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Artificial Neural Network-Based Prediction of Physical and Mechanical Properties of Concrete Containing Glass Aggregates

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Abstract

This comprehensive study analyzes the use of crushed glass as both fine and coarse aggregate in concrete, as well as the prediction accuracy of Artificial Neural Networks (ANN). The primary objectives are to understand the interactions between concrete's constituents and to assess the accuracy of ANN models in predicting concrete's mechanical and physical properties. This is achieved using a two-decade experimental results dataset of concrete's compressive and tensile strengths, slump, density, and the corresponding mix design proportions, including waste glass aggregate. A series of 70 concrete samples were carefully built and tested, with compressive strengths varying from 12 to 71 MPa and glass aggregate percentages ranging from 0-100%. These samples served as the basis for the creation of an input dataset and ANN targets. The ANN model underwent intensive training, validation, testing, and statistical regression analysis. The ANN models are exceptionally accurate, with a continuously low error margin of roughly 2%, highlighting their usefulness in matching experimental and predicted results. Validation techniques highlight the models' dependability, with consistently high coefficients of determination (R-values), including 0.99484, demonstrating their robustness in replicating complicated concrete properties. The data analysis shows a unique pattern, with optimum glass aggregate percentages in the range of 10–20%. Beyond this range, there is a noticeable decline in concrete properties. Finally, the study confirms the efficacy of ANN in predictive modeling while also validating the potential of crushed glass to replace natural aggregates in concrete.

Keywords: Glass Aggregates; Compressive Strength; Splitting Tensile Strength; Density; Slump; ANN.

1. Introduction

The construction industry, a crucial driver of economic growth, is currently facing two interconnected challenges: resource scarcity and environmental degradation. Large quantities of solid and non-biodegradable waste, including tens of millions of tons of waste glass, are worsening these problems, hence the need for breakthrough ideas in waste disposal management. Waste material recycling practices are among the most important sustainable methods. Particularly noteworthy in this regard is the application of crushed glass as an alternative to conventional aggregates for concrete manufacture, a possible solution that addresses both waste disposal and scarcity challenges [1, 2]. The recent endeavors of the industry show an episodic approach to implementing modern solutions that are not only solving environmental problems but also developing sustainable building construction through innovative practices. There are properties inherent in broken glass resulting from bottles and other items that have made it a more desirable substitute for concrete.

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Its native toughness, strength of density, and angular character make it perfectly suitable for operation, both as fine aggregate and as usable. Moreover, the different colors of broken glass offer an aesthetic value to concrete, rendering it applicable for wider use in construction projects [3–5]. The incorporation of crushed glass in concrete as a recycled material also eliminates the adverse impact on nature caused by disposing of glass wastes in landfills and avoids dependency on natural aggregates, reflecting some basic tenets inherent in sustainable construction practices. By utilizing reused materials in construction, a position of forward-looking behavior is reflected in addressing ecological challenges within the framework of sustainable and responsible building practices. The incorporation of recycled glass powder (RGP) and styrene-butadiene rubber as constituents in concrete symbolizes this pledge [6].

Over the last two decades, considerable research has been carried out to investigate the factors that influence the mechanical and physical performance of concrete made with waste glass aggregates, focusing on the compressive and tensile strength alongside other physical properties such as slump and density at various mixes containing different coarse and fine aggregate glass percentages from 0% to 100%. A detailed analysis was performed to investigate the mechanical properties of concrete pavements containing waste glass and found no significant reduction in the 28-day compressive and split-tensile strengths up to a 10% replacement dosage of fine aggregate with glass. Glass replacement beyond 10% led to reduced mechanical strengths [7]. Research was conducted to study the properties of concrete by replacing 0–60% coarse aggregate with crushed glass. This replacement did not have a significant effect on the properties of fresh concrete; however, the values of compressive strength declined with increasing crushed glass content, with 60% crushed glass replacement resulting in a 49% decrease in compressive strength [8]. Also, the effects of replacing sand with glass aggregate on the properties of alkali-activated mortar were studied. It was observed that the workability of the mortar increased with higher glass content due to its lower absorption compared to sand. The compressive strength decreased slightly by 7% at a 100% ratio [9]. The use of recycled waste glass as sand replacement in concrete at 0–100% replacement ratios in three concrete grades: 30, 45, and 60 MPa, was studied. The fresh density decreased with increasing glass content and increasing w/c ratio. On the other hand, higher-grade concrete mixtures with increased cement content have a higher density. No clear trend was observed in slump values, which is attributed to two opposing actions: the sharp edges and angular shape of crushed glass would reduce the slump and, at the same time, the impermeable smooth surfaces of glass [10]. Another study was carried out to study the effects of using crushed waste glass as replacements for fine and coarse aggregate in concrete at replacement ratios of 0–100% in steps of 25%. Concrete with a 25% aggregate replacement ratio showed almost no change in compressive strength, while concrete with glass ratios of 25–100% showed a significant reduction in compressive and tensile strengths. The workability of concrete containing waste glass showed a minimal decrease, which was attributed to the angular geometry of the waste glass aggregate [11].

An experimental study was conducted to determine the properties of concrete in which sand was replaced with 20–60% crushed waste glass. Workability decreased significantly with an increase in the quantity of recycled glass. In addition, at a 60% replacement ratio, the results observed a marginal reduction in strength [12]. A further experimental study was carried out on replacing fine aggregates with waste glass powder at 0–30% ratios by weight at 10% increments for 20 MPa-grade concrete. At a 10% replacement ratio, a marginal increment in the 28-day compressive strength was observed [13].

A research study used waste glass cullet as a partial replacement for coarse aggregate in concrete at ratios of 10–30% by weight. The substitution caused declines in the compressive strength that became significant with a high replacement ratio, with optimum compressive strength achieved at a 10% replacement ratio. The slump values showed a tendency to increase with an increase in glass aggregate [14]. Another study used recycled waste glass in proportions of 0–100% by weight to substitute sand in a 20 MPa-grade concrete mixture. The slump values showed a reduction tendency with increasing waste glass content. The compressive strength of concrete declined for glass contents of 75% and 100%, while concretes containing 25% and 50% glass content achieved higher compressive strength compared to the control mix [15]. Likewise, the use of glass cullets as a 100% sand replacement in concrete was investigated. The resulting mixtures had lower compressive strength compared to conventional mixtures [16]. In an additional study, fine aggregates were replaced by waste glass powder in 10%, 20%, and 30% ratios by weight for 20 MPa-grade concrete. The powder waste glass showed some pozzolanic properties, and therefore it worked as cement replacement and contributed towards strength development in concrete. The study indicated that waste glass can effectively be used as fine aggregate replacement up to 20% without substantial change in strength [17].

Along with the analysis of the mechanical and physical characteristics of glass-particle-containing concrete, past studies have given attention to high temperatures' effect on the interaction of these compositions. Studies carried out in this field mainly emphasized the behavior of concrete with the inclusion of glass aggregates at extreme temperatures, revealing information about its strength as a material. The performance of concrete with crushed glass and glass powder under high temperatures up to 600 °C was investigated, with replacement rates ranging from 10% to 30% by volume. Concrete with 10% glass powder substitution and 10%–20% crushed glass substitution exhibited better performance at room temperature and high temperature in terms of mechanical, physical, and durability properties compared to others [18]. Similar research investigated the mechanical properties of recycled glass concrete made with up to 30% crushed glass after exposure to elevated temperatures and found that adding recycled glass to concrete improved its residual mechanical properties compared to control concrete when exposed to temperatures up to 600 °C [19]. Finally, replacing fine and coarse aggregates with crushed glass was investigated to evaluate its effect on the properties of concrete at elevated temperatures. The results of this investigation showed that at temperatures up to 700 °C, the compressive strength of concrete with recycled glass decreased by 20% [20].

The study utilizes an Artificial Neural Network (ANN) model as a predictive tool to estimate various mechanical and physical properties of concrete based on experimental data. This involves training the ANN using a dataset comprising observations from laboratory tests on concrete mixes with varying glass aggregate percentages and other key variables. During training, the ANN learns complex relationships between input variables like aggregate content, ratios, and superplasticizer dosage and output properties such as compressive strength, tensile strength, density, and slump. Through iterative adjustments via backpropagation and optimization algorithms, the ANN fine-tunes its structure to capture underlying data patterns accurately. Once trained and validated, the ANN predicts concrete properties for future scenarios by inputting relevant mix parameters, validated against independent datasets. This process ensures reliability and accuracy in replicating concrete properties across different conditions. Overall, the ANN model enables efficient analysis and prediction of concrete properties, offering insights for sustainable construction practices and material optimization [21–23].

