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Optimizaion of Shear Capacity of Reinforced Concrete Beams Using Artificial Neural Networks

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Abstract
Reinforced concrete is a widely used construction material in various structures, and predicting shear capacity in reinforced concrete beams is a critical aspect of structural design. Conventional methods, such as ACI 318, often have limitations in capturing complex relationships among design variables, particularly in non-standard conditions. This study aims to develop a predictive model for the shear capacity of reinforced concrete beams Artificial Neural Networks (ANN). Experimental data encompassing geometric, material, and load parameters were collected from the literature to construct the dataset. The development process involved designing the ANN architecture, training the model, and validating it using performance metrics such as Mean Squared Error (MSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). The results indicate that the ANN model provides higher predictive accuracy compared to conventional methods, with a superior ability to capture complex variable relationships. Furthermore, this study offers practical implementation guidelines for utilizing the ANN model in predicting the shear capacity of reinforced concrete beams. The contributions of this research are expected to support the development of AI-based predictive methods in civil engineering, enhance design accuracy, and promote the adoption of modern technologies in civil engineering projects.
Keywords: shear capacity, concrete beams, Artificial Neural Networks (ANN)

INTRODUCTION

Reinforced concrete is the most widely used construction material in various types of buildings and infrastructure. One critical aspect in the design of reinforced concrete is the prediction of the shear capacity of concrete beams (Hagenauer & Helbich, 2022; Rodríguez-Hernández et al., 2021; Taher et al., 2021; Vanneschi & Silva, 2023; Yegnanarayana, 1994). Shear failure in reinforced concrete beams is a critical issue that can lead to sudden structural collapse without prior signs of distress, making it a key concern in structural design. (ACI Committee, 2019).

Conventional methods for determining the shear capacity of reinforced concrete beams often refer to empirical approaches found in various design standards, such as ACI 318 and Eurocode 2. These methods use geometric and material parameters, such as concrete strength, reinforcement area, and beam dimensions. While simple and widely used, these methods have limitations in capturing the complex relationships between variables, especially under non-standard conditions. (Husnain et al., 2024). Therefore, a more advanced and accurate approach is needed to improve the prediction of the shear capacity of reinforced concrete.

Artificial Neural Network (ANN) is an artificial intelligence method that has proven effective in modeling complex phenomena in various engineering fields, including civil engineering. ANN can learn the patterns of relationships between input and output variables without requiring explicit mathematical equations, making it more flexible than traditional methods. In previous research, ANN has been successfully used to predict the mechanical properties of concrete (Sarfarazi et al., 2024), such as compressive strength and elastic modulus, as well as the bending capacity of reinforced concrete. (Nafees et al., 2023)

This study aims to develop a prediction model for the shear capacity of reinforced concrete beams using the Artificial Neural Network (ANN) method. The study begins by identifying the key parameters that influence the shear capacity of reinforced concrete beams, such as concrete compressive strength, rebar area, spacing of reinforcement, beam geometry, and loading conditions (Fakhruddin et al., 2023; Hasan et al., 2022; IRWANTO & Santi, 2021; Trisnawathy, 2021; Yusup Solehudin & Walujodjati, 2021). Next, relevant experimental data will be gathered from literature or test results, processed into a dataset to be used as input for training and validating the ANN model. The next step involves designing the optimal ANN architecture, including selecting the number of hidden layers, the number of neurons per layer, activation functions, and training algorithms. Subsequently, the model training process will be conducted using the available dataset, followed by validation to ensure the accuracy of predictions (Buarlele et al., 2021; Firdausa et al., 2021; Mulyadi & Walujodjati, 2022).

The performance of the ANN model will be evaluated using metrics such as Mean Squared Error (MSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE), and compared with the results of conventional methods and experimental data. Additionally, this research aims to develop an application or practical guide for implementing the ANN model, which can be used in shear capacity calculations for civil engineering projects. The results of the study are expected to provide recommendations for improving the accuracy of shear capacity design for reinforced concrete beams and contribute to the development of modern AI-based prediction methods in civil engineering (Aryono. et al., 2020; Chandra, 2021; Hayu et al., 2020; Sahusilawane & Frans, 2022; Zheng et al., 2023; Zhu et al., 2023).

