Using Neural Networks to Prediction of compressive strength of heavy concrete

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Abstract. The article is devoted to the study of the process of predicting the compressive strength of concrete. Fully connected neural networks are used as a forecasting tool. The need for research is caused by the fact that concrete is one of the materials widely used in construction, and the existing automated tools have insufficient accuracy. The paper investigates the structure of a neural network: select of the number of layers, the number of neurons in layers, the activation function, the optimization method, the number of epochs, and the technique to prevent overfitting. Comparison of the obtained results with the results of laboratory tests showed that neural networks could achieve acceptable prediction accuracy. The coefficient of determination refers to the main indicators of the quality of forecasting. Now, the coefficient of determination is approximately equal to 0.889. In the future, the started research can be continued and the value of the coefficient of determination can be improved.

1 Introduction

Concrete is one of the most commonly used materials in construction. It owes this to its physical and mechanical characteristics, as well as durability. In addition, it can be obtained using local mineral materials. One of the main properties of concrete is compressive strength. In practice, the strength of concrete is usually determined based on the controlled hardening of concrete tested at the ages of 7, 14 and 28 days. In a real construction, concrete is subjected to multidirectional loads. However, in laboratory conditions, it is customary to conduct a uniaxial compression test [1].

To create an acceptable proportion of the concrete mixture, it is necessary to make several test mixtures and test them in the laboratory. Therefore, automated means of calculating the composition of the concrete mixture are used. One of these tools is an artificial neural network [2, 3]. A neural network can predict the proportions of a mixture based on statistical data from previously conducted experiments.

In [4], an analysis of works on predicting the properties of a concrete mixture, which use artificial intelligence methods to solve the problem, was carried out. In this paper, it is shown that the use of artificial intelligence methods gives better results compared to the

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results of mathematical modeling. And among the methods of artificial intelligence, neural networks show the highest accuracy. For example, in [5], on a training sample of 225 observations, a neural network with a direct connection and one hidden layer showed a determination coefficient R2 equal to 0.965. And in [6], a neural network trained on a data set of 168 observations showed R2 and RMSE values of 0.996 and 3.680 on the test set, respectively.

2 Materials and methods

The task of the study is to predict the compressive strength of a concrete mixture according to its specified ingredients. At the same time, a high accuracy of prediction should be achieved.

Neural networks are used in the work to solve the problem. Currently, there are various types of neural networks. Convolutional neural networks are mainly used for image processing, recurrent neural networks for natural language processing, and fully connected neural networks for data processing. Therefore, fully connected neural networks are used to solve the problem. Figure 1 shows the sequence of stages of the research process.
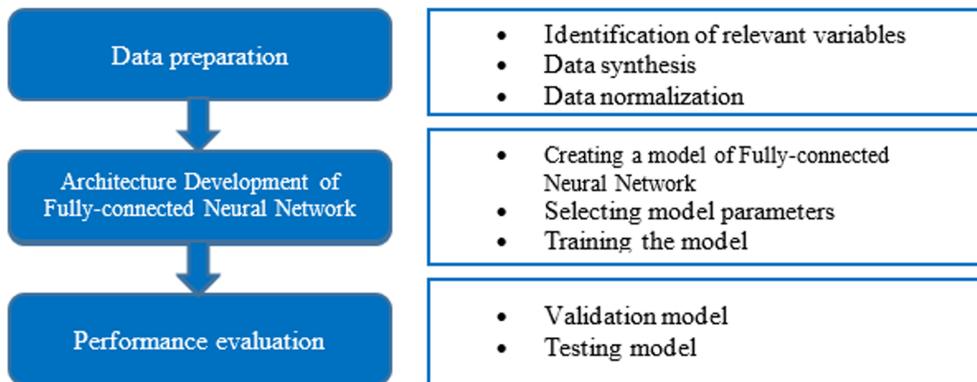

Fig. 1. The research process steps.

At the first stage, data preparation is performed.

2.1 Data preparation

2.1.1 Identify relevant variables.

The ingredients of the concrete mix are:
1) cement-water ratio;
2) absolute volume of aggregates;
3) proportion of sand;
4) water;
5) sand;
6) rubble;
7) cement.

