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ORIGINAL RESEARCH ARTICLE

PREDICTION MODELING OF 28-DAY CONCRETE COMPRESSIVE STRENGTH USING ARTIFICIAL NEUTRAL NETWORK

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ABSTRACT
Compressive strength of concrete at the age of 28 days is an important parameter for the design of concrete structures and waiting for that length of time to obtain the value can be tasky. This study developed an alternative approach using Artificial Neutral Network (ANN) to estimate or predict the compressive strength of concrete at 28th day from early age results. In the study concrete cubes of mix ratio 1:2:4 were cast with different water-cement ratios (0.4, 0.5, 0.6 and 0.65) and their seventh (7th) and twenty-eighth (28th) day strength were measured in the laboratory. In all, 400 cubes of 150 x 150 x 150mm of 200 sets were subjected to compressive strength test using Avery Denison Universal Testing Machine of 2000 kN load capacity at a constant load application of 15kN/s. ANN model was then developed using the time series tool of ANN in MATLAB 7.12.0 (R2011a) applying back propagation algorithm. Out of the 200 sets of results, 110 sets (55%) were used for the training of the network while 30 sets (15%) were used to validate and 60 sets (30%) to test the network. The result of the crushing test shows that the higher the compressive strength at seventh (7th) day the higher it will be at twenty-eighth (28th) day. The result of the ANN model shows a good correlation between the seventh (7th) day compressive strength and the twenty-eighth (28th) day compressive strength with training and validation correlation coefficients of 0.99751 and 0.99736 respectively. It was also found that the ANN model $f_{28} = 1.5344f_7 + 0.3092$ is quite efficient in determining the twenty-eighth (28th) day compressive strength of concreteas the predicted strength values match very well with those obtained experimentally with a correlation coefficient of 0.99675.

1.0 Introduction

Concrete is one of the most widely used building materials in the World because of its versatile application, satisfying performance in strength requirements and its ability to be moulded into a variety of shapes and sizes (Kayode and Ilessama, 2015). It is a synthetic construction material made by mixing of cement, fine aggregates, coarse aggregate and water in the correct proportion, and each of these components contribute to the strength of the concrete as reported by Gambhir (2004). The fine aggregates fill up the voids formed by the coarse aggregates; and cement fills up the voids of the fine aggregates as the lesser the voids the more the strength of concrete (Mehta and Monteiro, 2006).

The strength of concrete comprises mainly of the compressive, split tensile and flexural. In the construction industry, strength is a primary criterion in selecting concrete for a particular application. Concrete used for construction gains a significant component of its strength during the initial 3 to 4 weeks, but continues to do so over a long period of time after pouring (Chopra et al., 2015). The characteristic strength of concrete is defined as the compressive strength of a sample that has been cured for 28 days.

The use of concrete for mass concreting in huge civil projects like bridges, dams, power plants, are usually performed in several layers and the concrete strength of each layer must be achieved. Therefore, one has to wait for 28 days to achieve a 28-day strength for each layer of the concrete. This is time consuming and costly to perform as $28 \times n$ days will be needed to obtain the 28-day strength for n layers. However, to hasten the construction progress we must be able to predict the concrete strength based upon the early strength data. Therefore, rapid and reliable prediction for the strength of concrete would be of great significance.

The prediction of concrete strength and behaviour, therefore, has been an active area of research and a considerable number of studies have been carried out in it (Bamiyo et al., 2016; Zain and Abd, 2009; Zelic et al., 2004; Akkurt et al., 2004; Hwang et al., 2004; Kheder et al., 2003; Zain et al., 2002). It is well recognized that the prediction of concrete strength is important in the modernized concrete construction and engineering judgment (Dias and Pooliyadda, 2001).

Thus, for the sake of saving time, decreasing the cost of production of concrete and wastage of materials, the help of Artificial Neural Network (ANN) is taken to develop models, so that the knowledge extracted from these models, can be utilized to predict the strength of concrete.