In prior research, Nguyen et al. (2021) conducted a comprehensive exploration of ANN architectures for predicting the shear strength of FRP-reinforced concrete beams and reported strong performance ($R^2 \approx 0.96$) when tuning hidden layers, activation functions, and input features (e.g., geometry, reinforcement ratios, material strengths) using an experimental database of 125 specimens. Meanwhile, Nguyen et al. (2023) developed a hybrid PSO-ANN model to predict shear capacity in RC beams strengthened with FRCM composites and demonstrated improved accuracy over conventional ANN and code-based methods across 89 specimens. While these studies highlight the promise of data-driven modeling in shear capacity prediction, they also display limitations: the first is restricted to FRP-strengthened beams and does not fully address unreinforced or more general RC beams under varied conditions, and the second targets strengthened beams rather than ordinary reinforced concrete, leaving open the performance of pure ANN models for conventional RC shear scenarios across diverse datasets.

This study aims to apply ANN in predicting the shear capacity of reinforced concrete beams. By utilizing experimental data available in the literature, an ANN model will be developed to learn the relationships between material, geometric, and loading parameters. It is expected that the results of this research will provide more accurate predictions compared to conventional approaches and serve as an initial step in the application of data-driven technology in reinforced concrete structure design.

RESEARCH METHOD

This study is conducted to develop a prediction model for the shear capacity of reinforced concrete beams using Artificial Neural Network (ANN). The research methodology involves several stages:

Data Collection

Data on the shear capacity of reinforced concrete beams are collected from relevant and reliable literature. The key parameters gathered include the stirrup reinforcement diameter (ds), reinforcement area (Av), concrete compressive strength (f'c), beam width (b), beam height (h), beam moment of inertia (I), ultimate shear force (Vu), and shear capacity of the reinforcement (Vs) (Arief Septiono, 2014). This data will be organized into a structured dataset to be used for training and validating the ANN model (Prasetiawan, 2022).