In addition to the listed ingredients, the predictors of the data set include the design capacity. The initial data set contained 13 observations (Table 1). The volume of statistical

data provided is insufficient for the use of neural networks. Therefore, it is necessary to supplement the data set. For this purpose, additional data has been generated.

2.1.2 Data Synthesis

Theoretical calculations and tabular data were used to expand the data set. All calculations and tabular data corresponded to Russian interstate standards GOST 27006-2019 «Concrete. Squad Selection Rules» and GOST 24211 «Additives for concrete and mortar».

Table 1. The water demand of the concrete mixture depends on the fraction of crushed stone.

Cement	Water	Cement-water ratio	Absolute volume of aggregates	The proportion of sand in the mass of aggregates	Sand	Rubble	Design strength
192	135	0.89	723	0.51	959	921	9.6
223	145	1.04	713	0.5	927	927	12.8
283	155	1.32	694	0.49	884	920	19.2
344	170	1.60	674	0.47	824	929	25.6
405	185	1.88	654	0.45	765	936	32
466	205	2.17	635	0.43	710	941	38.4
527	215	2.45	615	0.41	656	943	44.8
588	230	2.73	595	0.39	604	944	51.2
649	240	3.02	576	0.37	554	943	57.6
710	135	3.30	556	0.35	506	940	64
771	145	3.58	536	0.34	474	921	70.4
831	155	3.87	517	0.33	443	900	76.8
953	170	4.43	478	0.31	385	857	89.6

The data set was expanded for each concrete class from B7.5 to B45 for concrete grade 40 (M40 grade concrete mix). The data set includes eight additional rows for each class. A fragment of the extended dataset is shown in Table 2.

Table 2. A fragment of an extended dataset.

Concrete class	Cement, x_1	Water, x_2	Cement-water ratio, x_3	Absolute volume of aggregates, x_4	The proportion of sand in the mass of aggregates x_5	Sand, x_6	Rubble, x_7	Design strength, x_8
B7.5	121	135	0.89	826	0.53	1138	1009	9.6
B7.5	130	145	0.89	813	0.53	1121	994	9.6
B7.5	139	155	0.89	800	0.53	1103	978	9.6
B7.5	152	170	0.89	781	0.52	1056	975	9.6
B7.5	165	185	0.89	762	0.52	1030	951	9.6
B7.5	183	205	0.89	736	0.51	976	938	9.6
B7.5	192	215	0.89	723	0.51	959	921	9.6
B7.5	206	230	0.89	704	0.51	933	896	9.6

Concrete class	Cement, x_1	Water, x_2	Cement-water ratio, x_3	Absolute volume of aggregates, x_4	The proportion of sand in the mass of aggregates x_5	Sand, x_6	Rubble, x_7	Design strength, x_8
B7.5	215	240	0.89	691	0.52	934	862	9.6
…	…	…	…	…	…	…	…	…
B45	407	135	3.02	734	0.45	858	1049	57.6
B45	438	145	3.02	714	0.44	817	1039	57.6
B45	468	155	3.02	694	0.43	776	1029	57.6
B45	513	170	3.02	665	0.42	726	1002	57.6
B45	558	185	3.02	635	0.4	660	990	57.6
B45	619	205	3.02	595	0.41	635	913	57.6
B45	649	215	3.02	576	0.37	554	943	57.6
B45	694	230	3.02	546	0.36	511	909	57.6
B45	724	240	3.02	526	0.35	479	890	57.6

This approach allowed us to expand the data set to 495 rows.

2.1.3 Data normalization.

As can be seen from Table 2, there is an imbalance between the values of the features in the source data. Their measurement ranges differ by several orders of magnitude. This can cause instability of the model, worsen learning outcomes and slow it down. Therefore, data normalization was performed for each predictor, according to the formula (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}, \tag{1}$$

where x_{min}, x_{max} – correspond to the boundaries of the measurement range of a particular predictor, x – is the current value of the predictor to be normalized, x_{norm} – is the normalized value of the predictor.