The Artificial Neural Network (ANN) is a form of Artificial Intelligence (AI) that attempts to mimic, in a very simplistic way, the human cognition capability to solve engineering problems that have defied solution using conventional computational techniques (Flood, 2008). A typical structure of ANN consists of a number of processing elements (PEs), or nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers as shown in Figure 1. The ANN modelling philosophy is similar to a number of conventional statistical models in the sense that both are attempting to capture the relationship between a historical set of model inputs and corresponding outputs (Shain et al., 2001).

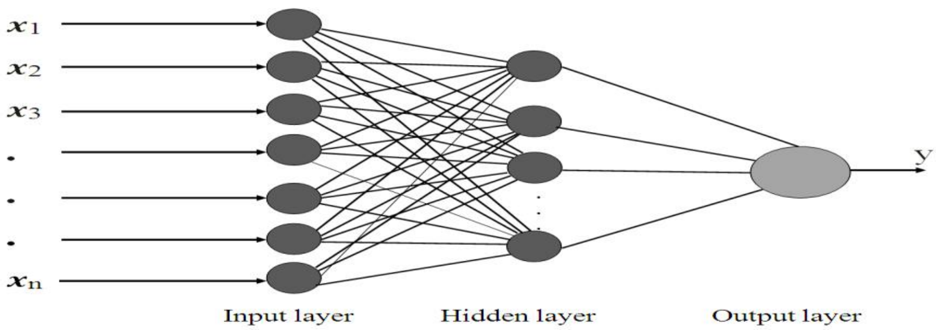

Figure 1: Typical Structure of ANN (Chopra et al., 2015)

Unlike conventional problem solving algorithms that are basically based upon statistical analysis by which many linear and nonlinear regression equations have been constructed to model such a prediction problem (Monjurul and Ahsanul, 2011), Artificial Neural Network can be trained to

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perform a particular task. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples. The ANN will then extrapolate the mapping between input and output data. After training, the ANN can be used to recognize data that is similar to any of the examples shown during the training phase (Rafiq, 2001). The ANN can even recognize incomplete or noisy data and also have the ability to self-organize, therefore enabling segmentation or coarse coding of data. This is an important feature that is often used for prediction, diagnosis or control purposes.

In general, ANN have the ability to simulate the behaviour of systems with limited modelling effort and provide speedy and reasonably accurate solutions in complex uncertainties and subjective situations. Thus, this study aims at investigating the feasibility of predicting the 28th day compressive strength of concrete with the aid of ANN using its strength obtained at the 7th day.

2. Materials and Methods

The materials used for this study were sourced within Kano State, Nigeria and the experimental procedures to arrive at the desired results were carefully followed. Also, the specification and quality of the test materials were kept same throughout the test

2.1. Materials

The binder used in this study was Ordinary Portland Cement (OPC), 3X brand manufactured by Dangote Cement Nigeria Plc. The cement was of grade 42.5 with a specific gravity of 3.14 as determined in accordance with BS 812 (1985). Naturally occurring clean sand, free of adulteration, obtained from river Challawa in Kano State was used as the fine aggregates. The specific gravity of the fine aggregate was found to be 2.6 and it was then classified as Zone-II after conducting sieve analysis in accordance to BS 882 (1992).

Crushed granite stones of 20mm nominal diameter with aggregates crushing value of 22% and specific gravity of 2.7 were used as the coarse aggregates. It was obtained from a standard quarry site of Abduljalil Hajaig and Sons Ltd in Kano State. The water used for mixing and curing was portable tap water from the Civil Engineering Laboratory of Bayero University Kano and satisfied ASTM C1602-12 specification of water for use in concrete mixtures. Artificial Neural Network toolbox in MATLAB (R2011a) package was used in developing the network architecture for the predictions in this study. The input variables for the proposed neural network consisted of water cement ratio (w/c), cement content, fine aggregate content, coarse aggregate content and 7th day compressive strength, while the output variable was the 28thday compressive strength.