Artificial Neural Network (ANN) applications in the context of concrete technology are rather complicated but at the same time revolutionary [24]. ANNs allow for predicting chloride penetration resistance and concrete compressive strength and can provide a complete approach to achieving the balance between durability representation and structural performance [25].

In addition, ANN was applied to several practical technological uses as well. ANN has proved to be a good predictive tool for the optimal tuff stone content in lightweight concrete, required to produce strong concrete yet with low weight [26]. ANN significantly enhances the estimation of mass characteristics in concrete floor slabs and dynamic response, providing an effective approach to assess complex structural dynamics and predict mass parameters [27]. Besides, owing to the intricate interplay of several components, ANN works as an accurate prediction tool for determining concrete compressive strength [28]. In addition, while looking into how supplementary cementitious materials (SCM) affect concrete compressive strength under hot conditions, ANN is extremely useful for unraveling fine-grained connections and finding the optimum usage levels of such additives to yield high-performance concretes at elevated temperatures [29]. Additionally, ANN was used to predict the bond strength in basalt FRP-reinforced self-compacting geopolymer concrete and the dynamic properties of concrete [30, 31]. The ability of the ANN to solve complex issues within concrete technology as well as its broad applicability over these diverse applications is demonstrated [32]. This study implements more complex techniques, such as ANN, to forecast the performance of concrete containing crushed glass as both fine and coarse aggregates.

The primary objectives are to understand the interactions between concrete's constituents and to assess the accuracy of ANN models in predicting concrete's mechanical and physical properties. This is achieved using a two-decade experimental results dataset of concrete's compressive and tensile strengths, slump, density, and the corresponding mix design proportions, including waste glass aggregate. Through the declared objectives, this research aims to provide major insights that can enlighten future building practices as well as contribute to a green and cost-effective construction industry.

The first part of this study, including the introduction, is an in-depth evaluation of the previous literature related to the topic under investigation. The following part presents the materials and methodology of this study in addition to the data sources used, which ends with concluding remarks based on the results and discussion. The proposed model was finally verified using a new dataset. The conclusion part brought together the findings from the study and recommended future research-related aspects.

2. Materials

A comprehensive review of the literature and experimental programs for the past twenty years has been conducted to study the mechanical and physical properties of concrete mixtures containing glass particles. In this regard, the performed experiments provided valuable indications regarding the optimization of concrete constituents and presented a wide range of mixed compositions with different strengths from 12 to 71 MPa. These studies explored the influence of glass aggregate replacement at ranges from 0% to 100%. The weight proportions of the principal constituents have been specified, including fine and coarse aggregates, water, cement, superplasticizers, and glass aggregate (fine and coarse) types. This diverse data set sets the base for interpreting intricate relationships between constituent elements and their impact on concrete behavior. Thorough studies greatly contribute to the development of concrete technology, producing and developing sustainable and innovative building materials. The following approach describes the process of data collection, preparation, and artificial neural network (ANN) model development for predicting compressive and tensile strengths, density, and slump values. Tables 1 and 2 show tabular data from previous experiments.

Table 1. Mix design proportions and data from prior experimental research

Reference	Glass %	Fine Glass (kg/m³)	Coarse Glass (kg/m³)	Cement (kg/m³)	Water (kg/m³)	Plasticizer (kg/m³)	Fine Aggregate (kg/m³)	Coarse Aggregate (kg/m³)
Topçu & Canbaz (2004) [8]	0	0	0	350	190	0	647	1120
	15	0	82	350	190	0	647	1037
	30	0	164	350	190	0	647	953
	45	0	246	350	190	0	647	869
	60	0	328	350	190	0	647	784
Khan & Sarker (2020) [9]	0	0	0	416.6	200.1	2.7	673.4	1107.1
	10	67.3	0	416.6	200.1	2.7	606	1107.1
	25	168.35	0	416.6	200.1	2.7	505	1107.1
	50	336.7	0	416.6	200.1	2.7	336.7	1107.1
	100	673.4	0	416.6	200.1	2.7	0	1107.1
	0	0	0	416.6	200.1	2.7	673.4	1107.1
	10	0	110.7	416.6	200.1	2.7	673.4	996.4
	25	0	276.8	416.6	200.1	2.7	673.4	830.3
	50	0	553.55	416.6	200.1	2.7	673.4	553.55
	100	0	1107.1	416.6	200.1	2.7	673.4	0
	0	0	0	416.6	200.1	2.7	673.4	1107.1
	10	67.3	110.7	416.6	200.1	2.7	606	996.4
	25	168.3	276.8	416.6	200.1	2.7	505	830.3
	50	336.7	553.6	416.6	200.1	2.7	336.7	553.55
	100	673.4	1107.1	416.6	200.1	2.7	0	0
Du & Tan (2014) [10]	0	0	0	378	185	0	741	1048
	25	185.25	0	378	185	0	575.75	1048
	50	370.5	0	378	185	0	370.5	1048
	75	555.75	0	378	185	0	185.25	1048
	100	741	0	378	185	0	0	1048
	0	0	0	487	185	0	649	1048
	25	162.25	0	487	185	0	486.75	1048
	50	324.5	0	487	185	0	324.5	1048
	75	486.75	0	487	185	0	162.25	1048
	100	649	0	487	185	0	0	1048
	0	0	0	578	185	0	572	1048
	25	143	0	578	185	0	429	1048
	50	286	0	578	185	0	286	1048
	75	429	0	578	185	0	143	1048
	100	572	0	578	185	0	0	1048

Table 2. Mix design proportions and data from prior experimental research

Reference	Glass %	Fine Glass (kg/m³)	Coarse Glass (kg/m³)	Cement (kg/m³)	Water (kg/m³)	Plasticizer (kg/m³)	Fine Aggregate (kg/m³)	Coarse Aggregate (kg/m³)
Olofinnade et al. (2016) [11]	0	0	0	275	138	0	550	1100
	25	138	275	275	138	0	413	825
	50	275	550	275	138	0	275	550
	75	413	825	275	138	0	138	275
	100	550	1100	275	138	0	0	0
Tamanna (2020) [12]	0	0	0	360	180	1.34	902	981
	20	126.4	0	360	180	1.34	775.6	981
	40	252.8	0	360	180	1.34	649.2	981
	60	379.2	0	360	180	1.34	522.8	981
Elavarasan & Dhanalakshmi (2016) [13]	0	0	0	383.2	191.6	0	654	1162
	10	65.4	0	383.2	191.6	0	588.6	1162
	20	130.8	0	383.2	191.6	0	523.2	1162
	30	196.2	0	383.2	191.6	0	457.8	1162

Hasan et al. (2023) [14]	0	0	0	395	177.75	0	805	989
	10	0	98.9	395	177.75	0	805	890.1
	15	0	148.35	395	177.75	0	805	840.65
	20	0	197.8	395	177.75	0	805	791.2
	25	0	247.25	395	177.75	0	805	741.75
	30	0	296.7	395	177.75	0	805	692.3
Olofinnade et al. (2018) [15]	0	0	0	275	138	0	550	1100
	25	137.5	0	275	138	0	412.5	1100
	50	275	0	275	138	0	275	1100
	75	412.5	0	275	138	0	137.5	1100
	100	550	0	275	138	0	0	1100
Wright et al. (2014) [16]	100	796.7	0	400	184	0	0	994.5
	100	737.4	0	437.9	184	0	0	994.5
	100	885.4	0	312.3	178	0	0	994.5
	100	848.1	0	333.7	160	0	0	994.5
	100	879.2	0	314.8	179.5	0	0	994.5
	100	799.7	0	373.9	179.5	0	0	994.5
	100	830.1	0	373.9	179.5	0	0	994.5
Vijaya et al. (2015) [17]	0	0	0	383	191.6	0	727	1103
	10	72.7	0	383	191.6	0	654	1103
	20	145.4	0	383	191.6	0	581.6	1103
	30	218.1	0	383	191.6	0	508.9	1103

3. Research Methodology

Figure 1 represents the methodological approaches implemented in this study and depicts a summary of the main parameters used in building the ANN model as a predictive technique. Also, Figure 1 provides an overview of the organized and logical approaches used to accomplish the main aims of this study. Every step was carefully designed and implemented. Considering the complexity of the experimental results, data collection techniques, and diagnostic perspectives. It illustrates the research process, including ANN predictor construction, training, and validation of the dataset, to prove the robustness, validity, and reliability of the proposed ANN model.