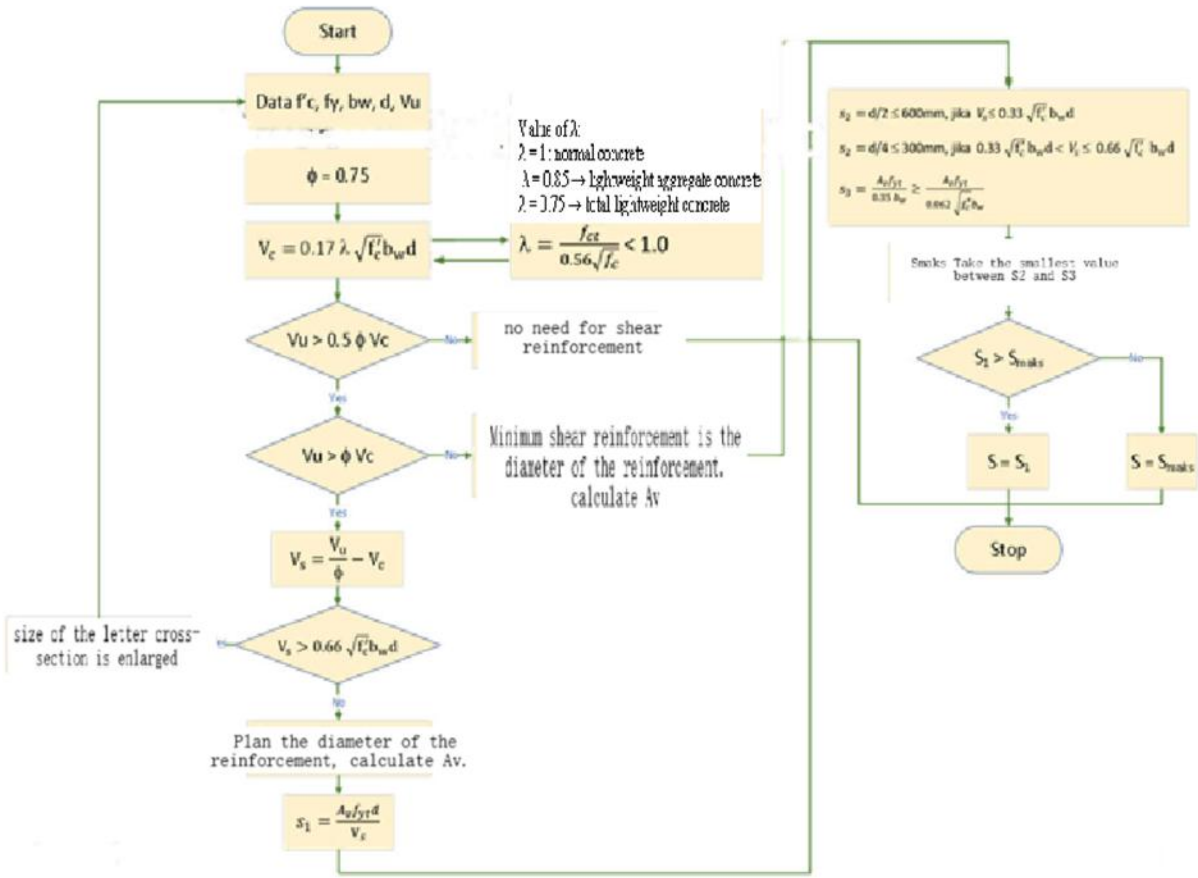

Figure 1. Data Collection Flow

Data Processing

The collected data will be processed to ensure the consistency, completeness, and cleanliness of the dataset. Outliers or incorrect values will be identified and processed to prevent them from affecting the model's performance. A normalization process will be carried out to ensure that all parameters have a uniform scale (Prasetiawan, 2022).

Development of ANN Model

The ANN model is designed by selecting the optimal architecture, including the number of hidden layers, the number of neurons per layer, the activation function, and the training algorithm (Mao et al.,

2024). The design process will be conducted using a trial and error approach to determine the configuration that provides the best performance. (Hammad et al., 2018)(Prasetiawan, 2022).
The mathematical equation generated from the prediction of permeability values as the output with the ANN simulation is as follows:
$Y = f(W_n \cdot X_n)$

Dengan:

Y : Predicted output

W_n : Correspondence weight

X_n : Input parameter

F : The transfer function used (sigmoid function)

The sigmoid transfer function is defined as:

$$f(x) = \frac{1}{1 + e^{-x}}$$

Model Training and Validation

The dataset was divided into two parts: training data and validation data. The ANN model was trained using the training data and then tested using the validation data to evaluate prediction accuracy. Cross-validation was used to reduce the risk of overfitting and ensure model generalization.

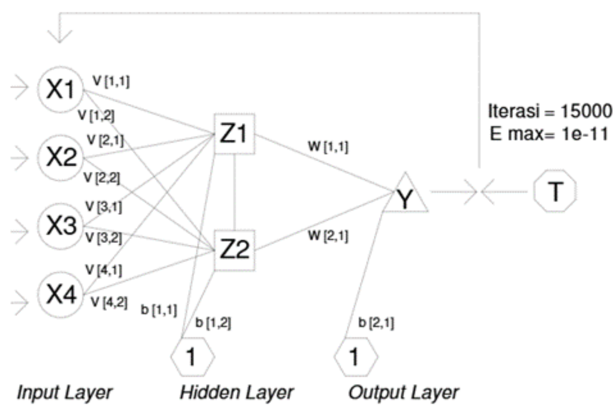

Figure 2. Artificial Neural Network Architecture

Model Performance Evaluation

The performance of the ANN model was evaluated using metrics such as Mean Squared Error (MSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). The predicted results from the model were compared with experimental values and results from conventional methods to assess the advantages of the ANN approach.

Development of Implementation Application

Based on the developed ANN model, a simple application or practical implementation guide was created to assist users in predicting the shear capacity of reinforced concrete beams in real-world projects.

Analysis and Conclusion Formulation

The research results were analyzed to draw conclusions regarding the effectiveness of ANN in predicting the shear capacity of reinforced concrete beams. These conclusions were as the basis for providing practical and academic recommendations.

RESULTS AND DISCUSSION

Description of the ANN Model

The architecture of the Artificial Neural Network (ANN) model used in this study is designed to predict the shear capacity of reinforced concrete beams based on various input parameters. This model utilizes a multilayer perceptron (MLP) structure consisting of several layers, including the input layer, hidden layers, and output layer, as shown in the figure 3.

