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ARTIFICIAL INTELLIGENCE AS APPLIED TO CLASSIFYING EPOXY COMPOSITES FOR AIRCRAFT

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Abstract. The problem of classification of epoxy composites used for the manufacture of aircraft structures is solved by machine learning methods: neural network, reinforced trees and random forests. Classification metrics were obtained for each method used. Parameters such as precision, recall, F1 score and support were determined. The neural network classifier demonstrated the highest results. Boosted trees and random forests showed slightly lower results than the neural network method. At the same time, the classification metrics were high enough in each case. Therefore, machine learning methods effectively classify epoxy composites. The results obtained are in good agreement with the experimental ones. The prediction accuracy score obtained using each method was greater than 0.88.

Keywords: aircraft, aerospace applications, thermal conductivity coefficient, artificial intelligence, neural network, machine learning.

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1. Introduction

The development and production of light aircraft requires intelligent design of composite materials. The high quality of small aircraft is ensured by high aerodynamic characteristics, which are provided by new composite materials (Tan et al., 2008). The use of composite materials ensures high quality of aerodynamic surfaces, durability and good repairability during operation in field conditions (Das et al., 2019; Guadagno et al., 2022). At the same time, the use of epoxy composite materials in elements of aircraft structures requires further research. In particular, the use of new composite materials offers great opportunities to reduce weight, increase UAV range. However, this is associated with new problems. One of the difficulties in the application of new materials with non-linear characteristics is their dynamic properties, which are determined by experimental studies. A proposed procedure for the experimental-numerical determination of the elastic-dissipative properties of composite materials is presented in the paper (Karpenko et al., 2023). The paper presents a theoretical and experimental study of extruded polystyrene in laminated composite structures used in aerospace engineering. The finite element method used for numerical simulation, combined with experimental measurements based on frequency response optimization, enabled the modelling of the behaviour of the porous structure of extruded polystyrene. Especially use the methods of artificial intelligence, which ensure the processing of a significant number of results with the receipt of additional physically correct information (Harris et al., 2001). The use of epoxy composites, the characteristic feature of which is a low temperature coefficient of linear expansion, allows to reduce the thermal stress of aircraft structures (Harris et al., 2002; Towsyfyan et al., 2020). In addition, the technology of selecting the properties of the fillers provides a wide variation in the properties of the epoxy composite. The optimal thermophysical properties of the epoxy composite are achieved by selecting the components and their quantitative ratio. The use of neural networks for these tasks allows to reduce the volume of field tests and to develop intelligent methods of quality control of epoxy composites (Dobrotvor et al., 2021; Niccolai et al., 2021).

A material experimental study is being conducted on the influence of the manufacturing technology of wound composite structures on their mechanical properties (including residual stresses). The cooling mode of the composite-resin epoxy structure is analyzed (Błażejewski et al., 2021). In particular, a study of the effect of cooling rate after curing on the mechanical response of thick-walled carbon fibre reinforced polymer (CFRP) rings is presented. The results presented showed that rapid cooling slightly reduces the mechanical performance of fibre-wound rings. In particular, computer processing of data obtained during thermophysical and mechanical tests of epoxy composites is essential for materials science (Lin et al., 2017). Such data processing aids in classifying epoxy composites based on the intellectualized analysis of their fillers. Heuristic

methods or the synthesis of algorithms from the statistical solution theory are also helpful (Lee Sanchez et al., 2021; Pal, 2007). However, statistical algorithms are not always efficient as part of real diagnostic methods because they have certain disadvantages: too high complexity in calculating likelihood functionals for many hypotheses under uncertainty; characteristics of real epoxy composites are not always well approximated.

Algorithms based on artificial neural networks are used in solving classification problems (Wei et al., 2018). Such algorithms learn from experimental data. They also aid in creating simple algorithms for computation and decision-making (Safavian & Landgrebe, 1991).

Theoretical provisions have been developed to evaluate and identify epoxy composite components based on fuzzy and neural network systems. Such systems help identify links and differences between conventional algorithms and those based on neural networks and fuzzy systems. Owing to this, it is possible determine synthesized evaluation systems advantages and additional capabilities.

Artificial neural network methods are widely used in classification tasks (Deng et al., 2018). A classification task involves assigning a sample to one of several non-overlapping sets. When solving classification problems, the diagnostic task consists of assigning the existing object characteristics to one or more known classes (according to the given data).