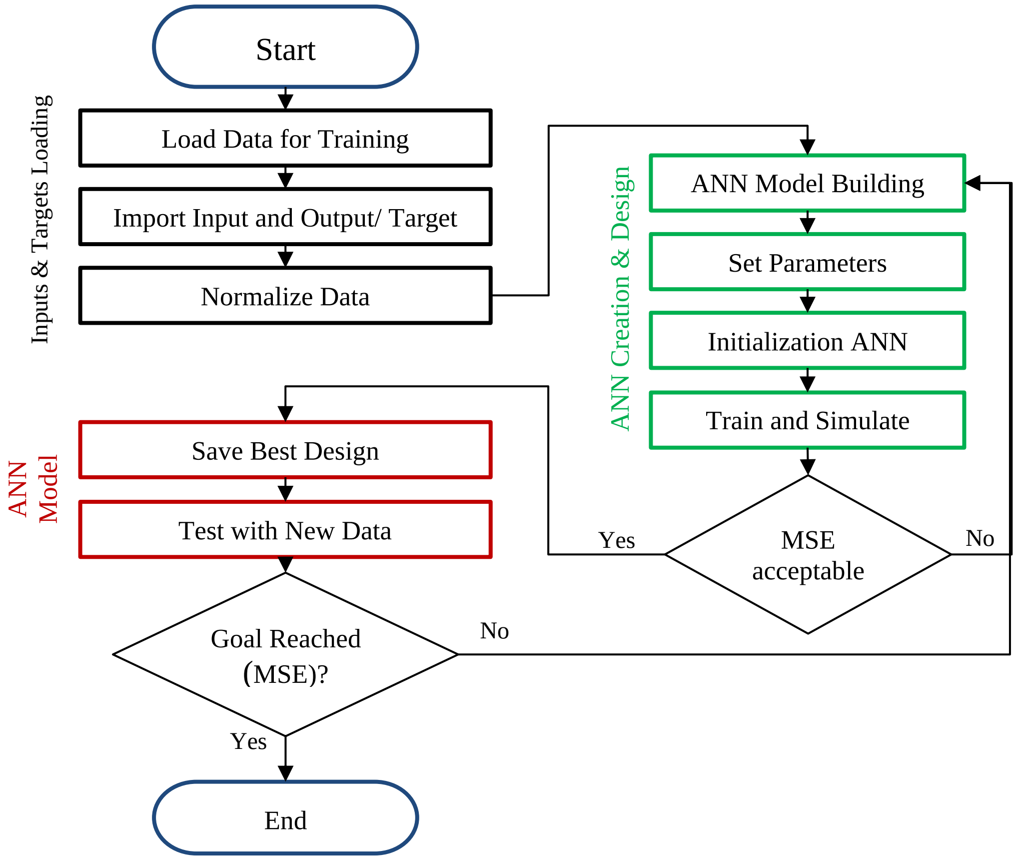

Figure 1. Methodology ANN predictor construction, training, and validation flowchart

3.1. Artificial Neural Network

Predicting the mechanical and physical properties of concrete with crushed glass as an aggregate replacement was conducted using a typical feedforward structure in an Artificial Neural Network (ANN) architecture. The input layer neurons are associated with prediction variables such as glass particle percentage and weight, coarse and fine aggregates, water, cement, and superplasticizer weights. In this layer, no activation function is employed. The techniques may have variable numbers of neurons on the hidden layers, as shown in Figure 2, using ReLU or tanh activation functions besides linear sigmoid. The output layer, responsible for predicting the mechanical and physical properties of concrete with glass aggregates, commonly has four neurons with linear activation. During the training, Adam or RMSprop with a fixed learning rate is used to minimize the mean squared error (MSE) loss function. For a different dataset, these model performance indicators are assessed by the Mean Absolute Error (MAE) or Roots Squared. This architecture offers an adaptable structure for extracting sensitive relationships between concrete constituents and properties. The model creation needed further refinement using hyperactive parameter adjustment and cross-validation.

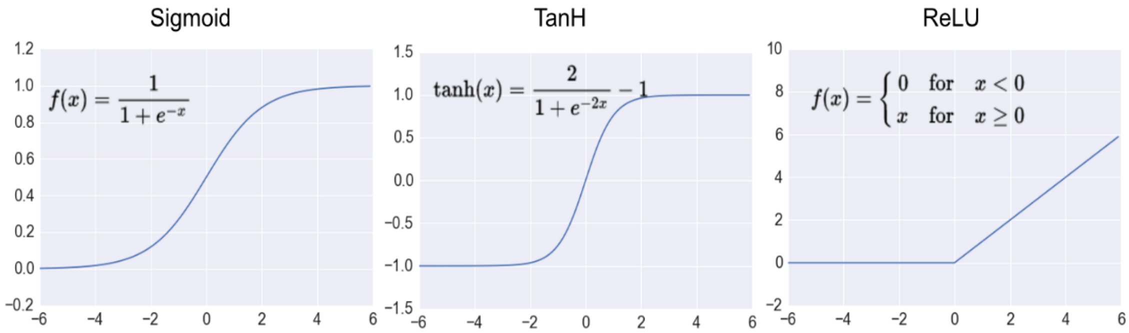

Figure 2. ANN Activation Functions

3.2. ANN Model Building and Implementation

Initially, it is necessary to gather the appropriate experimental data. This data is converted into a two-dimensional matrix; with each sample represented by a column and the total sample number indicating the number of rows. A new matrix with ***m*** columns is also needed, where ***m*** means the variables to investigate. After the data is collected, the second step of this process requires building ANN's structural design. Some significant architectural decisions are made at this stage, namely setting the number of layers, allocating neurons to every layer, and choosing a suitable activation function for each level. Starting from the architectural configuration, a set of major ANN parameters, including Mean Squared Error (MSE), and the number of training iterations are defined. The ANN model is then trained, and the MSE achieved is assessed.

The use of Artificial Neural Networks (ANN), especially within the MATLAB software suite framework, is a reliable and efficient method. There are various tools and approaches that MATLAB offers to form, train, as well as evaluate models of neural networks. Using the Neural Network Toolbox in MATLAB, complex ANN architectures can be designed by defining the network structure, which is composed of layers including several neurons and activation functions needed for glass particle-based concrete mechanical and physical prediction characteristics. The intuitive design of MATLAB makes it possible to prepare the data and train and validate ANN models based on different datasets acquired by experimental testing or non-destructive evaluations or simulations. The results obtained from 70 concrete specimens are summarized below. The creation and assessment of the ANN model benefited from the use of MATLAB code specialized in network design, training, and testing.

```
data1 = data';
in = data1(1:8,:)/1318.5;
tar = data1 (9:12,:);
net = newcf(in,tar,[8 16 32],{'logsig','logsig','logsig'});
net = init(net);
net.trainParam.goal=0;
net.trainParam.epochs=1000;
net = train(net,in,tar);
y = sim (net, in);
```

Figure 3 shows the three steps of the ANN architecture used. It is made up of 8 neurons in the input layer, two hidden layers with 16 and 32 neurons in each, and 4 neurons in the output layer. The activation function inside the hidden layer is Logsig, whereas it is linear within the output layer.

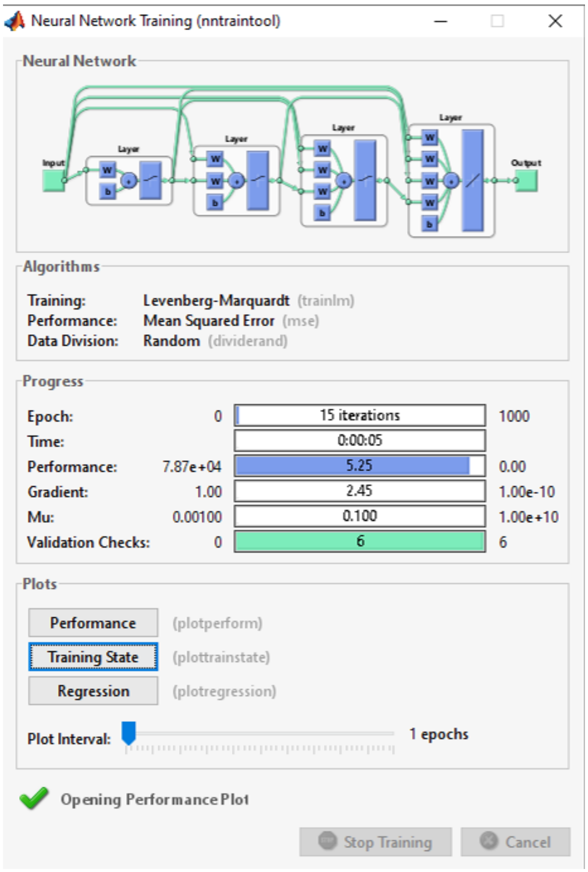

Figure 3. The Used ANN Architecture

4. Results and Discussion

The ANN model was trained using the experimental data given in Tables 3 and 4. The performance of the ANN model was very good, as it showed a considerable reduction in MSE. Figure 4 shows that the error was very low, which indicates that the predicted values were almost identical to the actual experimental results. The results of the ANN simulation were considered satisfactory since both training and validation MSE curves decreased smoothly to reach a stability point, as illustrated in Figure 4. The very small difference between the two curves points out that no overfitting took place, which indicates that training and validation specimens were meticulously selected to provide good predictions. Tables 3 and 4 confirm the MSE's forecast of close values of the actual and predicted outputs.