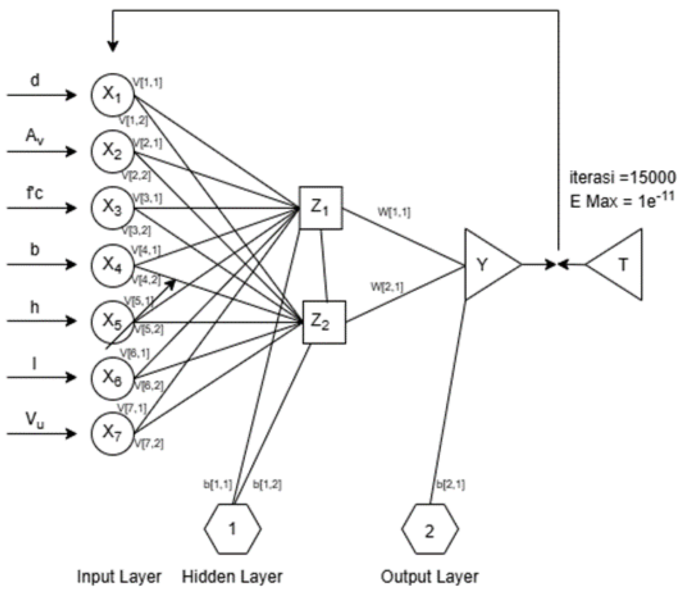

Figure 3. ANN Architectural Model

Training Data and Testing Data

This dataset is designed to predict the shear capacity of reinforced concrete beams using various relevant physical and mechanical parameters. The first parameter is the shear reinforcement diameter (ds), which influences the beam's ability to resist shear forces. In this dataset, the shear reinforcement diameter is fixed at 10 mm. The second parameter is the cross-sectional area of shear reinforcement (Av), which indicates the total area of steel material used. The variations in cross-sectional area in the dataset are 157 mm^2 and 314 mm^2, reflecting different shear reinforcement configurations.

Concrete compressive strength (f'c) is one of the key parameters as it directly influences shear capacity. The values of f'c in the dataset include variations of 20 MPa, 25 MPa, and 30 MPa to reflect low to medium-quality concrete. Geometric parameters such as the width of the cross-section (b) and the total height of the beam (h) are also considered, with b ranging from 200 mm to 400 mm, and h ranging from 320 mm to 800 mm. Additionally, the moment of inertia (I) is calculated based on the dimensions of b and h, with values ranging from 546.1x106 mm⁴ to 17.07x109 mm⁴, which indicate the beam's resistance to deformation due to shear forces..

From the load side, the dataset includes Vu, which represents the total shear load applied to the beam, with values ranging from 150,000 N to 1,000,000 N. The shear capacity influenced by shear reinforcement (Vs) is also calculated and varies from approximately 148,879 N to 1,055,820 N. With these parameter variations, the dataset provides a solid foundation for training and testing the Artificial Neural Network (ANN) model in predicting the shear capacity of reinforced concrete beams. This allows the model to recognize complex patterns and relationships between these parameters, thereby providing accurate prediction results.

Table 1. Input data and target output of ANN

X_1	X_2	X_3	X_4	X_5	X_6	X_7	Y
d_s	A_v	f'c	b	h	I	V_u	V_s
mm	mm^2	Mpa	mm	mm	mm^4	N	N
10.00	157.00	25.00	200.00	320.00	546133333.33	150000.00	153333.33
10.00	157.00	25.00	250.00	450.00	1898437500.00	300000.00	314583.33
10.00	157.00	25.00	250.00	500.00	2604166666.67	350000.00	370833.33
10.00	157.00	25.00	300.00	600.00	5400000000.00	500000.00	526666.67
10.00	157.00	25.00	300.00	700.00	8575000000.00	600000.00	635000.00
10.00	157.00	25.00	350.00	700.00	10004166666.67	700000.00	740833.33
10.00	157.00	25.00	350.00	800.00	14933333333.33	800000.00	845000.00
10.00	157.00	25.00	400.00	800.00	17066666666.67	900000.00	946666.67
10.00	157.00	20.00	200.00	320.00	546133333.33	150000.00	158260.06
10.00	157.00	20.00	250.00	450.00	1898437500.00	250000.00	256934.34
10.00	157.00	20.00	300.00	600.00	5400000000.00	450000.00	474780.19
10.00	157.00	30.00	200.00	320.00	546133333.33	150000.00	148879.23
10.00	157.00	30.00	250.00	450.00	1898437500.00	300000.00	306430.73
10.00	157.00	30.00	250.00	500.00	2604166666.67	350000.00	361686.51
10.00	157.00	30.00	300.00	600.00	5400000000.00	500000.00	513304.35
10.00	157.00	30.00	300.00	700.00	8575000000.00	600000.00	619251.56
10.00	157.00	30.00	350.00	700.00	10004166666.67	700000.00	722460.15
10.00	157.00	30.00	350.00	800.00	14933333333.33	800000.00	823843.00
10.00	157.00	30.00	400.00	800.00	17066666666.67	900000.00	922487.24
10.00	314.00	20.00	200.00	320.00	546133333.33	150000.00	158260.06
10.00	314.00	20.00	250.00	450.00	1898437500.00	250000.00	256934.34
10.00	314.00	20.00	300.00	600.00	5400000000.00	450000.00	474780.19
10.00	314.00	30.00	200.00	320.00	546133333.33	150000.00	148879.23
10.00	314.00	30.00	250.00	450.00	1898437500.00	300000.00	306430.73
10.00	314.00	30.00	250.00	500.00	2604166666.67	350000.00	361686.51
10.00	314.00	30.00	300.00	600.00	5400000000.00	550000.00	579971.02
10.00	314.00	30.00	300.00	700.00	8575000000.00	650000.00	685918.22
10.00	314.00	30.00	350.00	700.00	10004166666.67	750000.00	789126.82
10.00	314.00	30.00	350.00	800.00	14933333333.33	850000.00	890509.67
10.00	314.00	30.00	400.00	800.00	17066666666.67	1000000.00	1055820.57

Data Normalization Process: Presenting the data normalization process conducted to facilitate model training, such as transforming the data range to [0,1] or [-1,1].