2.2 Architecture Development of Fully connected Neural Network

Each output measurement depends on each input measurement. A fully connected layer is a function from R^m in R^n. Each output measurement depends on each input measurement.

2.2.1 Creating a model of Fully-connected Neural Network

The neural network consists of five layers. Its architecture is shown in Figure 2. The first hidden layer of Dense has 165 neurons, the next three hidden layers of Dense have 200 neurons each, and the last output layer of Dense has one neuron. The output signal Y is the predicted concrete density. All layers have a ReLU activation function.

2.2.2 Training the model

One of the common regularization methods is the Dropout method. This method allows you to deal with retraining. It is used when the curves of the loss function on the validation and

training samples diverge, but the qualitative characteristics have not reached acceptable values. It is set after every hidden layer except the output one. The probability of dropping out of units is set to 0.3.
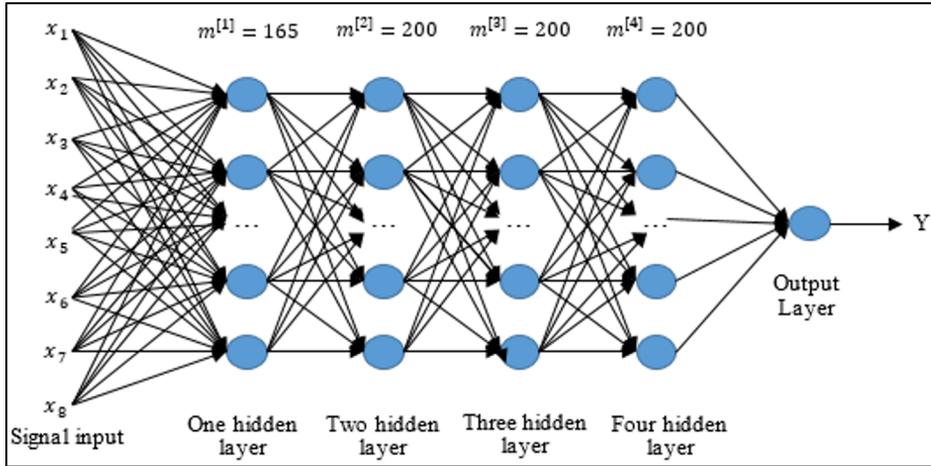

Fig. 2. A multilayer deep fully connected network.

2.2.3 Selection of model parameters

In this paper, forecasting is solved as a regression problem. Therefore, the root-mean-square error and the mean absolute error are used as a loss function and metric, respectively. As an optimization method, the adamax optimizer is used, which is a variant of the Adam optimization algorithm with adaptive learning rates.

3 Result and Discussions

The main experiments carried out in the work included: the study of the network architecture (the number of neurons and layers) and the study of the parameters of the neural network.

3.1 Network architecture research

Four variants of the number of hidden layers were considered in the experiment: 2, 3, 4, 5 (Table 3).

Table 3. Influence of the number of hidden layers purpose *mae*.

Type of experiment	2 hidden layers	3 hidden layers	4 hidden layers	5 hidden layers
mae	0.543	0.42	0.24	0.45

An increase in the number of hidden layers from 2 to 4 led to a decrease in the value of MAE. However, with a further increase in the number of hidden layers, the value of MAE increased. This indicates that adding additional hidden layers can improve the accuracy of the model and reduce the prediction error, however, too many layers can lead to a deterioration in the performance of the model and increase the error. For each layer, the

number of neurons in the layer was determined in the range from 50 to 300 in increments of 50. Then the best interval was considered in increments of 10. Thus, it was found out that the optimal values for the hidden layers are as follows: the first one is 165, the rest are 200 neurons, the output layer is one neuron. Also, sigmoidal type activation functions and ReLU activation function were selected for each layer. As a result, the ReLU function is selected for all layers.

Experiments were also carried out to determine the optimal value of the butch (Table 4)).

Table 4. The effect of the size of the butch on the value *mae*.