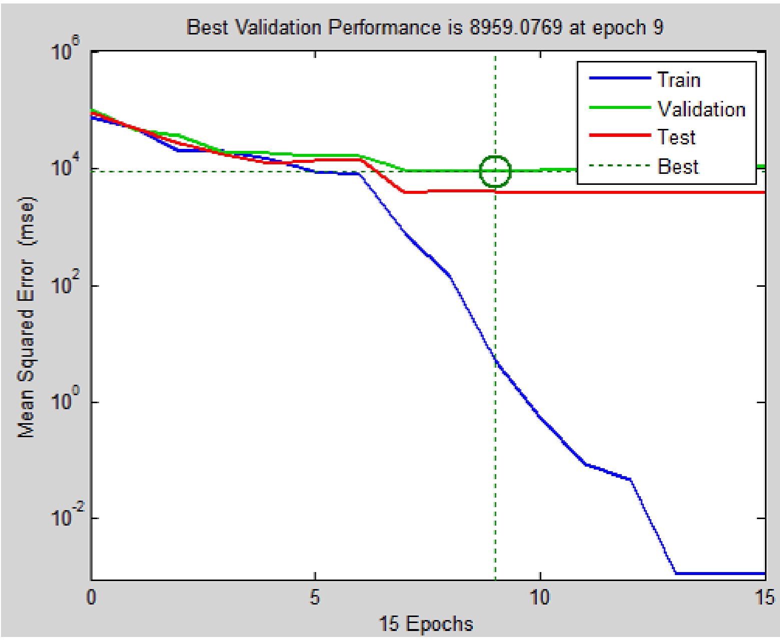

Figure 4. The ANN performance indication graph

Tables 3 and 4 constitute a comprehensive representation of data obtained from past laboratory experiments, alongside outputs generated using Artificial Neural Networks (ANN). The listed criteria include significant characteristics like compressive and tensile strengths, density, and slump that describe the mechanical-physical features of concrete. However, a closer look at the results shows that there is a high correlation between the experimental and ANN-simulated data. A visible pattern indicating the optimum 10% to 20% glass aggregate inclusion range is remarkable. However, noticeable degradation in material properties can be observed across this range. This observation arising through the comparison of laboratory and ANN data not only emphasizes the reliability of artificial intelligence technology but also provides important insights into the efficient utilization of glass aggregates as a concrete composition.

Table 3. Experimental and ANN results of compressive and tensile strengths, concrete density and slump

Reference	Experimental Results				ANN Predicted Results			
	Compressive Strength (MPa)	Tensile Strength (MPa)	Density (kg/m^3)	Slump (mm)	Compressive Strength (MPa)	Tensile Strength (MPa)	Density (kg/m^3)	Slump (mm)
Topçu & Canbaz (2004) [8]	23.5	2.590	2340	95	22.9	2.58	2346	99
	21.67	2.340	2335	100	21.7	2.87	2356	103
	20.02	3.001	2340	80	20.8	2.95	2349	82
	16.12	2.350	2330	90	17.3	2.43	2337	91
	12.04	1.630	2335	80	13.4	1.59	2340	81
Khan & Sarker (2020) [9]	39.5	4.216	2399.9	85	39.7	4.22	2402	85
	40.5	4.269	2399.9	80	40.7	4.26	2403	80
	37	4.080	2399.9	90	37.2	4.11	2405	90
	36	4.025	2399.9	100	32.1	4.10	2387	108
	23.5	3.252	2399.9	90	22.1	2.95	2353	95
	39.5	4.216	2399.9	85	39.7	4.22	2402	85
	43	4.399	2399.9	95	43.1	4.33	2402	95
	39	4.189	2399.9	85	38.2	4.21	2384	85
	33	3.854	2399.9	120	32.1	3.91	2399	118
	30.5	3.705	2399.9	135	31.4	3.66	2395	135
	39.5	4.216	2399.9	85	39.7	4.22	2402	85
	36.5	4.053	2399.9	105	34.2	3.69	2402	103
	26	3.421	2399.9	90	26.2	3.43	2399	90
	15	2.598	2399.9	185	13.9	2.59	2437	187
	12.5	2.372	2399.9	215	10.4	2.32	2392	220
Du & Tan (2014) [10]	55.1	4.310	2375	120	52.0	4.20	2375	119
	56.5	4.230	2370	95	54.3	3.91	2285	93
	47.5	4.450	2360	90	47.5	4.48	2365	88
	45.2	4.420	2350	110	44.5	4.42	2376	107
	47.6	4.710	2340	100	46.1	4.65	2344	97
	57.2	4.620	2395	95	55.1	4.62	2400	95
	60.3	4.330	2390	105	59.4	4.41	2394	105
	62.1	4.650	2378	115	62.0	4.59	2381	114
	56.1	4.680	2372	110	56.5	4.71	2375	108
	60.1	4.690	2360	104	61.2	4.75	2363	102
	67.2	4.720	2450	95	65.8	5.05	2465	93
	65.1	4.720	2450	120	64.7	4.72	2454	120
	68.3	4.610	2400	100	68.4	4.68	2403	100
	70.2	4.620	2395	110	70.5	4.60	2395	110
	71.1	5.400	2383	115	72.2	5.11	2286	115

Table 4. Experimental and ANN results of compressive and tensile strengths, concrete density and slump

Reference	Experimental Results				ANN Predicted Results			
	Compressive Strength (MPa)	Tensile Strength (MPa)	Density (kg/m^3)	Slump (mm)	Compressive Strength (MPa)	Tensile Strength (MPa)	Density (kg/m^3)	Slump (mm)
Olofinnade et al. (2016) [11]	20	3.800	2063	20	18.8	4.14	2460	19
	20	3.000	2064	16	18.7	3.09	2062	15
	16	2.500	2063	16	15.6	2.50	2056	18
	15	2.300	2064	15	14.4	2.27	2055	16
	14	2.100	2063	15	14.3	2.10	2059	14
Tamanna (2020) [12]	40	3.400	2399	90	37.4	3.44	2398	88
	43	3.400	2372	60	39.9	3.15	2361	57
	32	3.500	2369	65	31.4	3.53	2372	63
	36	3.000	2356	40	34.2	3.11	2538	42
Elavarasan & Dhanalakshmi (2016) [13]	30.33	2.300	2391	65	30.2	2.52	2397	68
	31.33	2.520	2391	68	31.1	2.63	2397	70
	31	3.210	2391	73	30.7	2.83	2395	66
	29.66	3.100	2390.8	60	29.4	3.04	2396	60
Hasan et al. (2023) [14]	39.1	4.195	2366	39	38.2	4.80	2365	38
	41	4.295	2366	42	39.0	4.42	2366	41
	40.4	4.264	2366	46	38.7	4.25	2367	46
	34.8	3.957	2366	55	32.5	4.11	2371	57
	35.65	4.005	2366	61	33.6	3.95	2382	63
	32.81	3.842	2366	63	31.1	3.76	2397	64
Olofinnade et al. (2018) [15]	20.11	3.008	2375	55	19.7	3.21	2385	53
	23.75	3.269	2356	50	24.4	3.35	2356	54
	23.21	3.232	2321	50	23.2	3.29	2320	52
	18.75	2.905	2285	44	18.4	2.92	2283	43
	14.15	2.523	2240	40	14.1	2.55	2238	39
Wright et al. (2014) [16]	37.4	4.102	2375	114	39.0	4.13	2381	112
	34.9	3.963	2354	127	35.6	4.94	2383	124
	27.9	3.543	2370	38	29.1	3.66	2367	36
	29.2	3.625	2336	32	31.2	3.91	2375	31
	29	3.612	2368	127	30.2	3.60	2372	124
	28.1	3.556	2348	140	29.5	3.58	2353	136
	32.7	3.836	2378	127	29.6	3.88	2342	125
Vijaya et al. (2015) [17]	22.77	3.201	2389	25	23.3	3.15	2380	26
	25.88	3.413	2356	27	26.4	3.11	2350	28
	29.84	3.664	2322	29	31.0	3.17	2314	30
	24.66	3.331	2295	26	24.4	3.27	2301	26

A comparative study between the experimental and ANN-predicted values is presented in Figures 5 to 8.