Table 2. Data normalization

No	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Y
	ds	Av	f'c	b	h	I	Vu (N)	Vs
	mm	mm2	Mpa	mm	mm	mm4	N	N
1	1.00	0.50	0.83	0.50	0.40	0.03	0.15	0.15
2	1.00	0.50	0.83	0.63	0.56	0.11	0.30	0.30
3	1.00	0.50	0.83	0.63	0.63	0.15	0.35	0.35
4	1.00	0.50	0.83	0.75	0.75	0.32	0.50	0.50
5	1.00	0.50	0.83	0.75	0.88	0.50	0.60	0.60
6	1.00	0.50	0.83	0.88	0.88	0.59	0.70	0.70
7	1.00	0.50	0.83	0.88	1.00	0.88	0.80	0.80
8	1.00	0.50	0.83	1.00	1.00	1.00	0.90	0.90
9	1.00	0.50	0.67	0.50	0.40	0.03	0.15	0.15
10	1.00	0.50	0.67	0.63	0.56	0.11	0.25	0.24
11	1.00	0.50	0.67	0.75	0.75	0.32	0.45	0.45
12	1.00	0.50	1.00	0.50	0.40	0.03	0.15	0.14
13	1.00	0.50	1.00	0.63	0.56	0.11	0.30	0.29
14	1.00	0.50	1.00	0.63	0.63	0.15	0.35	0.34
15	1.00	0.50	1.00	0.75	0.75	0.32	0.50	0.49
16	1.00	0.50	1.00	0.75	0.88	0.50	0.60	0.59
17	1.00	0.50	1.00	0.88	0.88	0.59	0.70	0.68
18	1.00	0.50	1.00	0.88	1.00	0.88	0.80	0.78
19	1.00	0.50	1.00	1.00	1.00	1.00	0.90	0.87
20	1.00	1.00	0.67	0.50	0.40	0.03	0.15	0.15
21	1.00	1.00	0.67	0.63	0.56	0.11	0.25	0.24
22	1.00	1.00	0.67	0.75	0.75	0.32	0.45	0.45
23	1.00	1.00	1.00	0.50	0.40	0.03	0.15	0.14
24	1.00	1.00	1.00	0.63	0.56	0.11	0.30	0.29
25	1.00	1.00	1.00	0.63	0.63	0.15	0.35	0.34
26	1.00	1.00	1.00	0.75	0.75	0.32	0.55	0.55
27	1.00	1.00	1.00	0.75	0.88	0.50	0.65	0.65
28	1.00	1.00	1.00	0.88	0.88	0.59	0.75	0.75
29	1.00	1.00	1.00	0.88	1.00	0.88	0.85	0.84
30	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Model Performance

The performance evaluation of the Artificial Neural Network (ANN) model in predicting the shear capacity of reinforced concrete beams is conducted using several metrics and visualizations. One of the metrics used is the Mean Squared Error (MSE), which measures the average squared difference between the predicted values and the actual data, providing an indication of how far the model's predictions are from the true values.

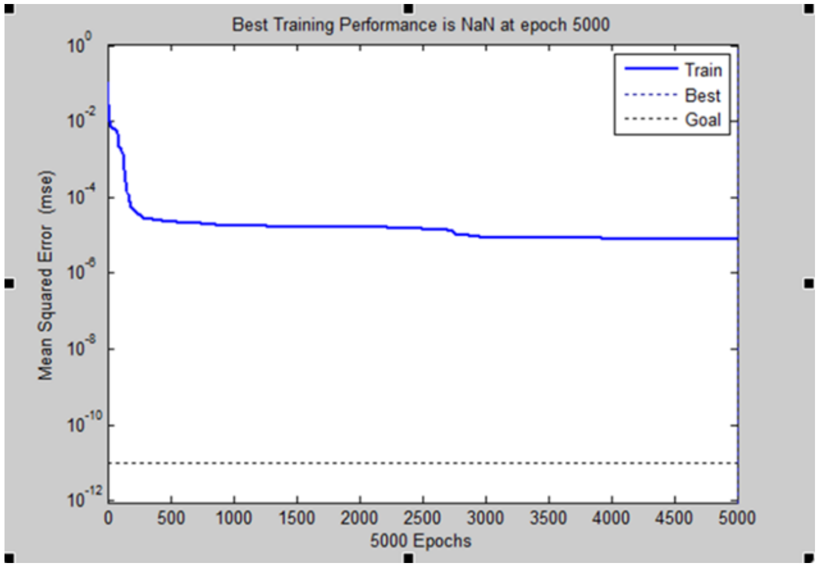

Figure 4. performance evaluation

In addition, R-squared (R^2) is used to assess how well the ANN model can explain the variability of the data, with values approaching 1 indicating excellent predictive ability.