2.2. Method

A grade 25 concrete was produced using water/cement ratio of 0.4, 0.5, 0.6 and 0.65 as shown in Table 1. Fifty (50) concrete cubes were cast for each mix proportion using 150mm x 150mm x 150mm metal moulds. A total of 200 sets of concrete cubes were cast, de-moulded after 24hours and then immersed in water for curing ages of 7 and 28 days respectively.

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Table 1: Concrete Mix Proportion

Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)	Water (kg/m^3)	Water Cement Ratio (W/C)
360.4	720.8	1441.7	144.2	0.4
348.8	697.6	1395.2	174.4	0.5
337.6	675.2	1350.4	202.6	0.6
332.2	664.5	1329.0	216.0	0.65

2.2.1 Compressive Strength

The compressive strengths of the cubes were carried out using the mix proportions in Table 1. Mixing was done manually and cast in steel cube molds of 150mm and cured in water for 7 and 28 days. A total of 400 cubes amounting to 200 sets were tested at the end of each curing regime. The samples were crushed in accordance with BS EN12390-3 (2009) using the Avery Denison Compressive Testing machine of 2000 kN load capacity at constant loading rate of 15kN/s and the average loading rate taken. The compressive strength was taken as the maximum compressive load the cube can carry per unit areas and was calculated as follows:

$$Compressive \quad strength = \frac{F}{A} \tag{1}$$

2.2.2 Network Development, Training, Validation and Testing

ANN tool box in MATLAB (R2011a) was used in developing the network architecture. Input data in the form of 6-column matrix containing the input parameters: water content (kg/m^3), cement content (kg/m^3), fine aggregates (kg/m^3), coarse aggregates (kg/m^3) and 7th day compressive strength (N/mm^2) were fed into the workspace. These automatically made the input neurons in the input layer to be six (6). The training algorithm adopted for the study in the feed forward network is the Levenberg – Macquardt's and after several random trials, the number of neurons in the hidden layer for optimal convergence was found to be three (3). Since the output parameter is one (1) (28th day compressive strength), the number of neurons in the output layer was one (1). The final network architecture for the study and the workflow showing the step-by-step ANN development processes are as shown in Figures 2 and 3 respectively.

