Проблемы искусственного интеллекта. 2026. N 1 (40). С. 4-14
Problems of Artificial Intelligence. 2026;1(40):4-14.
Искусственный интеллект и машинное обучение
Научная статья

УДК 004.032.026
doi: 10.24412/2413-7383-2026-1-40-4-14

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RECOMMENDATION SYSTEM FOR DETERMINING THE METAL PROPERTIES BASED ON NEURAL NETWORK

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РЕКОМЕНДАТЕЛЬНАЯ СИСТЕМА ДЛЯ ОЦЕНКИ СВОЙСТВ МЕТАЛЛОВ НА ОСНОВЕ НЕЙРОННОЙ СЕТИ

В статье описывается рекомендательная система, предназначенная для определения свойств металлов. Разработана структура экспертной подсистемы, предназначенной для определения номинальных значений свойств металлов. Показан фрагмент базы знаний о металлах, содержащий набор правил об их свойствах. Разработана нейронная сеть для уточнения значений свойств металлов. Показаны результаты моделирования разработанной нейронной сети.
Ключевые слова: нейронные сети, свойства металлов, экспертная подсистема, классификация.

The paper describes a recommendation system that is designed to determine the properties of metals. A structure of an expert subsystem is developed which designed to determine the nominal values of the properties of metals. A fragment of the knowledge base of metals, which contains a set of rules on their properties, is shown. Neural network is developed a to refine the values of the properties of metals. The results of simulations of the developed neural network are shown.
Key words: neural networks, metal properties, expert subsystem, classification.

Introduction

Industrial level of development countries is characterized by the amount of production and product range and their quality indicators. Lack of quality control at the enterprise can result in breaching to products operation conditions and their premature destruction. This situation leads to property damage and serious consequences such as: explosive situation, fire, poisoning the environment and the tragic loss of life. Thus, the problem of life support at the enterprise is inextricably linked with the task of quality control. Methods of solving this problem are to use objective physical control methods, such as metallographic analysis. Necessity in developing methods for automated quality control of metals is caused by the increased requirements which are set to the metal's quality of different groups and classes.

Metallographic analysis of metals is getting under the microscope images of metal microstructures and their recognition. Identification of the metal properties is made by processing of metallographic images and determination of quantitative characteristics of metals from these images. The existing techniques is characterized high automation degree for the recognition of metallographic images and too low determination accuracy of metal mechanical properties. Therefore, the problem of increasing the accuracy of determining the characteristics and properties of metals is important.

Related Works

Among the most significant works in the field of automation of metallographic analysis, performed earlier by other authors, one can single out papers [1- 5]. The application of neural networks for determining the mechanical metal properties remains relatively underexplored [6]. Traditionally, researchers have applied on conventional techniques and neural networks to classify several image microstructures to automate metallographic analysis [7-11]. In particular, studies [12] and [13] showed the potential of CNNs as alternative tools for microstructure classification. Study [14] proposed a framework for the automatic classification of steel microstructures. The work of the latter authors highlighted the challenges associated with manual microstructural classification, which is often prone to human error and subjectivity.

The study [15] provides user guide to select the architecture of a convolutional neural network based on factors such as computational efficiency, training duration, accuracy. The study [16] offers a review of computer vision methods for representing visual data in microstructural images. In study [17] developed a framework for the automated identification of features such as pores, particles, grains, etc.

But all these studies offer techniques which can determine only the quantitative characteristics of metals, such as, grain size, and can not determine the metal properties (limit of metal strength etc.).

To determine the properties of metals recommendation system was established that is based on using the multilayer neural network. The proposed recommendation system allows for the implementation of two main actions for determining the properties of metals:

1. Determination of the nominal values of metals properties and group of their using by an expert subsystem.

2. Evaluation of metals properties by neural network with the definition of real property values of metals.

Design of the Expert Subsystem of the Recommendation System for Determining the Metal Properties

The structure of the expert subsystem, which is designed for determination of the nominal values of metals properties and group of their using, is on figure 1.

The database contains information on the parameters of the metallographic analysis, the chemical composition of metals and their characteristics. Expert subsystem as a system based on knowledge contains in its structure the knowledge base of metals and a logical conclusions module.

