with a contribution of 16.45% (relative importance value of 0.1645), followed closely by the water–cement ratio, which contributed 15.58% (relative importance value of 0.1558). Coarse aggregate exhibited a comparatively lower influence, accounting for 5.99% of the total contribution with a relative importance value of 0.0599. In contrast, coconut shell aggregate (CSA) and the percentage replacement of CSA showed minimal effects on slump prediction, contributing only 1.65% and 1.54%, respectively, with relative importance values of 0.0165 and 0.0154. These results indicate that fine aggregate, cement, and the water–cement ratio are the dominant factors governing the slump behavior of coconut shell aggregate concrete, while CSA-related parameters have a relatively minor influence within the range of data considered in this study.

6.3.2 Connection weight

The Connection Weight Analysis was conducted to determine the directional influence of the input variables on the slump of CSA concrete. The results indicated that fine aggregate exhibited a strong positive influence on slump, suggesting that an increase in fine aggregate content leads to higher slump values and improved workability. Similarly, the water–cement ratio showed a positive relationship with slump, indicating that higher water–cement ratios enhance the fluidity of the concrete mixture and consequently increase slump. In contrast, cement content demonstrated a negative influence on slump, implying that an increase in cement content tends to reduce workability and decrease slump under the conditions considered in this study. Furthermore, coconut shell aggregate (CSA) content and the percentage replacement of CSA were found to have relatively minor effects on slump compared with the other input variables, indicating a limited influence on workability within the range of mixtures investigated. These findings provide valuable insight into the role of individual mix constituents in governing the slump behavior of coconut shell aggregate concrete.

7 Discussion

The developed ANN model demonstrates a satisfactory ability to predict the slump of CSA concrete, as reflected by the obtained performance metrics. The analysis of input parameters indicates that fine aggregate exerts the most significant influence on slump, as confirmed by the Garson Algorithm (relative importance = 0.5879). This observation is consistent with the fundamental role of fine aggregate in controlling particle packing, surface area, and water demand, all of which directly affect workability. The water–cement ratio also shows a notable contribution, highlighting its importance in governing the fluidity and consistency of the concrete mix. Similarly, cement content influences the paste volume, thereby affecting lubrication between particles. In contrast, coarse aggregate, CSA, and their percentage replacement exhibit comparatively lower direct influence within the studied range. This suggests that while these parameters affect the overall mix behavior, their impact on slump is secondary compared to fine aggregate and water-related properties. The observed trends are generally consistent with findings reported in the literature, where workability is primarily governed by paste characteristics and fine aggregate content. The inclusion of CSA introduces variability due to its higher water absorption and irregular surface texture; however, its direct contribution to slump appears limited when compared to other parameters. Despite these promising results, the model has certain limitations. The ANN architecture employed is relatively simple, consisting of a single hidden neuron, which may restrict its ability to capture highly complex relationships. Additionally, the dataset is limited to 65 samples collected from different sources, which may introduce variability due to differences in experimental conditions. Therefore, the model performance may be improved with a larger and more consistent dataset, as well as a more optimized network structure.

Table 3. Comparison of experimental and predicted slump value

Mix ID	Actual Slump (mm)	Predicted Slump (mm)	Error (mm)	% Error
Validation Mix	110	114.36	4.36	3.97

8 Conclusions

This study presents the development of an Artificial Neural Network (ANN) model for predicting the slump of CSA concrete. Based on the results obtained, the following conclusions can be drawn:

- The ANN model achieved satisfactory predictive performance, with R^2=0.7150 for training and R^2=0.6046 for testing, indicating its capability to capture the relationship between mix constituents and slump.
- Error metrics (RMSE and MAE) demonstrate acceptable accuracy for practical engineering applications.
- Validation using an independent mix resulted in a low prediction error of 3.97%, confirming the reliability of the model.
- Sensitivity analysis revealed that fine aggregate is the most influential parameter, followed by cement and water-related properties, while CSA and its replacement percentage have relatively lower direct impact.
- The integration of Garson Algorithm and Connection Weight analysis improves model interpretability, addressing the "black box" limitation of ANN.

CRediT authorship contribution statement

B. Ranjith Babu: Conceptualization, Data curation, Investigation, Methodology, Software, Formal analysis, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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