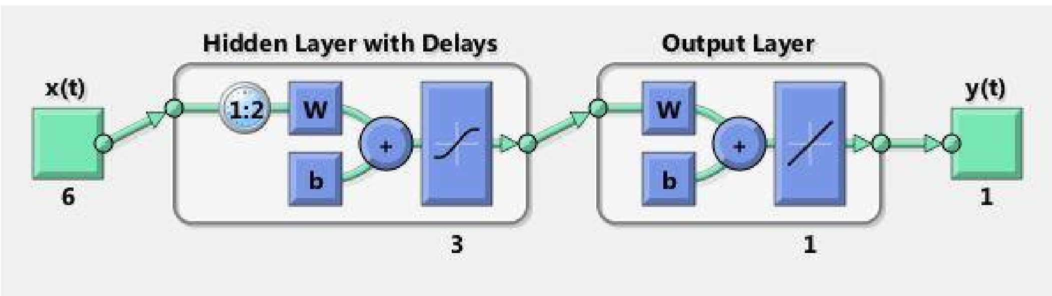

Figure 2: Final Artificial Neural Network Architecture

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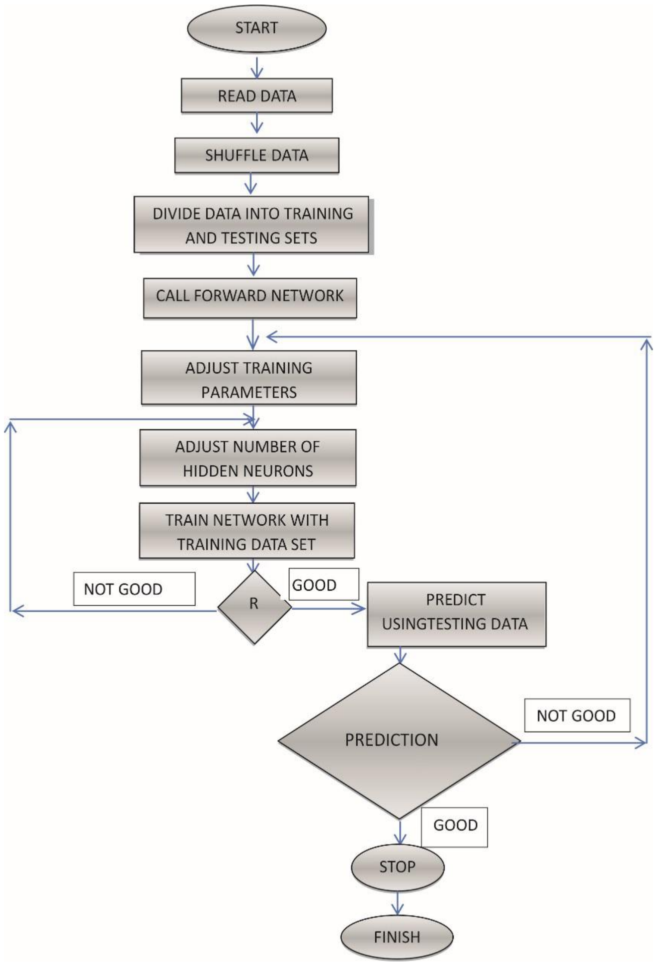

Figure 3: Flow Chart for the Artificial Neural Network Development

The imported data were randomized automatically by the system and divided into three (3); 55% for training, 15% for validation and 30% for testing. Thus, among the 200 data sets for this study, 110 randomly collected data were used in the training stage to construct the ANN model, 30 for validation and the remaining 60 data set were used in testing the network to estimate the model performance. The network was trained and retrained until it understood the relationship between the input variables and the 28th day compressive strength (output variable).

Back-propagation, as one of the most well-known training algorithms for the multilayer perception (MLP), which is a gradient descent technique that minimizes the error for a particular training pattern in which it adjusts the weights by small amount at a time, was used. However, it was recommended by El-Chabib and Nehdi (2005) that a sigmoid function be employed as transfer function for the hidden layers because it was non-linear, differentiable, continuous, and it varies monotonically between 0 and 1 (log-sigmoid) or -1 and 1 (tan-sigmoid). Momentum rate and learning rate values were determined and the model was trained through iterations. The trained model was tested with the input values and the results found were close to experiment results. The values of parameters used in this study were as follows:

Number of input layer units = 6

Number of hidden layers = 3

Number of output layer unit = 1

Learning cycle = 24

3. Results and Discussion

This section presents the results of the laboratory tests for concrete cubes strengths in order to form the database of sets of data for use in the artificial neural network modelling. It also describes the findings on the suitability of ANN in the prediction of 28th day concrete compressive strength.

3.1 Compressive Strength of Concrete Cubes

The prepared samples of 150mm by 150mm by 150mm with four different water cement ratios (0.4, 0.5, 0.6, 0.65) were tested at 7th and 28th days using compression machine and their strength results were obtained as shown in Table 2.

Table 2: Results of Compressive Strength at Various Concrete Mix Constituent

Concrete Mix Constituent (kg/m^3)				Compressive Strength (N/mm^2)	
W/C ratio	Cement	Coarse Aggregate	Fine Aggregate	7th Day	28th Day
0.4	360.4	1441.7	720.8	24.9	38.0
0.5	348.8	1395.2	697.6	20.1	30.5
0.6	337.6	1350.6	675.2	16.0	23.7
0.65	332.2	1329.0	664.5	14.3	22.1