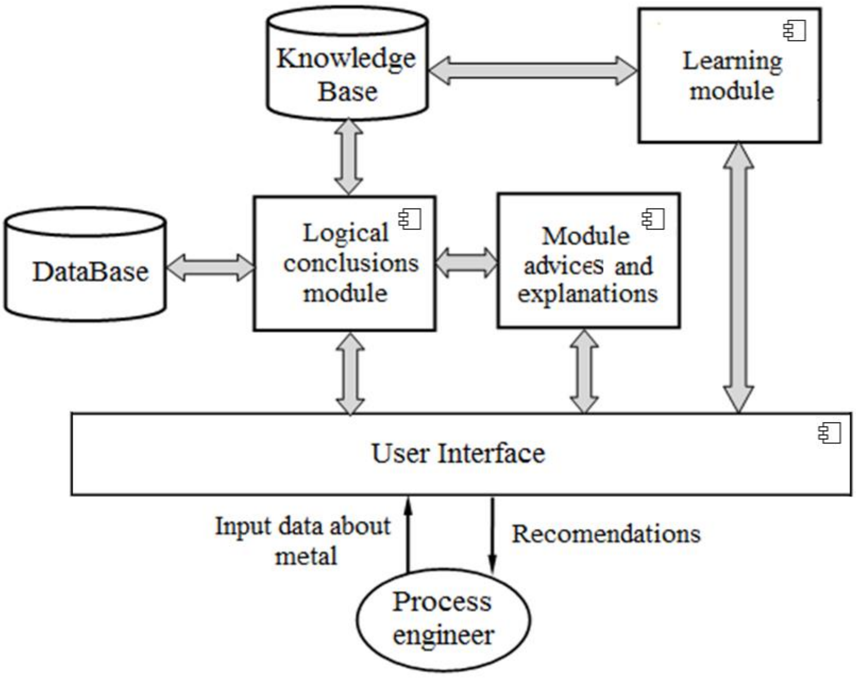

Figure 1 – The expert subsystem structure of the recommendation system for determining the metal properties

According to input mechanism expert subsystem works as follows:

1. Process engineer establishes the necessity to identify the properties of metal and gains on the user interface to the request.

2. Logical conclusions module performs the search for solutions from the knowledge base, according to the algorithm and provides a specific interface for the introduction of data request.

3. Logical conclusions module asks the database according to the properties required to metal for performing a user's request.

4. Database answer, which is obtained after selection, will be as a list where metals are arranged in time request order for metallographic analysis.

5. In the end expert system user can request the entire line of reasoning that led to this choice.

To maintain the knowledge base and its supply with knowledge about metals and their properties, which were obtained from an expert there is a separate module. Another component of the expert subsystem is user's interface which is necessary for proper date transfer during metallographic analysis in a convenient form for manipulation of knowledge.

To present the knowledge have been used the production model. Productions in the knowledge base are given in the following form:

$$Pr = < num_{Pr}; L; A \Rightarrow h; MC_{Pr}; MD_{Pr} >, \quad (1)$$

where num_{Pr} - the name of the product (in its capacity as the proposed use of the serial number of products in the knowledge base); L - application area of products ("chemical factor", "physical factor, etc.); $A \Rightarrow h$ - the production core, where $A=\{A_n\}$ - the set of assumptions, which describe some situations, $h=\{h_j\}$, - a set of hypotheses that are considered in the process of inference, if the parcel will be satisfied; MC_{Pr} and MD_{Pr} - a measure of confidence and a measure of distrust in the hypothesis h respectively.

This expression is an interpretation of the production core «IF A_1 and/or ... A_n, THEN h_j».

This model of knowledge described the regulations for determining following properties of metal:

σ_B - tensile strength of metal;

σ_T - yield strength of the metal;

σ_5- elongation of the metal;

gr - a group of metal.

The model of knowledge describes the regulations for steels for various purposes. The following is a fragment of the knowledge base according to a production model:

< 1; mechanical properties of steel; IF mr = «Ст0» THEN σ_B = 300 MPa, σ_5 = 22%, gr = «constructional»; 1; 0 >

< 2; mechanical properties of steel; IF mr =«Ст1кп2» THEN σ_B = 310-400 MPa, σ_5 = 33%, gr = « constructional»; 1; 0 >

< 3; mechanical properties of steel; IF mr = «Ст1сп» THEN σ_B = 320-420 MPa, σ_5 = 30%, σ_T = 190-220 MPa, gr = « constructional »; 1; 0 >

< 4; mechanical properties of steel; IF mr= «Ст2кп» THEN σ_B = 330-420 MPa, σ_5 = 32%, gr = « constructional »; 1; 0 >

< 5; mechanical properties of steel; IF mr = «Ст3пс» THEN σ_B = 380-490 MPa, σ_5 = 25%, gr = « constructional »; 1; 0 >

< 6; mechanical properties of steel; IF mr = «Ст4сп» THEN σ_B = 420-540 MPa, σ_5 = 23%, σ_T = 240-270 MPa, gr = « constructional »; 1; 0 >

< 7; mechanical properties of steel; IF mr = «Ст5сп» THEN σ_B = 500-640 MPa, σ_5 = 19%, gr = « constructional »; 1; 0 >

The model shows that the value MC_{Pr} = 1, and MD_{Pr} = 0, which is explained by the fact that data on the nominal properties of steel were obtained from the standards.