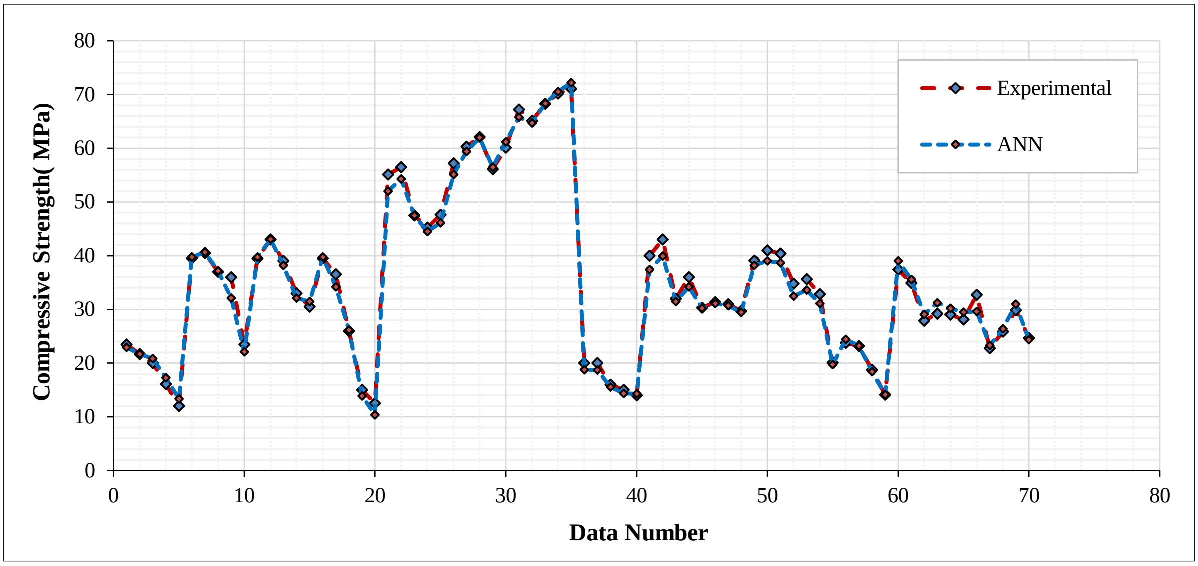

Figure 5. Compressive strength (Experimental and ANN-predicted)

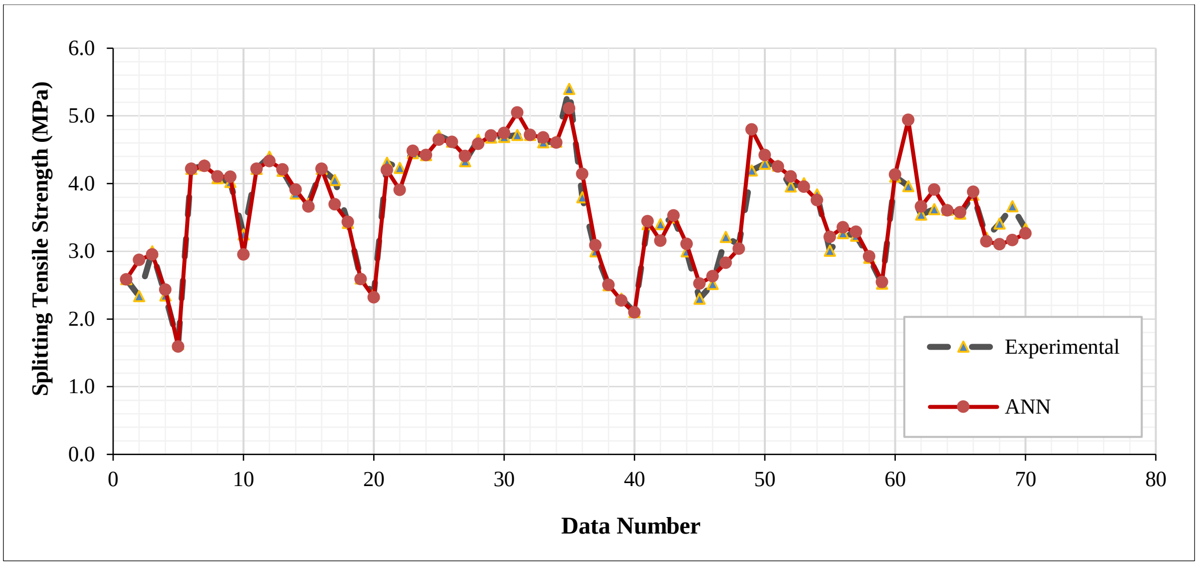

Figure 6. Splitting tensile strength (Experimental and ANN-predicted)

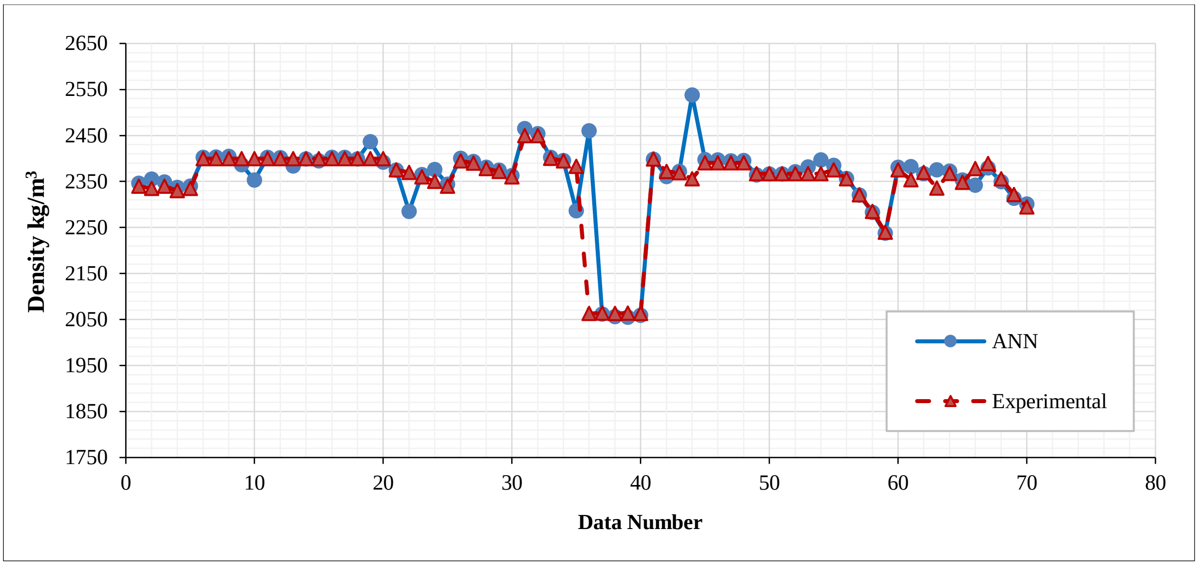

Figure 7. Concrete density (Experimental and ANN-predicted)

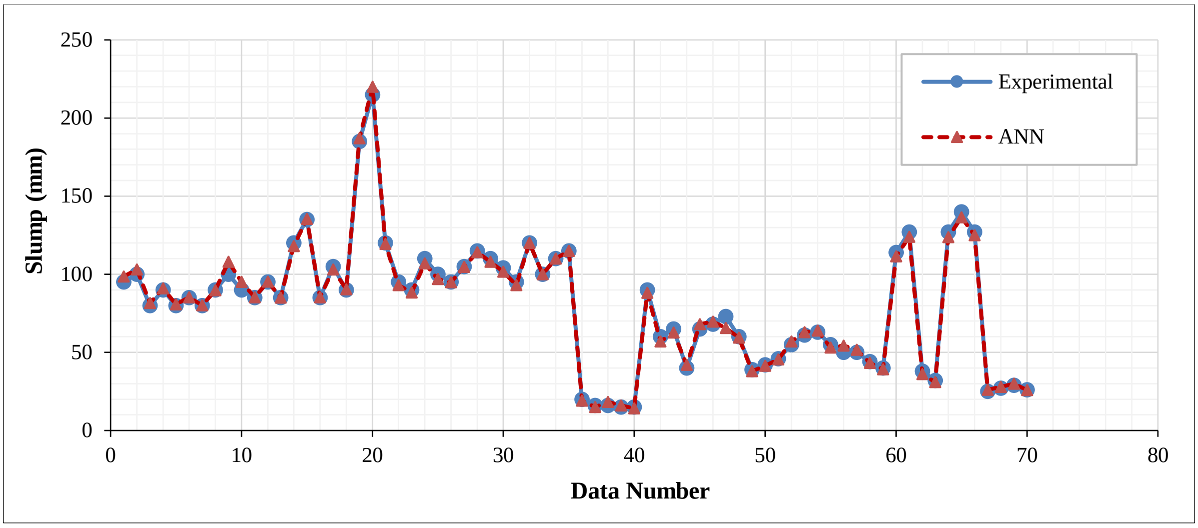

Figure 8. Concrete slump (Experimental and ANN-predicted)