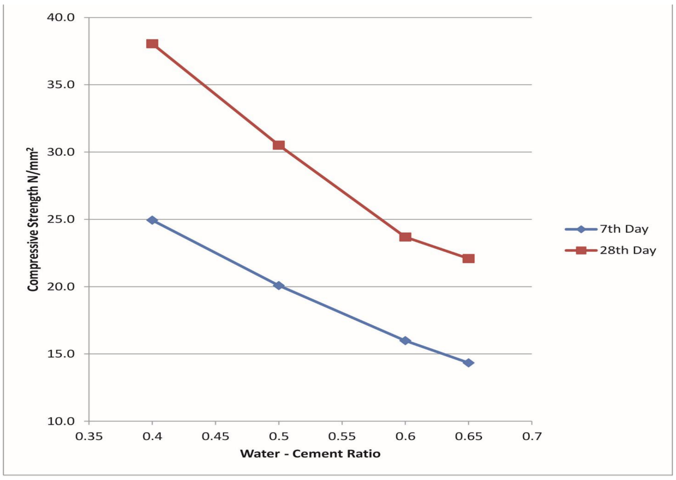

Figure 4: Compressive Strength at Various Water-Cement Ratio

Figure 4 shows the relationship between compressive strength (N/mm^2) at 7th and 28th day with water-cement ratio, this shows an inverse relationship, where the compressive strength decreased with increase in water-cement ratio, hence the compressive strength increased with increase in cement content and decreased with increase in water content. Also from Table 2 it can be deduce that the compressive strength decreased with decrease in fine and coarse aggregate content, hence a direct relationship exist between compressive strength and aggregates content.

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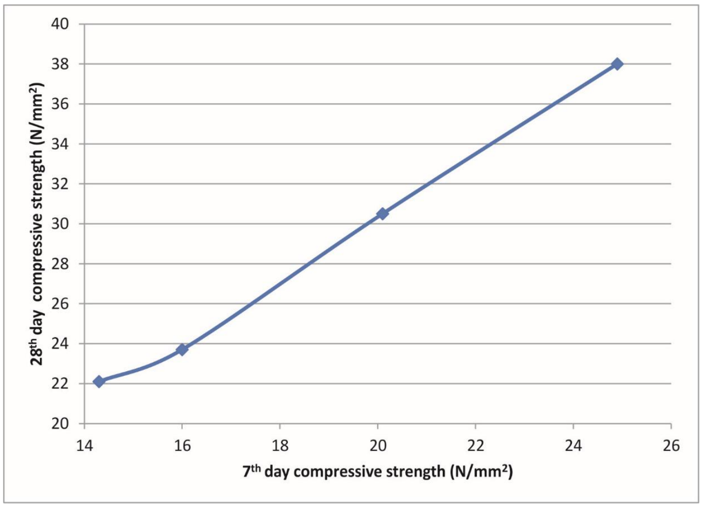

Figure 5: Relationship between 7th and 28th Day Compressive Strength

Figure 5 shows an approximately linear relationship between the 7th day and the 28th day concrete strength, with the 28th day increasing with increase in the 7thday strength. The relationship between the 28thday and 7thday concrete strength is defined by Equation (2).

$$f_{28} = 1.5344 f_7 + 0.3092 \tag{2}$$

where:

f_{28} = 28th day compressive strength (N/mm2)

f_7 = 7th day compressive strength (N/mm2)

Table 3: Comparison between Experimental and Mathematical Model Strengths at 28th Day

Experimental result (N/mm^2)	$f_{28} = 1.5344f_7 + 0.3092$
38	38.52
30.5	31.15
23.7	24.86
22.1	22.25

The comparison between the experimental 28th day strength and the 28th day strength obtained using the mathematical model as in Equation (2) is presented in Table 3. It was observed that the model result is slightly higher than the experimental results.

3.2 Outcomes of the ANN

The results of the network testing after training and validation shows that the predicted 28th day compressive strength of concrete are very close to those measured in the laboratory. This is an indication that the network has learned the relationship between the input and the output values during the training. The comparison between the measured and predicted compressive strength at 28th day are shown in Figures 6 and 7.

