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Analysis of neural network results based on experimental data during indentation

N Babushkina[1], *A* Lyapin[1], *A* Kovaleva[1,*]

[1]Don State Technical University, 1 Gagarin square, Rostov-on-Don, 344000, Russia

Abstract. The article is devoted to the development of machine learning methods for classes of technical problems, including determining the properties of materials. According to the authors, the neural network approximation algorithm is able to take into account the behavior of materials in various experimental conditions. The article provides illustrative examples of how a neural network with a single hidden layer can approximate a function of several variables with a given accuracy. As part of the study, a number of experimental measurements were made. The structure of the neural network and its main components are described.

1 Introduction

Conducting an experiment on real objects provides a low degree of control over its running, since the non-laboratory environment is not isolated from extraneous influences. Therefore, existing methods of non-destructive testing of material properties have low accuracy, repeatability, and statistical reliability. Therefore, it is necessary to use methods that are less dependent on the conditions of the experiment. This method can be used to select an approach using neural networks for processing research results. The neural network is able to take into account the behavior of materials in various conditions.

Formally, the problem of training a neural network in forecasting problems is formulated as an approximation problem. It is necessary to build a neural network (approximating function) that will take the same values (with a given accuracy) not only on the data of those participating in the training (approximate interpolation problem), but also on the data of the control set that did not participate in the training.

One of the most important advantages of neural networks is their ability to form an accurate approximation for nonlinear functions of any duration.

This point of view is seen in the works of T. V. Filatova [1], who believes that the use of neural networks provides a high quality of approximation and can be used to analyze and predict the state of an object.

Noteworthy are the works performed by a group of specialists led by Katsuba Yu. N. In their work [2], the authors note that one of the most important qualities of neural networks is their ability to study the dynamics of behavior of nonlinear systems automatically, if the architecture of the neural network contains at least three layers.

* Corresponding author: copybird@yandex.ru

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It follows from the above that special attention in this area should be paid to approaches to choosing the structure of a neural network, methods for its training, determining the optimal number of neurons on the hidden layer, etc.

For example, in the works [3, 4], researchers developed a technology for processing multidimensional data using neural networks. The authors note that it is difficult to find the most optimal network structure and learning algorithm for the task at hand.

Numerous studies by the authors [5, 6, 7, 8] show that a neural network with a single hidden layer can approximate any continuous function of many variables with a given accuracy. The main thing is that this network has a sufficient number of neurons and the initial values of the weight coefficients should be correctly selected.

Analysis of literature sources in this area [9, 10, 11, 12, 13, 14, 15], allows us to conclude that it is advisable to use a neural network algorithm to determine the properties of materials in the process of shock indentation. The aim of the study is static processing of data obtained during the experiment, investigation of the dependencies of the material characteristics of metals, selection of optimal parameters of the neural network.

2 Materials and methods

Experimental data for the study were obtained during impact indentation of the surface of several metal samples.

To solve this problem, we consider 2 approaches based on the nature of the input effect of the neural network:

- the first approach involves splitting the source data for each type of metal into training and control samples (figure 1).
- in the second approach, several groups of metals that are not involved in network training are used as a control sample (figure 2).

The values are normalized to the range [0,1]. Data normalization is performed using the following formula:

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where $\bar{x}$ – is the normalized value;
x_{min} – minimum parameter value for the entire sample;
x_{max} – the maximum value of the parameter for the entire sample.

The statistical distribution of the sample was studied, and the numerical characteristics of the distribution (mathematical expectation, variance) were determined.

The neural network was created using Google Colaboratory using the TensorFlow and Keras libraries.

The neural network has a four-layer structure. Location of neurons in layers: 50, 30, 12, 1.

Several groups of metals were selected for analysis, grouped by hardness groups: 96 HB, 182 HB, 197 HB, 30HGSA, 271 HB, 450 HB.

For each type of metal, the number of experiments obtained during indentation is 9-11 values.

The output of the neural network is the Brinell hardness parameter (HB).

3 Results and discussions

Let's look at the results of the neural network. Table 1 shows the initial data for approach 1 and the values obtained by the neural network during training. The number of epochs varied from 10 to 500.

Table 1. Results of approach 1.

Hardness group, HB										
	96			182			197			
Source	112	114	102	125	190	172	190	198	200	204
10 epochs	122	120	116	135	183	192	205	208	218	222
20 epochs	127	121	111	129	182	176	203	196	205	207
30 epochs	123	119	103	121	201	178	196	181	204	207
50 epochs	118	117	106	139	193	187	190	171	181	207
100 epochs	116	114	100	129	197	188	192	193	191	215
500 epochs	107	114	96	157	188	178	188	198	190	212

Table 2. Results of approach 1.

Hardness group, HB										
	30HGSA			271			450			
Source	207	214	192	271	280	284	415	398	321	417
10 epochs	213	204	208	266	327	262	410	415	391	412
20 epochs	207	221	190	255	287	264	413	416	385	407
30 epochs	212	222	185	288	257	283	416	407	395	404
50 epochs	205	210	198	270	309	283	411	412	383	400
100 epochs	196	215	174	276	315	264	416	418	373	407
500 epochs	234	205	213	278	284	283	415	373	365	403

Visually, the results of approach 1 are shown in figure 1.