Thus, the model was developed with the possibility to develop a knowledge base on the steel for the expert system, which is designed to define the properties of steel and its usage group.

Defined metal properties by expert system are nominal values, which are described in international standards. However, the values of these properties can be changed, which is explained by the presence of nonmetallic inclusions in metal and other defects. The second stage of the method is designed to evaluate the properties of metals on the base of existing defects in the metal. To solve this problem there used multi-layer neural network.

Let the nominal values of metal properties to be the set of input values X, and the calculated values of the properties are set Y. Then:

$$Y_i = f(X_i) \quad (2)$$

where, Y_i – a vector of output values (a metal properties);

X_i – a vector of input variables (the quantitative characteristics of metals and the nominal values of the metal properties).

$$X = \{mr, Su, Ox, P, ph, \sigma_{B_n}, \sigma_{T_n}, \sigma_{5_n}\}, \quad (3)$$

$$Y = \{\sigma_B, \sigma_T, \sigma_5\}, \quad (4)$$

where, mr - steel grade;

Su - the value of the contents of sulfides in the metal;

Ox - the value of the contents of oxides in the metal;

ph - the value of the phase relations in the metal;

σ_{Bn} - nominal tensile strength of metal;

σ_{Tn} - the nominal yield strength of the metal;

σ_{5n} - nominal value of elongation of the metal;

σ_B - adjusted value, the tensile strength of metal;

σ_T - improved value of the yield point of the metal;

σ_5 - improved value of elongation of the metal.

Tasks of the definition of the output vector Y elements perform a neural network (Figure 2).

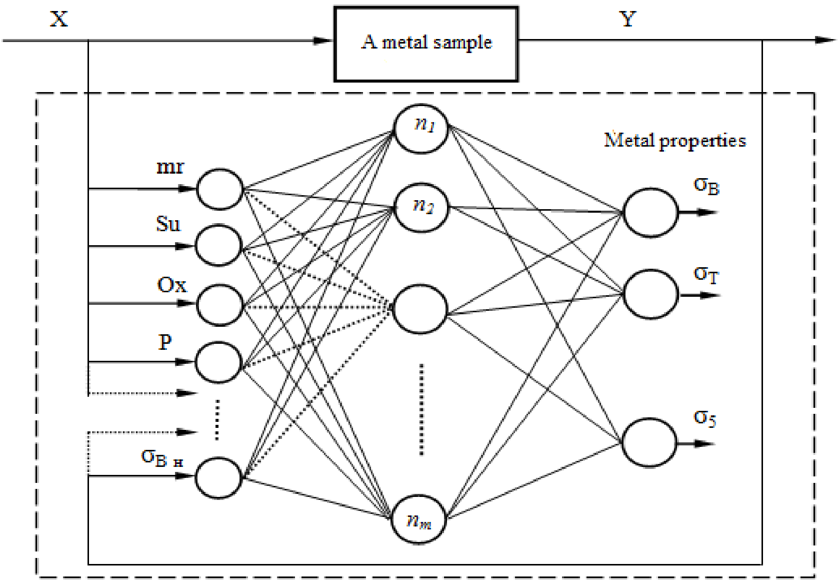

Figure 2 – Structure of the proposed neural network to determine metal properties

The neural network has the structure of a multilayer perceptron. The number of neurons in the input layer depends on the number of defects in the metal and the characteristics that affect the properties of metals (non-metallic inclusions, etc.).

The size of the hidden layer increases relatively to the input, through the allocation of the parameters of the characteristics of the phase ratio in the metal (phases ferrite and pearlite). Ratio of phases is used to refine the metal properties, because the value of carbon is determined on this basis, which affects metal properties. The size of the output layer is determined by the number of the metal properties. Training the neural network produced by the backpropagation algorithm with a sigmoid activation function:

$$y_j = \frac{1}{1+e^{-x_j}} \quad (5)$$

Measuring the quality of the metal properties determining was performed by calculating the mean-square error:

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_i - y(k_i))^2 , \quad (6)$$

where, E – Determination Error;

y_i - the value of the i-th network output for calculated values of the metal properties;

$y(k_i)$ - the value of i-th output standard network, which corresponds to a class of the metal.