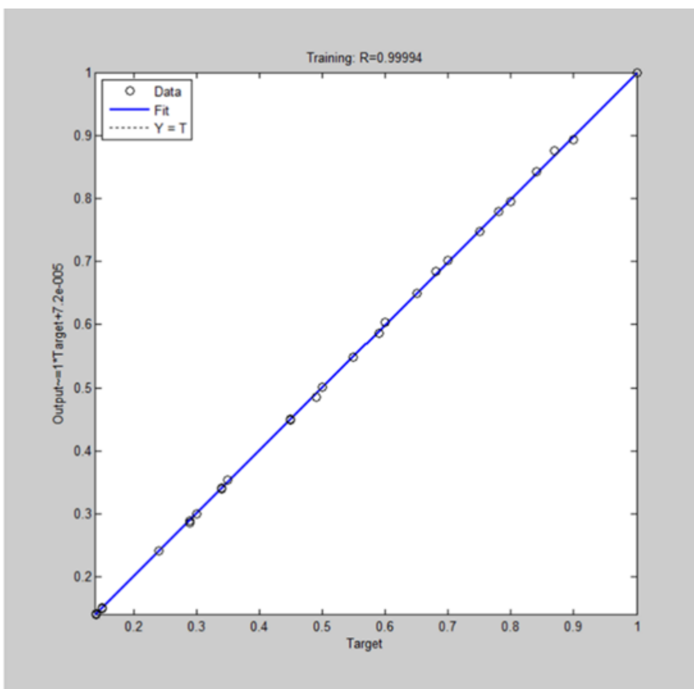

Figure 5. performance evaluation

Mean Absolute Percentage Error (MAPE) is also used to measure the average percentage error between the predicted and actual values, making it easier to interpret the relative error level. This evaluation is complemented by a comparison graph between the predicted shear capacity generated by the ANN model and the actual values from experimental data, providing a direct visualization of the model's performance.

The prediction accuracy level is calculated to provide information on the model's ability to predict shear capacity based on test data, which is an important indicator in assessing the reliability of the developed ANN model. Below is the empirical formula generated by the ANN