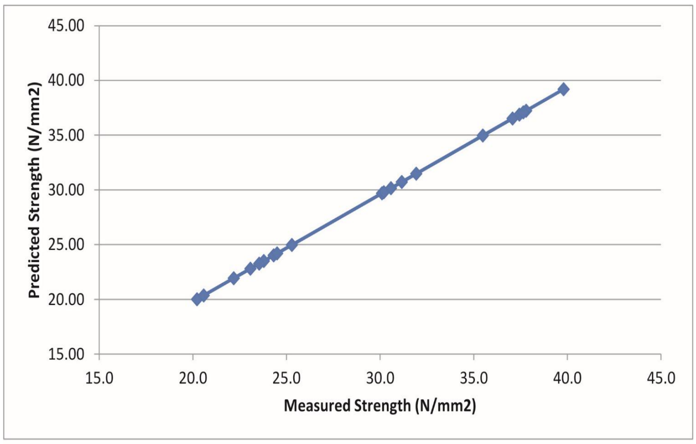

Figure 6: Relationship between Measured and Predicted 28th Day Compressive Strength

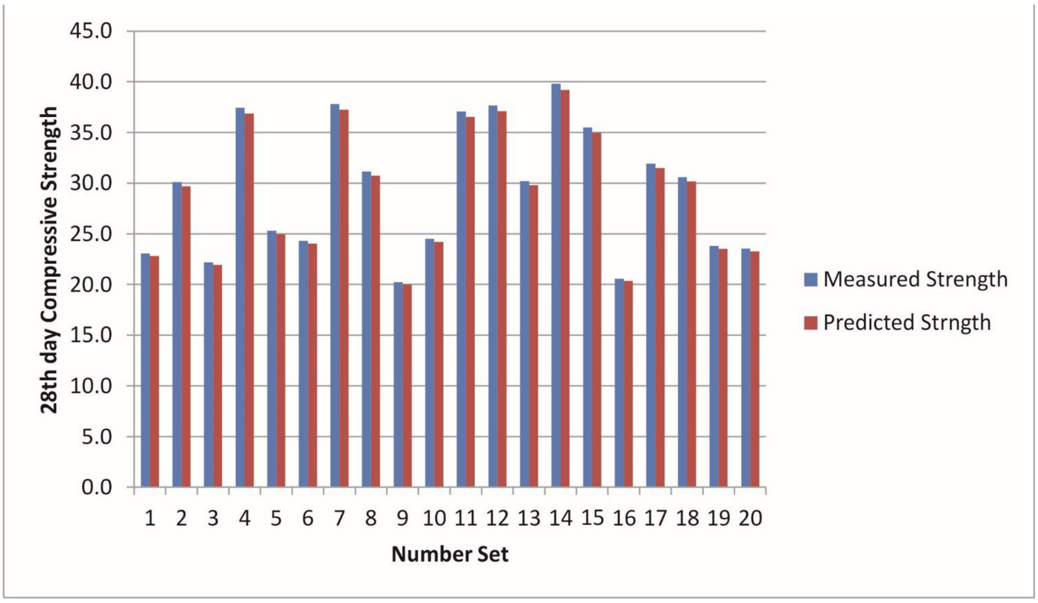

Figure 7: Comparison between Measured and Predicted 28th Day Compressive Strength

In general, the R value for the training data set was larger than that for the testing set, that is, the neural network made better prediction for the training data sets than the testing data set. The combination of transfer function composed of tan-sigmoid and linear function gives a good result. Figure 8 shows the relationship between output targets and predicted values obtained through the training and testing process. The model shows very good correlation for both the training (R = 0.99751), validation (R = 0.99736) and testing data (R = 0.99482) and the general correlation of R = 0.99675.