After training, the values of training accuracy and loss functions were obtained, which are shown in Figure 3.

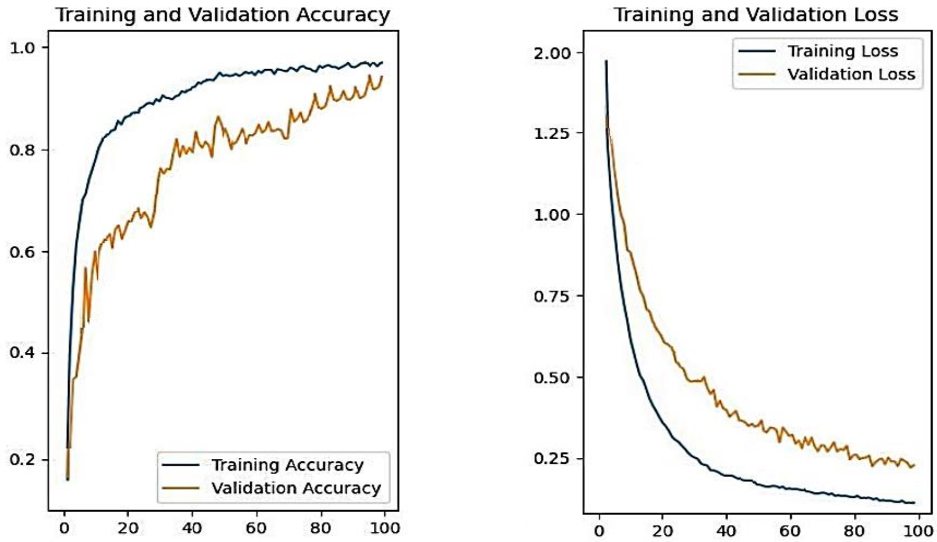

Figure 3 – Accuracy and loss graphs for the developed neural network.

The test samples contains information about 300 steel samples. For 288 grades of steel the properties have been identified (determined) correctly.

Experimental Studies of the Recommendation System for Determining the Metal Properties

To realize the expert subsystem and the neural network for determining metal properties the specialized software was developed by the authors (Figure 4).

The functions of the developed specialized software in analysis mode are as follows:

1) Setting by the user of the type of analysis of microstructures of alloys;

2) Input of the image of the metal microstructure;

3) Preliminary processing of the microstructure images (by the proposed authors technique in studies [18], [19]);

4) Quantitative assessment of the metal (by the proposed author technique in studies [18], [20]);

5) Determination of the grade and properties of the metal (by the proposed author technique which was described in this study);

6) Formation of a conclusion and producing recommendations regarding the analyzed metal sample (by the module of advices and explanations in Figure 1).

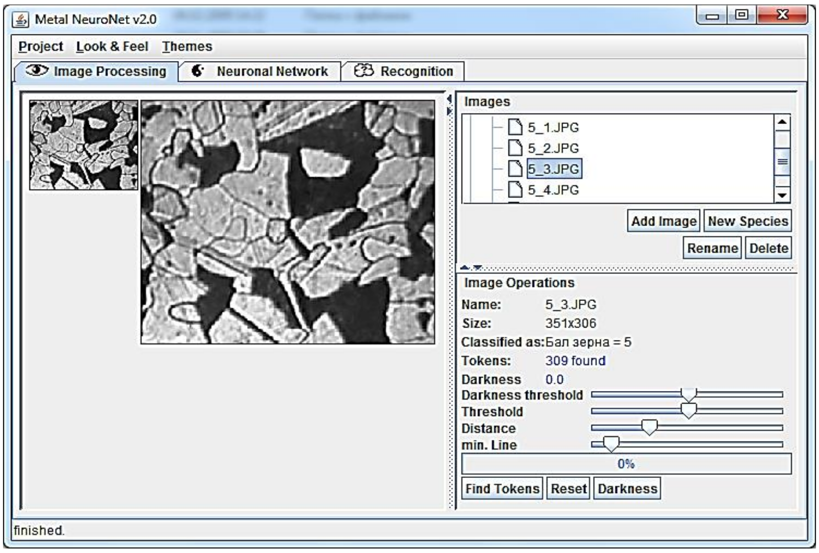

Figure 4 – Developed software the recommendation system for automated metallographic analysis

The general statistics of neural network determination of steel properties are shown in Table 1.