$$Y=-3.332241861+6.438879971(Z1)+0.767602797(Z2)$$

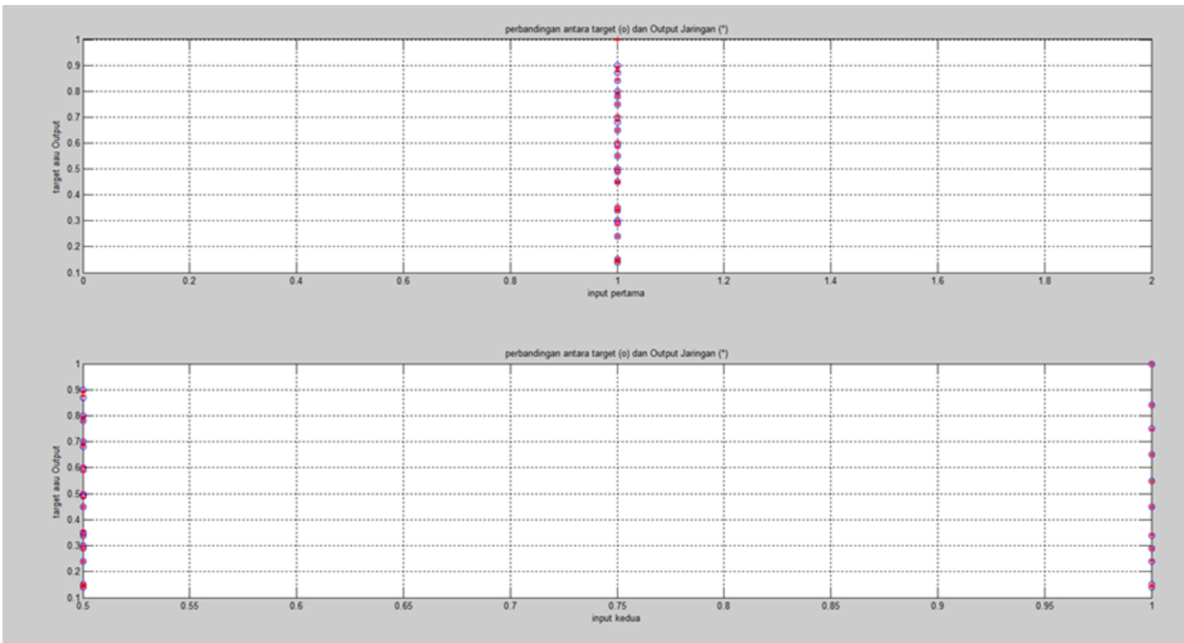

Figure 6. Comparison of targets with outputs

Model ANN Accuracy Analysis

The prediction results using the ANN model are compared with predictions based on formulas or standards, such as ACI 318. This discussion aims to highlight the advantages or disadvantages of the ANN model compared to traditional methods in predicting the shear capacity of reinforced concrete beams.

The advantages of the ANN model in handling non-linear data and the complexity of relationships between parameters that affect shear capacity are emphasized. The benefits of ANN can be seen from the error between the shear capacity calculated using conventional methods and the shear capacity calculated using the empirical formulas generated by ANN. The errors can be observed in Table 3.

Table 3. ANN Output and Error between Target Output and ANN Target

X_1	X_2	X_3		X_5	X_6	X_7	Y	Zin1	Zin2	Z1	Z2	Y (Empiris)	Y (ANN)	Error of the Empirical Equation
ds	Av	f'c	b	h	I	Vu	Vs							
mm	mm2	Mpa	mm	mm	mm4	N	N							
1.00	0.50	0.83	0.50	0.40	0.03	0.15	0.145	-0.318	7.177	0.421	0.999	0.147	0.148	1%
1.00	0.50	0.83	0.63	0.56	0.11	0.30	0.298	-0.223	7.028	0.444	0.999	0.296	0.296	1%
1.00	0.50	0.83	0.63	0.63	0.15	0.35	0.351	-0.190	6.825	0.453	0.999	0.349	0.349	1%
1.00	0.50	0.83	0.75	0.75	0.32	0.50	0.499	-0.096	6.478	0.476	0.998	0.499	0.499	0%
1.00	0.50	0.83	0.75	0.88	0.50	0.60	0.601	-0.031	5.795	0.492	0.997	0.602	0.602	0%
1.00	0.50	0.83	0.88	0.88	0.59	0.70	0.702	0.031	5.804	0.508	0.997	0.703	0.702	0%
1.00	0.50	0.83	0.88	1.00	0.88	0.80	0.800	0.094	4.845	0.524	0.992	0.800	0.800	0%
1.00	0.50	0.83	1.00	1.00	1.00	0.90	0.897	0.156	4.743	0.539	0.991	0.898	0.899	0%