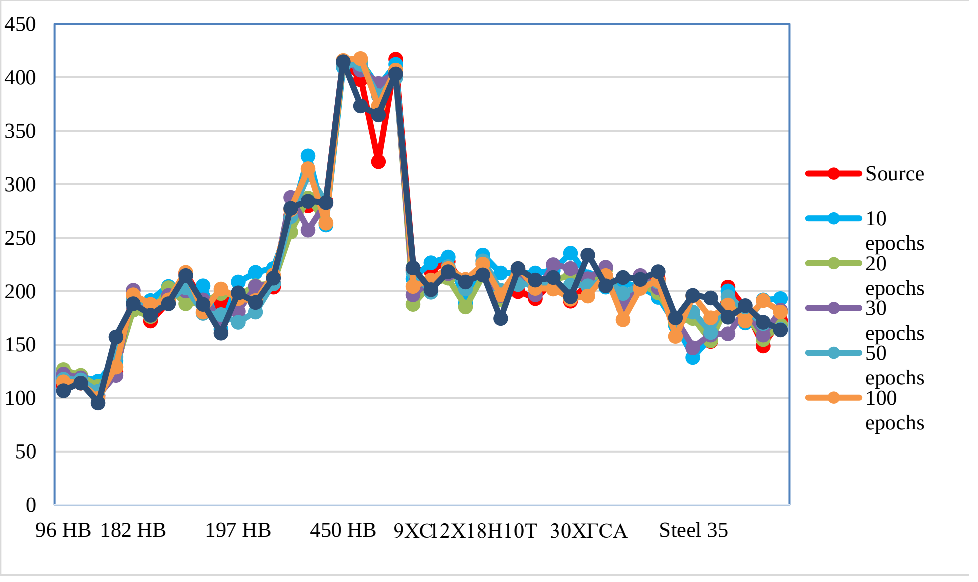

Fig. 1. Comparison of hardness values for different number of epochs. Approach 1.

Table 3 contains data from the second approach and values obtained by the neural network during training.

Table 3. Results of approach 2.

Hardness group, HB								
	197							
Source	207	204	203	211	190	189	198	200
10 epochs	232	212	208	221	373	204	225	206
20 epochs	235	231	242	233	114	212	220	215
30 epochs	237	215	198	195	155	207	203	208
50 epochs	207	226	201	200	139	202	190	217
100 epochs	232	211	217	219	373	195	211	203
500 epochs	235	209	212	213	92	200	197	194

Table 4. Results of approach 2.

Hardness group, HB								
	30HGSA							
Source	205	207	197	214	199	192	193	203
10 epochs	267	211	188	222	218	227	180	187
20 epochs	230	217	202	229	202	223	191	203
30 epochs	238	231	214	219	201	232	195	194
50 epochs	250	232	230	211	215	199	186	201
100 epochs	212	206	190	213	196	212	176	203
500 epochs	227	198	199	205	216	209	199	205

Visually, the results of approach 2 are shown in figure 2.

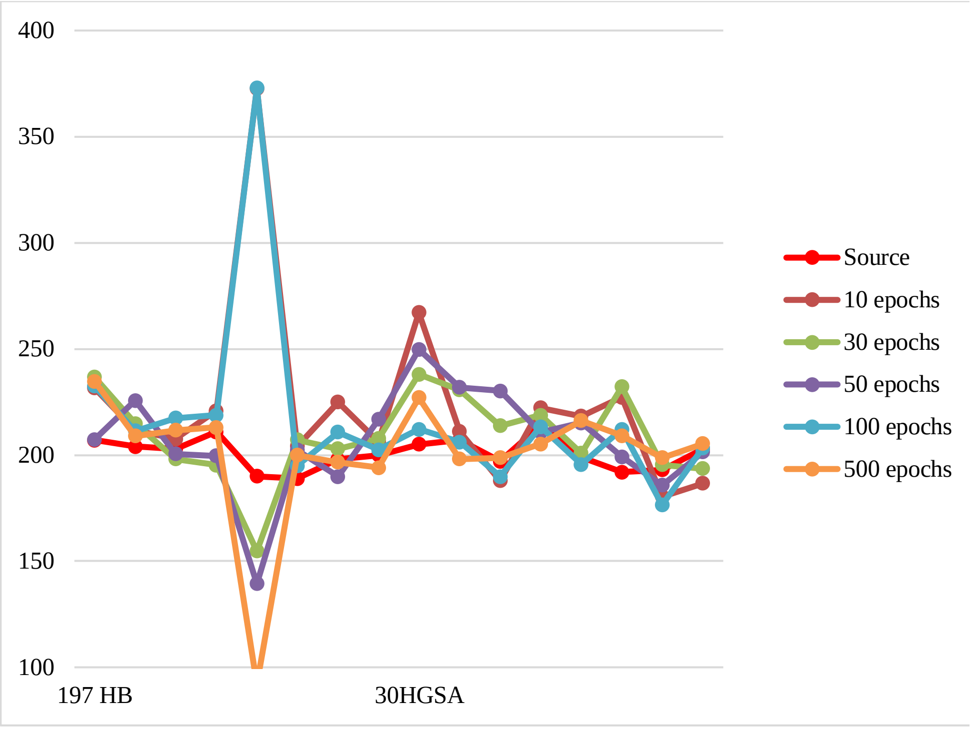

Fig. 2. Comparison of hardness values for different number of epochs. Approach 2.

4 Conclusions

Thus, this article discusses the results of a neural network with different input parameters.

The results of the study allow us to draw the following conclusions:

- the neural network can approximate the function with sufficient accuracy in various conditions for obtaining experimental data;
- the results of the first approach have a higher accuracy compared to the second approach, which can be observed in the example of the 97 HB group. At the same time, the second approach is possible for practical application, given that the test set is entire groups of metals that do not participate in training;
- the largest deviation from the expected values is observed at 10 epochs of training, the smallest - at 100 epochs of training.

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