Table 1. General statistics of neural network determination of steel properties

Steel Grade	The total amount of the steel samples	The number of correct identified samples		Accuracy of the neural network	The full probability of correct alloy property determination, %
		The tensile strength of metal	Value of the yield point of the metal		
steel C 70W2	120	112	118	0.92	95
steel C 70W1	105	102	99	0.91	96
steel A 622	86	80	82	0.91	94
steel S420N	90	87	88	0.90	97

Thus, the developed neural network can effectively determine the mechanical properties of steels in general with an accuracy of 92%. The experimental data in Table 1 indicate that in the proposed recommendation system in 95% of cases (381 out of 401) the tensile strength of metal was correctly calculated and in 96.5% of cases (387 out of 401) the value of the yield point of the metal was correctly calculated.

In the future, the developed recommendation system can be used to evaluate a different equipment in the iron and steel works, for example, to evaluate the mechanical metal properties of the pipes, long steel products, etc. In addition, developed recommendation system can be used for metallographic testing of the torpedo ladle car hull to assess the current condition of the hull metal. In the case of the torpedo ladle cars, non-destructive metallographic testing is applied using portable metallographic microscopes.

Conclusion

The general results of the study are:

1. The recommendation system for determining the metal properties based on neural network was developed. The recommendation system is based on an analysis of different types of defects and characteristics of the metal using an expert subsystem and neural network. This made a decision-making process when choosing a metal group automatic. Adequacy of this technique is confirmed by a low value of mean-square error of the neural network.

2. The software was developed to automate the metallographic analysis for determining such metal properties as the tensile strength of metal and value of the yield point of the metal. Evaluation of the developed software functioning demonstrated an increase in the efficiency of metalographic analysis, which is expressed in a decrease in the amount of time spent on determining the metal properties by 5 times.

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RESUME

V. A. Emelianov, S. G. Chernyi, N. Yu. Emelianova, A. A. Kochkarov, S. V. Prokopchina
Recommendation System for Determining the Metal Properties Based on Neural Network

Background: Existing studies offer techniques which can determine only the quantitative characteristics of metals, such as, grain size, and can not determine the metal properties (limit of metal strength etc.). To determine the properties of metals recommendation system was established that is based on using the multilayer neural network. In this paper, we propose an approach that combines using expert subsystem and multilayer neural network for determining the properties of metals in two steps: determination of the nominal values of metals properties and group of their using by an expert subsystem and evaluation of metals properties by neural network with the definition of real property values of metals.

Materials and methods: The proposed recommendation system is based on an analysis of different types of defects and characteristics of the metal using an expert subsystem and neural network. This made a decision-making process when choosing a metal group automatic. Adequacy of this technique is confirmed by a low value of mean-square error of the neural network.

Results: The developed neural network can effectively determine the mechanical properties of steels in general with an accuracy of 92%. The proposed recommendation system in 95% of cases the tensile strength of metal was correctly calculated and in 96.5% of cases value of the yield point of the metal was correctly calculated.

Conclusion: The software was developed to automate the metallographic analysis for determining such metal properties as the tensile strength of metal and value of the yield point of the metal. Evaluation of the developed software functioning demonstrated an increase in the efficiency of metalographic analysis, which is expressed in a decrease in the amount of time spent on determining the metal properties.

РЕЗЮМЕ

В. А. Емельянов, С. Г. Черный, Н. Ю. Емельянова, А. А. Кочкаров, С. В. Прокопчина
Рекомендательная система для оценки свойств металлов на основе нейронной сети

В данной статье предложена структура экспертной подсистемы рекомендательной системы для оценки свойств металлов и описана продукционная модель базы знаний экспертной подсистемы.

Выполнено проектирование и моделирование многослойной нейронной сети для определения свойств металлов. Отмечается низкая ошибка обучения и высокая точность предложенной структуры многослойной нейронной сети в задаче определения свойств металлов.

Для реализации предложенной экспертной подсистемы и многослойной нейронной сети разработано программное средство, позволяющее по анализируемому образцу металла, определять его механические свойства. Приведены результаты экспериментального исследования предложенных средств, которые демонстрируют высокую вероятность корректного определения механических свойств исследованных сталей разных марок.

Реализация рекомендательной системы с учётом предложенных моделей позволяет решить задачу повышения эффективности определения и оценки механических свойств металлов за счёт использования многослойных нейронных сетей.

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Статья поступила в редакцию 18.12.2025.