However, the issues of choosing the network topology, determining the number of layers and neurons, interpreting weight coefficients and displacements, and evaluating their relevance remain unaddressed, particularly in classification tasks. Another pending issue is choosing the number of features used. On the one hand, multiple features used in constructing the classifier give more information for dividing into classes. On the other hand, the classification algorithm may become more complex.

Therefore, it is essential to optimize the chemical composition and technological parameters that enhance the heat resistance of polymer composites. Owing to this, improvements caused by advanced thermomechanical research methods, data processing, and the classification of epoxy composites based on the analysis of their fillers will become more pronounced.

This research aims to classify epoxy composites using machine learning methods (neural networks, boosted trees, and random forests) based on analyzing thermal conductivity coefficients and the concentration of their fillers (mass fraction of the filler).

2. Material and methods

Understanding the effect of polyfunctional fillers on epoxy composite properties is essential for their diagnostic evaluation. Epoxy polymers filled with aerosil, γ-aminopropyl aerosil, aluminum oxide, and chromium oxide were classified using the most versatile and efficient learning algorithms, such as neural networks, boosted trees, and random forests (Mohanty et al., 2009; Pidaparti & Palakal, 1995; Yasnii et al., 2018; Yasniy et al., 2024). This is done with the participation of a teacher. Teacher participation consists of providing knowledge in the form of input-output pairs. The teacher formulates and transmits a desired response to the neural network. This response results from the optimal actions the neural network should perform. Network parameters are adjusted based on the training vector and the error signal, that is, a difference between the desired and actual signals at the network output.

Neural networks are complex mathematical models designed on the principles underlying the functioning of the biological neural networks of the human brain. They imitate the structure and functioning of the human brain to process information in the same way (Haykin, 2009). They create a system that learns from examples and adapt to new data, just as a human learns from experience. Mathematical models of neural networks use nodes or neurons connected to each other in a certain way to transmit and transform signals (Figure 1). These models are widely used in various industries to solve the problems of classification, prediction, etc.

The neuron operation algorithm is based on the following formulas (Equation (1)):

$$\begin{aligned} NET_{jl} &= \sum_i w_{ijl} \times x_{ijl}, \\ Out_{jl} &= F\left(NET_{jl} - \theta_{jl}\right), \\ x_{ij(l+1)} &= Out_{il}, \end{aligned} \tag{1}$$

where i is the number of entries into the layer; j is the neuron number in the layer; l is the layer number; x_{ijl} is the i-th input signal of the j-th neuron in layer l; w_{ijl} is the weight factor of the i-th entrance of the j-th neuron in layer l; NET_{jl} is the NET signal of the j-th neuron in layer l; Out_{jl} is the output signal; F is the non-linear activation function; θ_{jl} is the threshold level of the neuron.

The boosted tree algorithm is a method of learning with a teacher. It belongs to the combined machine learning methods that improve the accuracy of predictions by combining several models (Gorunescu, 2011; Wasserman, 1989). This approach creates a sequence of trees, where each subsequent tree is constructed based on the errors of previous trees. That is, each tree is trained based on the errors made by previous trees, which allows us to reduce the overall error of the model gradually. The basic process gives weight to misclassified samples so that the next tree handles them better. Thus, during each iteration, the emphasis is on those samples that are difficult to classify. This allows the model to become more accurate gradually. Once created, all the trees are combined, and classification

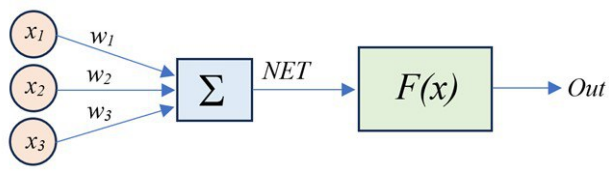

Figure 1. An artificial neuron model (Haykin, 2009)

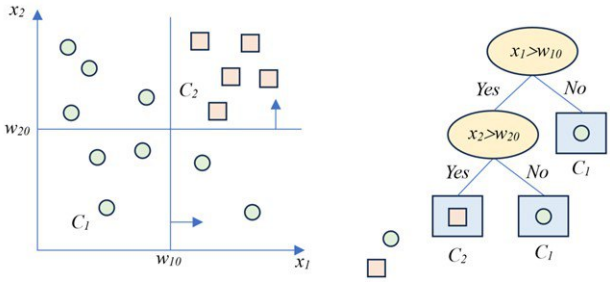

Figure 2. Example of a dataset and the corresponding decision tree. Oval nodes are decision nodes, and rectangles are leaf nodes (Alpayndin, 2010)

is done by voting or averaging the predictions of individual trees. Owing to this approach, the boosted tree algorithm is suitable for processing various data types, providing for a high-precision classification. This makes it popular for many applied problems (Figure 2).