Figures 5-8 show the remarkable proximity observed between experimental and Artificial Neural Networks (ANN) predicted data, which is attributed to extensive database inclusion. This dataset covers a wide range of concrete strengths and glass aggregate percentages, including all concrete ingredient weights as well as variable percentages of glass aggregate. This wide range of data reveals the interaction between these factors and enables a deeper understanding of the impact of glass aggregate on concrete characteristics. Additionally, the broad dataset confirms the strength and reliability of ANN-predicted results. An increase in glass aggregate percentage results in decreased compressive and tensile concrete strengths consequently. This phenomenon is due to the weaker bond between the hardened cement paste and the smooth surfaces of glass aggregates. In addition, glass aggregate is weaker compared to natural aggregates. The slump values are highly related to the water/cement ratio and the use of superplasticizers in concrete mixtures. It is worth mentioning that the increased glass aggregate percentage increases slump due to almost zero water absorption of glass and, at the same time, decreases slump due to the high angularity of external glass aggregate surfaces. Concurrently, the density results show sensitivity to the weights of concrete constituents used, which points out that composition has a major importance in deciding the concrete density. This broad knowledge underlines the complicated nature of factors that influence the properties of concrete containing glass aggregate.

The results show a clear trend wherein the optimum percentages of glass aggregate are between 10% and 20%. For concrete mixes with glass aggregate percentages higher than 20%, there is a clear decline in concrete properties. The analysis highlights the importance of properly selecting the mix design proportions, including glass aggregate content in concrete mixes, to find an optimum balance between sustainability, material efficiency, and the overall satisfactory performance of concrete.

In this study, the optimal range of glass aggregate was found to be 10% to 20%. This range is favorable for the concrete properties, as characteristics such as increased tensile strength, good shock absorption, and weathering capability also overshadow those of other percentages of the aggregate mixture. The works made of concrete with particles of glass as an aggregate, from 10% to 20%, have the best results in terms of compression strength, tension strength, density, and slump value. This interval represents the golden percentage of glass aggregates, where numerous benefits were provided to counterbalance the serious issues of high concentrations. However, when the glass aggregate content reaches upper levels of 20%, there is a darkness in the properties of concrete. Consequently, the most exposed to corrosive conditions experience a drop in compressive and tensile strengths as well as reduced density and workability of the concrete content, as measured by slump values of the fresh mix. The amount of glass incorporations that exist in the concrete may cause the matrix to diminish as a result of a lack of bonding and excess porosity. Consequently, the mechanical and physical performances of the concrete are degraded, which occurs from the decrease in the properties of the mix with a smaller percentage of glass aggregates.

As a result, the appropriate volume of glass aggregate in the range of 10% to 20% between them comes to the forefront as a key factor for attaining an acceptable property of the concrete. With the optimal composition of glass concrete, producers, designers, and engineers can take advantage of the positive credentials of glass aggregate in concrete projects and, on the other hand, minimize the possible negative results. This inference suggests a clear path to sustainable concrete production and encourages deliberate exploration of using recycled materials in construction.

The regression analysis was done using MATLAB software. Figure 10 presents a step-by-step comparison between the predicted and experimental results. There is a random and symmetric distribution of the data points above or below the 45-degree line, showing homogeneity in variance for this dataset. The closures of the mentioned data point to a line, indicating that the model fits well, as shown in Figure 9. This conclusion underpins the high accuracy of predicting values by showing how few deviations occur in real comparison with ideal diagonal alignment. The overall determination coefficient, or R-value, of 0.9985 confirms the validity model developed hereinabove. This high R-value confirms the suggested model's validity and accuracy in predicting values with precision.

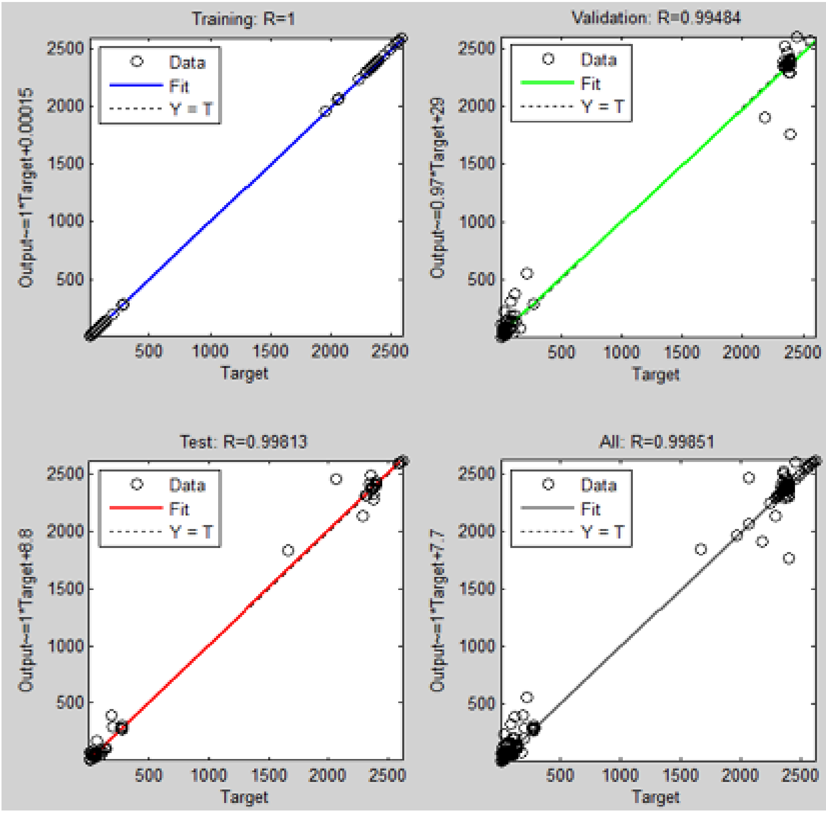

Figure 9. Regression analysis results (R-Values for training, testing, validation, and all datasets)

5. Proposed ANN Model Verification

The generated Artificial Neural Network (ANN) was used for predicting extra datasets obtained from existing literature, therefore verifying the efficiency of the proposed models. The dataset, outlined in Table 5, was collected from three independent years of past research, including a wide range of concrete compositions with varied percentages of glass aggregates.

Table 5. Mix design proportions and data from previous experimental research for ANN-Mode Verification

Reference	Glass %	Fine Glass (kg/m^3)	Coarse Glass (kg/m^3)	Cement (kg/m^3)	Water (kg/m^3)	Plasticizer (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)
Saand et al. (2017) [33]	0	0	0	429.9	193.5	0	644.9	1289.7
	4	26.13	0	436.13	196.3	0	628.1	1308.4
	8	52.37	0	437	196.64	0	603.1	1310.9
	12	79	0	439.5	197.77	0	580.23	1318.5
	16	104.2	0	435	195.7	0	548.3	1304.8
	20	129.4	0	432	194.3	0	518.5	1295.8
	24	155.2	0	431.6	194.2	0	492.2	1294.8
	28	180.8	0	431.1	194	0	465.8	1293.3
	32	206	0	429.8	193.4	0	438.6	1289.2
	36	229.3	0	425.2	191.3	0	408.5	1275.7
	40	250.8	0	418.5	188.3	0	376.9	1255.5
Drzymala et al. (2020) [34]	0	0	0	290	175	3	1034	881
	10	100	88	290	175	3	934	793
	30	313	264	290	175	3	721	617
	50	517	440	290	175	3	517	441
	100	1034	881	290	175	3	0	0

	0	0	0	385	140	5.25	936	936
	10	79.2	0	385	140	4.55	842.4	936
	20	158.4	0	385	140	4.2	748.8	936
	30	237.6	0	385	140	4.2	655.2	936
	40	316.8	0	385	140	3.85	561.6	936
	50	396	0	385	140	3.85	468	936
	0	0	0	440	160	7.2	890	890
	10	75.3	0	440	160	6.8	801	890
Ali & Al-Tersawy (2012) [35]	20	150.6	0	440	160	6.8	712	890
	30	225.9	0	440	160	6.8	623	890
	40	301.2	0	440	160	6	534	890
	50	376.5	0	440	160	6	445	890
	0	0	0	495	180	8.1	846	846
	10	71.6	0	495	180	7.65	761.4	846
	20	148.2	0	495	180	7.65	676.8	846
	30	214.7	0	495	180	7.65	592.2	846
	40	286.3	0	495	180	6.75	507.6	846
	50	357.9	0	495	180	6.75	423	846

Table 6 presents the most comprehensive list of parameters perfectly delivered by the proposed and, hence, carefully constructed ANN model for this specific aim. This model is an archetype, merging the creative powers of cutting-edge algorithms and current computation capabilities, which brings to light the ability of Artificial Neural Networks (ANNs) to outperform subsequently familiar problems even well beyond the initial training dataset. Using a bold mixture of neural ties and repetitive learning, the ANN achieves proficiency in the art of recognizing and copying that complex hidden within a wide range of architectural forms and innovative concrete distribution. Its capacity to bind the diversity of variants present in hydraulic binders and compress those data, rendering them in a meaningful and descriptive way, outlines ANN's remarkable agility and strength.