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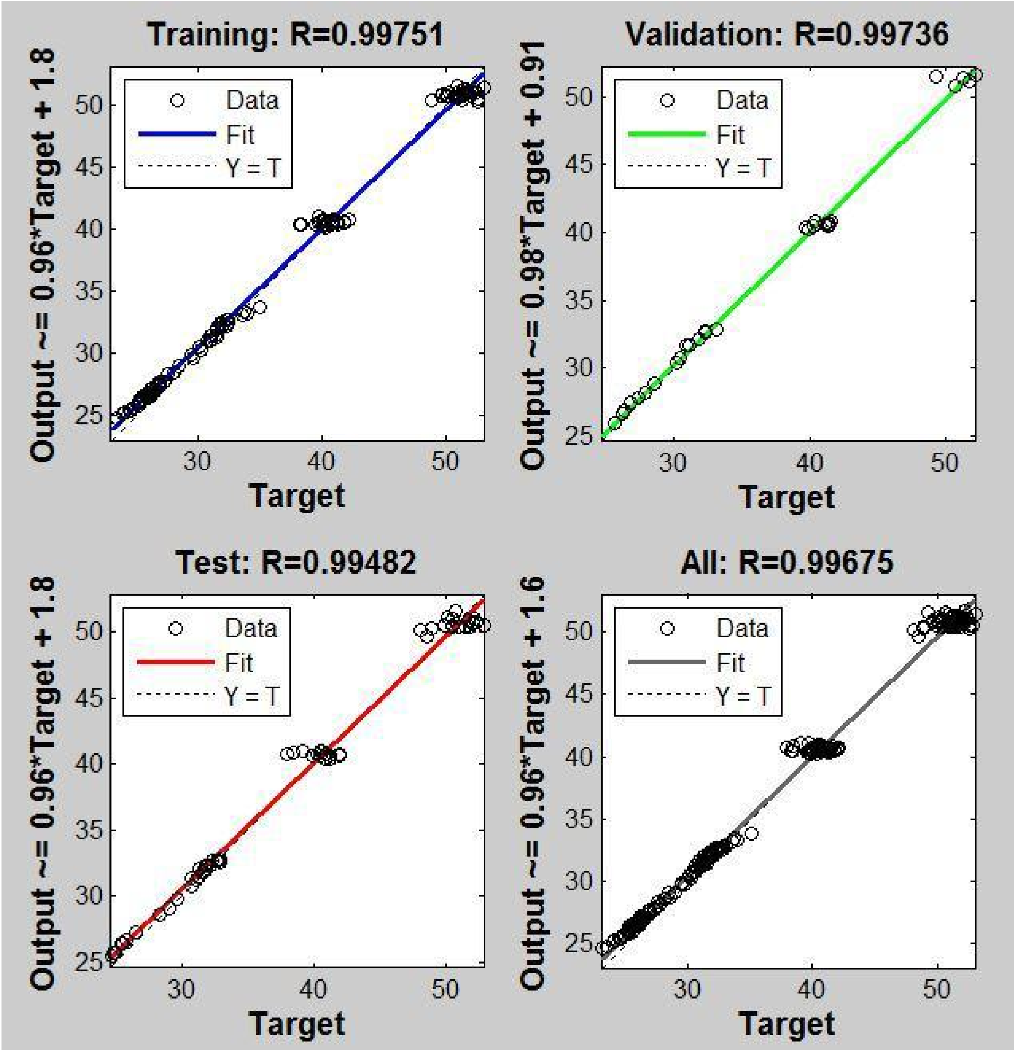

Figure 8: Correlation Between Measured and ANN Predicted Result

4. Conclusion

From the study, the following conclusion and observations were drawn.

The 28thday compressive strength was found to be directly proportional to 7th day compressive strength. It has been demonstrated in this study that the ANN model $f_{28} = 1.5344f_7 + 0.3092$ was quite efficient in determining the 28th day compressive strength of concrete asit was found that the measured compressive strength and predicted strength are very close with a correlation of 0.99675. Mathematical model results are slightly higher than the experimentally results.

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