X_1	X_2	X_3		X_5	X_6	X_7	Y	Zin1	Zin2	Z1	Z2	Y (Empiris)	Y (ANN)	Error of the Empirical Equation
ds	Av	f'c	b	h	I	Vu	Vs							
mm	mm2	Mpa	mm	mm	mm4	N	N							
1.00	0.50	0.67	0.50	0.40	0.03	0.15	0.150	-0.314	8.618	0.422	1.000	0.153	0.153	2%
1.00	0.50	0.67	0.63	0.56	0.11	0.25	0.243	-0.256	8.511	0.436	1.000	0.244	0.244	0%
1.00	0.50	0.67	0.75	0.75	0.32	0.45	0.450	-0.129	7.962	0.468	1.000	0.447	0.447	1%
1.00	0.50	1.00	0.50	0.40	0.03	0.15	0.141	-0.321	5.736	0.420	0.997	0.140	0.140	1%
1.00	0.50	1.00	0.63	0.56	0.11	0.30	0.290	-0.227	5.587	0.444	0.996	0.288	0.288	1%
1.00	0.50	1.00	0.63	0.63	0.15	0.35	0.343	-0.193	5.384	0.452	0.995	0.341	0.341	0%
1.00	0.50	1.00	0.75	0.75	0.32	0.50	0.486	-0.100	5.037	0.475	0.994	0.489	0.489	1%
1.00	0.50	1.00	0.75	0.88	0.50	0.60	0.587	-0.035	4.354	0.491	0.987	0.589	0.589	0%
1.00	0.50	1.00	0.88	0.88	0.59	0.70	0.684	0.028	4.363	0.507	0.987	0.690	0.689	1%
1.00	0.50	1.00	0.88	1.00	0.88	0.80	0.780	0.091	3.404	0.523	0.968	0.776	0.775	1%
1.00	0.50	1.00	1.00	1.00	1.00	0.90	0.874	0.152	3.302	0.538	0.964	0.872	0.872	0%
1.00	1.00	0.67	0.50	0.40	0.03	0.15	0.150	-0.315	9.248	0.422	1.000	0.152	0.152	1%
1.00	1.00	0.67	0.63	0.56	0.11	0.25	0.243	-0.257	9.141	0.436	1.000	0.243	0.243	0%
1.00	1.00	0.67	0.75	0.75	0.32	0.45	0.450	-0.130	8.591	0.468	1.000	0.446	0.446	1%
1.00	1.00	1.00	0.50	0.40	0.03	0.15	0.141	-0.322	6.366	0.420	0.998	0.140	0.140	1%
1.00	1.00	1.00	0.63	0.56	0.11	0.30	0.290	-0.228	6.216	0.443	0.998	0.289	0.288	1%
1.00	1.00	1.00	0.63	0.63	0.15	0.35	0.343	-0.194	6.014	0.452	0.998	0.342	0.341	0%
1.00	1.00	1.00	0.75	0.75	0.32	0.55	0.549	-0.064	5.624	0.484	0.996	0.549	0.548	0%
1.00	1.00	1.00	0.75	0.88	0.50	0.65	0.650	0.001	4.941	0.500	0.993	0.651	0.650	0%
1.00	1.00	1.00	0.88	0.88	0.59	0.75	0.747	0.063	4.950	0.516	0.993	0.751	0.750	0%
1.00	1.00	1.00	0.88	1.00	0.88	0.85	0.843	0.126	3.991	0.531	0.982	0.844	0.843	0%
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.000	0.224	3.846	0.556	0.979	0.998	0.998	0%

From table 4, the maximum error is 2% and the minimum is 0%, meaning no error occurred. The 2% error occurred at a variation:

Table 4. Data with the biggest error

ds	Av	f'c	b	h	I	Vu	Vs
mm	mm2	Mpa	mm	mm	mm4	N	N
10.00	157.00	20.00	200.00	320.00	546133333.33	150000.00	158260.06

Potential Application of the ANN Model in Practice

he potential application of the ANN model in reinforced concrete structure design in the field, especially in predicting shear capacity during the initial design phase. The results of the validation using data outside of the ANN input data can be seen in Table 5.

Table 5. Validation data using data outside of the ANN input data

X_1	X_2	X_3	X_4	X_5	X_6	X_7	Y	Zin1	Zin2	Z1	Z2	Y (Empiris ANN)	Error Persamaan Empiris
ds	Av	f'c	b	h	I	Vu	Vs						
mm	mm2	Mpa	mm	mm	mm4	N	N						
1.000	1.000	0.900	0.750	0.875	0.502	0.600	0.595	-0.033	5.848	0.492	0.997	0.599	1%
1.000	0.500	1.000	0.750	0.813	0.402	0.570	0.562	-0.053	4.698	0.487	0.991	0.563	0%
1.000	0.500	0.933	0.875	0.875	0.586	0.745	0.748	0.062	4.901	0.515	0.993	0.748	0%
1.000	0.500	1.000	1.000	1.000	1.000	1.000	1.000	0.225	3.216	0.556	0.961	0.985	1%
1.000	1.000	1.000	0.875	0.938	0.721	0.800	0.795	0.095	4.496	0.524	0.989	0.799	0%
1.000	1.000	1.000	0.500	0.438	0.042	0.210	0.212	-0.279	6.259	0.431	0.998	0.206	2%

From Table 5. the validation data using data outside the ANN input data, the maximum error that occurred in the validation data for 20% of the total data was 2%. Therefore, the empirical formula generated by the ANN can be applied to other cases outside the ANN input data.

The practical benefits of the ANN model, such as time savings and increased efficiency in reinforced concrete beam design, are highlighted. This section also examines how the ANN model can be used to improve the accuracy of shear capacity calculations compared to existing standard calculations.

CONCLUSION

The application of Artificial Neural Networks (ANN) in predicting the shear capacity of reinforced concrete beams has demonstrated high effectiveness, with validation results showing a maximum error of only 2% and, in some cases, zero error, establishing strong reliability and confidence in applying the derived empirical formula to cases beyond the original dataset. Given these promising results, future research could explore integrating ANN with other machine learning approaches or hybrid modeling techniques to further enhance predictive accuracy, extend applicability to more complex structural conditions, and evaluate long-term performance under varying environmental and loading scenarios.

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