Table 6. Experimental and ANN results of compressive and tensile strengths, concrete density, and slump for ANN-Model verification

Reference	Experimental Results				ANN Predicted Results			
	Compressive Strength (MPa)	**Tensile Strength (MPa)**	**Density (kg/m^3)**	**Slump (mm)**	**Compressive Strength (MPa)**	**Tensile Strength (MPa)**	**Density (kg/m^3)**	**Slump (mm)**
Saand et al. (2017) [33]	31.5	3.765	2558	26	31.7	3.40	2574	21
	34.75	3.954	2595	29	34.8	3.86	2599	29
	39.25	4.203	2600	31	35.8	4.00	2601	33
	44	4.450	2615	34	41.3	4.16	2612	39
	38	4.135	2588	37	36.9	3.93	2588	37
	33	3.854	2570	39	32.3	3.76	2573	38
	30.25	3.690	2568	42	30.3	3.67	2571	41
	28.5	3.581	2565	45	28.1	3.55	2568	44
	26.5	3.453	2557	48	25.9	3.41	2561	47
	24.25	3.303	2530	51	24.0	3.26	2534	50
	23.5	3.252	2490	54	23.2	3.19	2494	53
Drzymala et al. (2020) [34]	46.19	4.559	2300	124.7	45.6	4.62	2306	124
	39.95	4.240	2290	141.1	37.9	4.87	2301	139
	31.17	3.745	2180	167.5	31.4	3.67	2190	169
	14.16	2.524	1960	191	15.2	2.53	1970	191
	4.23	1.380	1660	200	5.2	1.31	1680	205

	46.3	4.7	2402	267	48.5	4.87	2301	262
	43.5	4.2	2387	270	43.8	3.67	2190	270
	41.5	4.2	2372	273	41.7	2.53	1970	273
	40.4	4.1	2358	275	42.7	1.31	1680	285
	38.2	3.9	2343	282	38.2	4.32	2409	282
	35.6	3.2	2329	283	35.5	4.20	2382	282
	62.2	6.8	2387	268	61.8	4.25	2366	269
	59.4	6.2	2373	270	55.7	4.17	2352	263
Ali & Al-Tersawy (2012) [35]	53.2	5.8	2359	272	53.0	3.92	2338	272
	51.6	5.7	2346	273	51.6	3.23	2325	273
	48.4	5.2	2331	275	48.6	6.82	2385	275
	47.5	4.9	2318	276	47.9	5.99	2385	276
	67.7	7.1	2375	270	67.4	5.77	2360	270
	65.2	6.8	2362	272	65.7	5.73	2349	278
	61.6	6.5	2354	273	61.6	5.20	2334	274
	58.5	6.4	2336	276	58.7	4.91	2321	276
	55.8	6.2	2322	276	56.1	7.10	2375	276
	53.6	5.5	2309	277	54.5	6.74	2367	279

A comparative study was conducted between the experimental and ANN-predicted values. The results of this study are presented graphically in Figures 10 to 13.

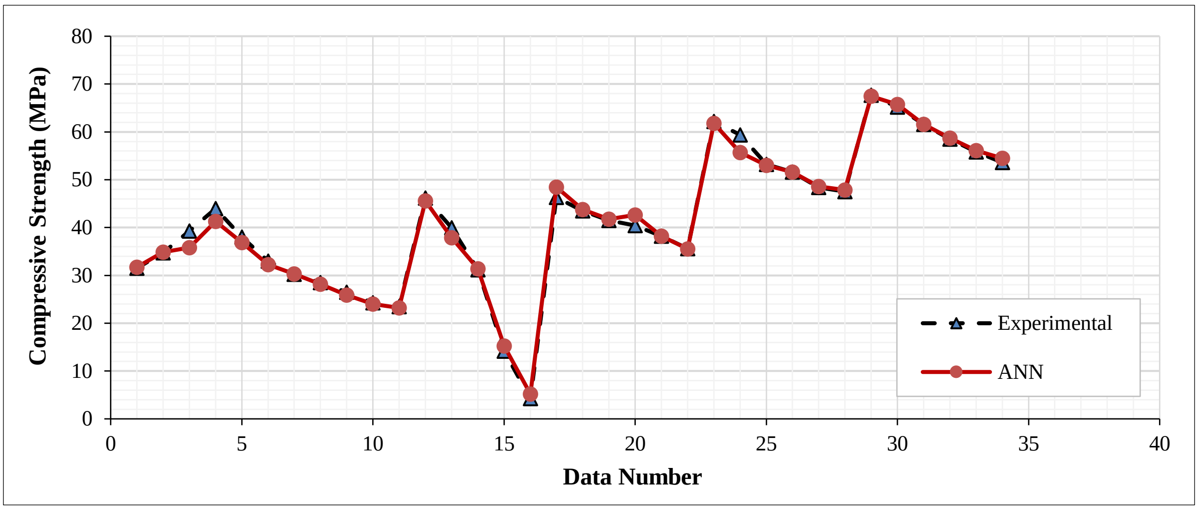

Figure 10. Concrete compressive strength (Experimental and ANN-predicted)

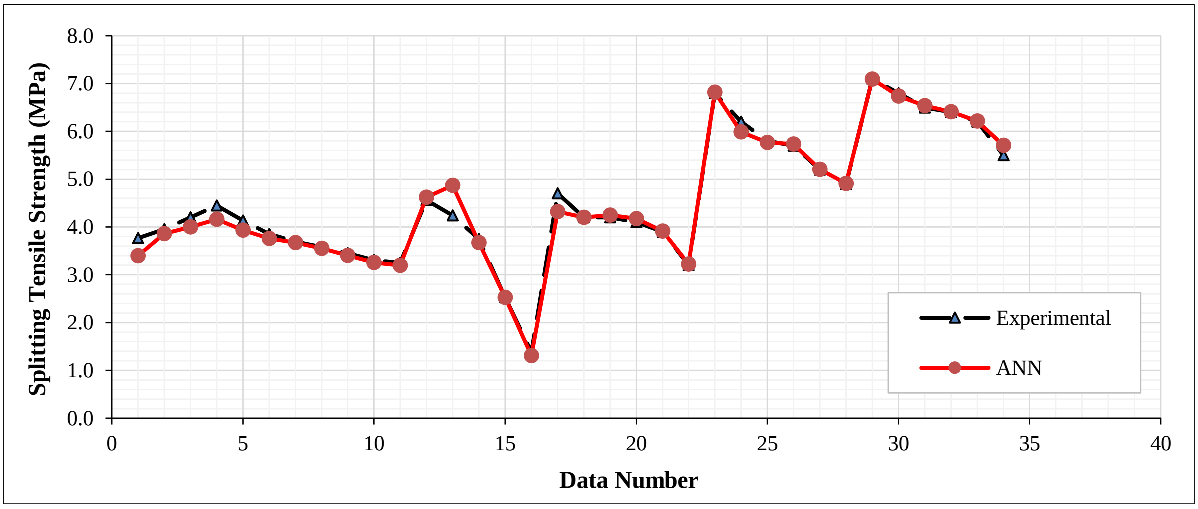

Figure 11. Concrete splitting tensile strength (Experimental and ANN-predicted)