Type of experiment	Size of the butch		
	128	256	512
mae	0.543	0.32	0.412

The analysis of the table shows that the optimal size of the batch is 256.

Next, a neural network with a given architecture was trained and tested. As a result, the values of the average absolute error (MAE) were obtained, which amounted to 0.543. The value is very high, therefore, it became necessary to investigate the external parameters of the neural network.

3.2 Investigation of neural network parameters

In this series of experiments, experiments with various optimizers were first carried out. The optimal optimizer turned out to be adamex. In addition, the number of epochs was determined (Table 5).

Table 5. Influence of the number of epochs assignment *mae*.

Type of experiment	Number of epochs							
	200	300	400	500	600	700	800	900
mae	0.543	0.32	0.22	0.0024	7.2574 e-04	6.0364 e-04	5.1575 e-04	6.0708 e-04

Although an increase in the number of epochs generally leads to a decrease in parameter changes, there is some increase at the last stage of training (from 800 to 900 epochs).

In addition, experiments have been conducted with various optimizers. The optimal optimizer turned out to be adamex.

3.3 Final results

Final results of the conducted experiments:
- determination coefficient r2_score = 0.8893353477867147;
- the root-mean-square error on the validation sample val_loss: 0.0056;
- average absolute error val_mae: 0.0552.
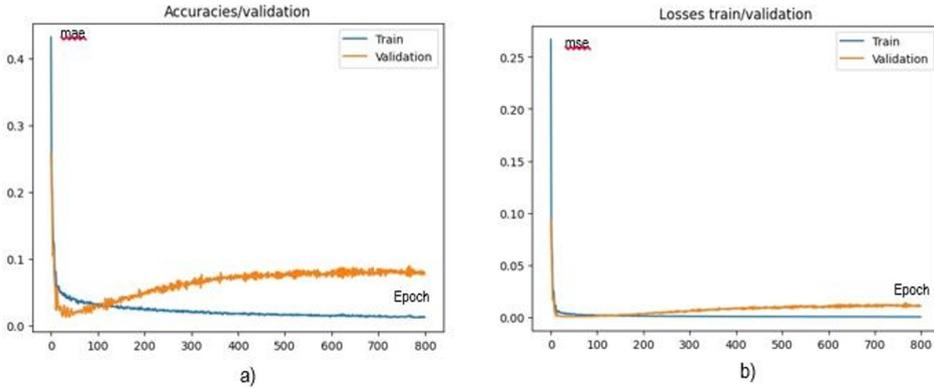
Dependency graphs are shown in Figure 3.

Fig. 3. Final results: a) dependences of accuracy on the number of epochs in the validation sample; b) curves of the loss function in the validation sample.

3.4 Comparison of results

Laboratory tests were carried out on concrete mixtures calculated theoretically and by a neural network. To do this, in the neural network architecture, three neurons corresponding to the main ingredients are specified in the output layer: sand, rubble and cement. The results are presented in tables 6 and 7.

Table 6. Comparative table of neural network results and laboratory tests.

Neural network result	Compressive strength (MPa) after a full-scale experiment		
	after 7 days	after 14 days	after 28 days
9.611284	4,2	5,8	9,6
12.981687	4,5	6,4	12,8
57.306694	40,9	52,6	57,3

Table 7. Comparative table of the results of theoretical calculations and laboratory tests.

Neural network result	Compressive strength (MPa) after theoretical calculation		
	after 7 days	after 14 days	after 28 days
9,6	1,9	5,6	9,4
12,8	3,9	5,7	12,5
57,6	26,8	51,1	57,1

As a result, it can be noted that, in principle, the results obtained are not bad, but they can be improved by studying other external parameters of the neural network.

4 Conclusion

The prediction is based on a fully connected deep learning neural network. The study of the neural network structure and its external parameters is carried out. The results of the field experiment showed that the neural network calculates the predicted strength of concrete

more accurately than theoretical calculations. The average accuracy of theoretical calculations is 0.982, and the average accuracy of neural network calculations is 0.994. This means that the neural network is one hundredth of the value more accurate.

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