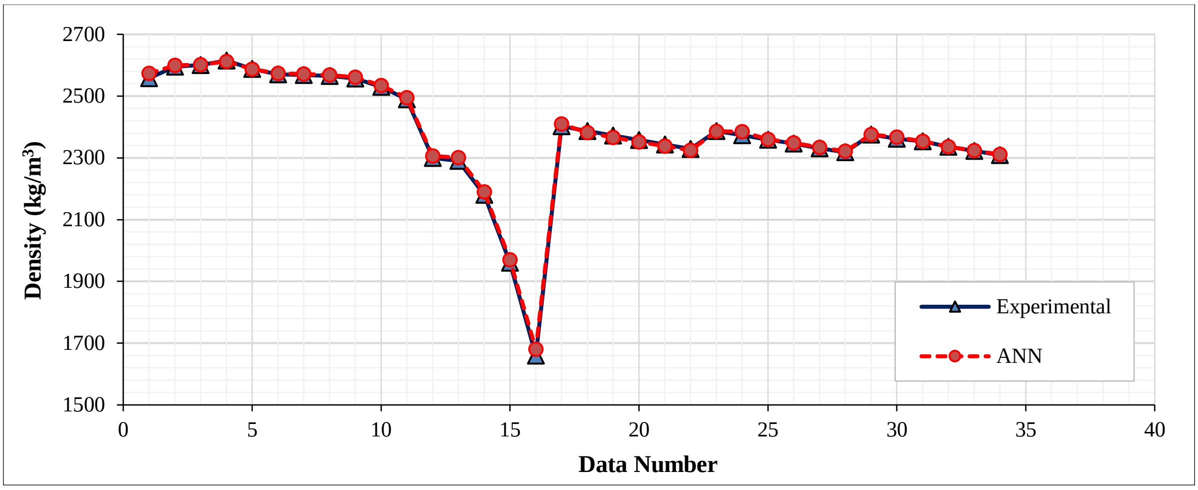

Figure 12. Concrete density (Experimental and ANN-predicted

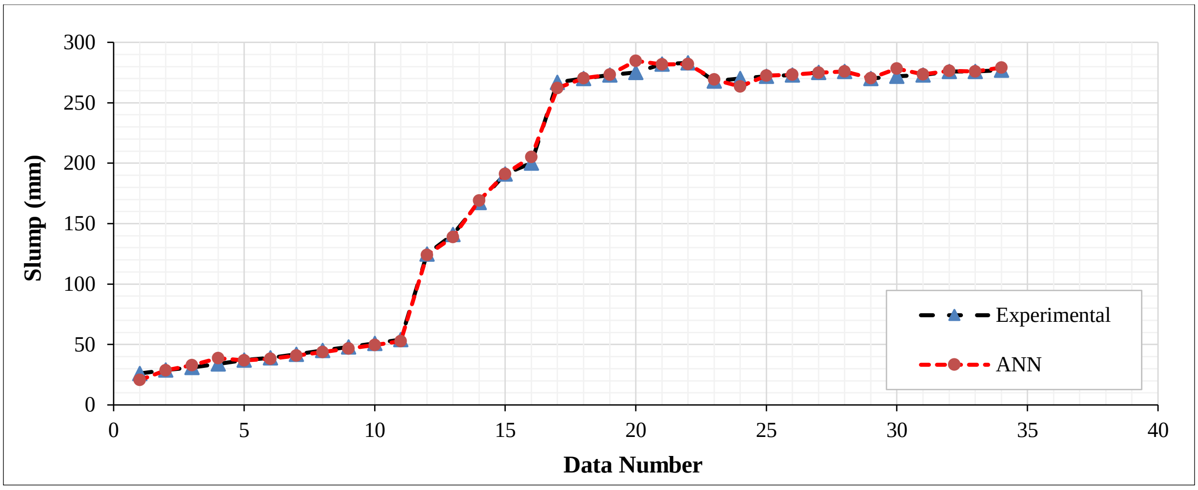

Figure 13. Concrete slump (Experimental and ANN-predicted)

The ANN appears to be quite effective in this case, as when the data obtained from the experiment is closely matched with Figures 10 through 13, their striking similarity enhances the confidence as presented in Table 6. Careful comparison shows minimal discrepancy, resulting in little difference between the datasets. Moreover, the average difference between both datasets stays below 2% throughout all results. This exceptionally close agreement confirms the ability of the ANN model to reach down into and perfectly reproduce the detailed mechanics and physics underlying concrete properties. Along with that, the coefficient of determination (R-value), which is obtained because of the validation process, indicates that the ANN model is reliable for the forecasting model, with an outcome of about 0.99484. Such a high R-value just abilities the model of ANN to predict the bytes behavior of waste glass concrete firmly and just affirms the ability of the ANN model. The fact that the empirical results comported sufficiently with the modeled values, with the statistical significance (R-value) being very high as well, further vindicates the performance of the developed ANN methodology, especially its precision in faithfully reproducing the actual ways in which waste glass concrete operates as a material.

ANN models deserve a lot of recognition as they produce an error rate of approximately 2% and in a consistent manner, which means that the predictive models must be accurate and reliable. This does not exceed the maximum error in the reduction and indicates the accuracy of the data obtained in the laboratory experiment and the data predicted by the ANN models. The reliability in the performance of the ANN models that shows the ability to represent and recreate the multidimensional and dynamic actions of the specimens incorporating the aggregate mix is thus evident. The low error margin percentage revealed by this model implies that ANN models can correctly predict yield strength, total porosity, dry density, and slump with a high degree of accuracy, which inspires confidence in their dependability. As such, stakeholders in the civil engineering industry can use these forecasting technologies with peace of mind to guide their decision-making processes, choose optimal concrete composition, and be aware of the performance of glass-infused cement in real-life case studies.

The validation methods that are included in this study to check the credibility of the ANN models by using supplementary measures of experimental data are an essential part of model fitness checking to observe representational ability. Upon integrating diverse datasets acquired from multiple sources of experimental data, including past research, the verification process therefore equips the ANN models with a comprehensive and representative dataset, thereby ensuring that these models are exposed to the envisaged representation. The ANN models can thus represent a broader concrete aggregate spectrum: Different combinations of increased glass-to-cement aggregates and harder concrete strengths can also be accommodated. Because of this, the ANN models are more capable of learning and comprehending the complex connections between input attributes (like very fine overlay percentages, cement consumption, and water-cement ratio) and consequent physical properties (including compressive strength, tensile strength, density, and slump). In addition to this, the brand-new thing that can be checked by comparing the calculated values from ANN models against validated experimental data would be the ANN models' precision and credibility. The comparisons between predicted and experimental values as well as the results demonstrate the ANNs' proficiency in approximating experimental outcomes, thereby exhibiting their ability to be replicated experimentally. The meaningful relationships between concrete mixture components and its properties demonstrated through the calibration and validation process reinforce the ANN models' generalization and prediction ability concerning working conditions that may vary. In conclusion, using successful validation strategies will increase the trust and reliability of the ANN simulation systems, so that developers and practitioners in the building industry can synthesize optimal concrete batches and make concrete performance predictions with more confidence.

6. Conclusions

Several conclusions that arise from this comprehensive study on the use of crushed waste glass to replace natural fine and coarse aggregate in concrete, combined with the predictive capabilities of Artificial Neural Networks (ANN), can be summarized as follows:

- The research relies, in part, on a 20-year database with different concrete strength and glass aggregate contents as well as specimen constituent weights. This wide-range dataset is an excellent starting point for acquiring a deep understanding of the complex interaction between constituents in concrete mixes.
- The accuracy of the ANN models is demonstrated by the complete overlap between experimental and predicted values. Throughout all analyses, the reported error margin is low and constant, around 2%.
- The validation process shows the ANN model to be reliable, with coefficients of determination (R-values) often showing high accuracy. The validation R-value of 0.99484 reflects the robustness of predictive tools in simulating complexities within concrete.
- The results reveal a distinct trend, whereby the optimal percentages for glass aggregate addition are between 10% and 20%. Higher glass content leads to an obvious decline in concrete properties.
- This research has proven the effectiveness of ANN in predictive modeling. This in-depth study of factors influencing concrete behavior provides details on the use of glass aggregates in concrete to pave the way for future advancements in sustainable concrete technology.

The prospects of study in this field show potential for further research and development. Future studies should be directed toward glass quality and properties to improve concrete properties, considering the differences in particle size, shape, or surface characteristics. A more detailed investigation of impacts on the environment and life cycle assessments could provide a deeper understanding of the sustainability of waste glass concrete. Other methods, including machine learning algorithms and deep learning models, could be applied alongside ANN to enhance the accuracy of predictions. Such a future line of research can not only change established methods but also open the door for innovative, eco-friendly concrete technology solutions.

7. Declarations

7.1. Author Contributions

Conceptualization, F.M., A.A.Y., E.A., J.A.O., and J.A.A.; methodology, F.M., A.A.Y, E.A., J.A.O., and J.A.A.; formal analysis, F.M., A.A.Y., and E.A.; writing—original draft preparation, F.M., A.A.Y., E.A., J.A.O., and J.A.A.; writing—review and editing, F.M., A.A.Y., E.A., J.A.O., and J.A.A. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available in the article.

7.3. Funding

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7.4. Acknowledgements

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7.5. Conflicts of Interest

The authors declare no conflict of interest.

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