The random forests method uses an ensemble of decisions generated by several decision trees to improve the accuracy and stability of predictions. This method constructs multiple decision trees during learning and issues the most common class of each individual tree (for classification purposes) (Qing & Li, 2024). Random forests lower the risk of overtraining and improve the overall performance of the model (Figure 3).

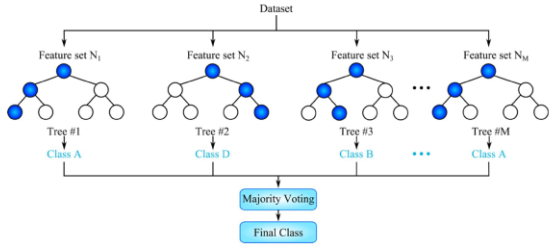

Figure 3. Random forest diagram with *M* decision trees. The final classification is determined by a majority vote generated by the results of individual decision trees classification (Khozeimeh et al., 2022)

3. Dataset

An analysis of experimental studies on the development of polymer composite materials with an epoxy matrix was carried out, considering the requirements for the polymer matrix, dispersed, and fibrous fillers, both at the stage of obtaining the materials and in the operating conditions. The use of dispersed and fibrous active fillers in composite systems provides regulation of the technological modes of formation (Stukhlyak, 1996). This makes it possible to increase the physical, mechanical, and thermophysical characteristics and regulate the rheological properties of polymer composite materials.

The scheme of the epoxy composite is given in Table 1 (Mykytyshyn, 2002). Epoxy resin ED-20, which has the following positive properties, was chosen as the basis of polymer composite materials: high adhesive strength, the ability to form at room temperatures, little shrinkage in the approval process, and manufacturability when applied to the surface of a complex profile. Chromium oxide Cr_2O_3 with a particle size of up to 30 μm, aluminum oxide Al_2O_3 with a particle size of 30–100 μm, A-175 aerosil with a particle size of up to 5 μm were utilized as dispersive fillers, which are the most famous in the creation of polymer composite materials with an epoxy matrix (Table 1).

4. Results and discussion

During training, the dataset was divided into two unequal parts: a training sample and a test sample. The sample contained 16,056 elements, of which 70% were randomly selected from all experimental data at different temperatures, and 30% were left to evaluate the prediction quality. In particular, the 70/30 ratio for splitting the dataset into training and testing sets is a widely accepted standard in machine learning. Specifically, 70% for the training set provides enough data for the model to effectively learn to detect patterns, especially in cases where the available data is limited, while 30% for the testing set allows for a reliable assessment of the model's performance without the risk of overfitting that can arise from insufficient testing data. Thus, the 70/30 ratio is a compromise between efficient training of the model and a reliable assessment of its accuracy. The thermal conductivity coefficient, the filler mass fraction concentration, and temperature were the input parameters in the classification of epoxy polymers filled with aerosil, γ-aminopropyl aerosil, aluminum oxide, and chromium oxide. Figure 4 shows a specific technological route for classifying epoxy polymers.

The macro and weighted average (Deng et al., 2018) were selected to compare the model classification accuracy. Normalized confusion matrices were obtained for each method. Figures 5 and 6 show the confusion matrices obtained for the absolute values and the classification accuracy, respectively.

Table 1. The effect of temperature on the temperature coefficient of linear expansion for different fillers (Mykytyshyn, 2002)

Fillers	Concentration	Thermal coefficient of linear expansion, $\alpha \times 10^{-5}$, K^{-1}		
		293-323K	323-353K	353-383K
Al_2O_3	30	8.12	15.34	27.42
Cr_2O^3	30	7.72	12.76	22.15
Aerosil	2	6.92	10.43	12.44
γ-aminopropyl aerosil	2	5.73	9.16	11.21

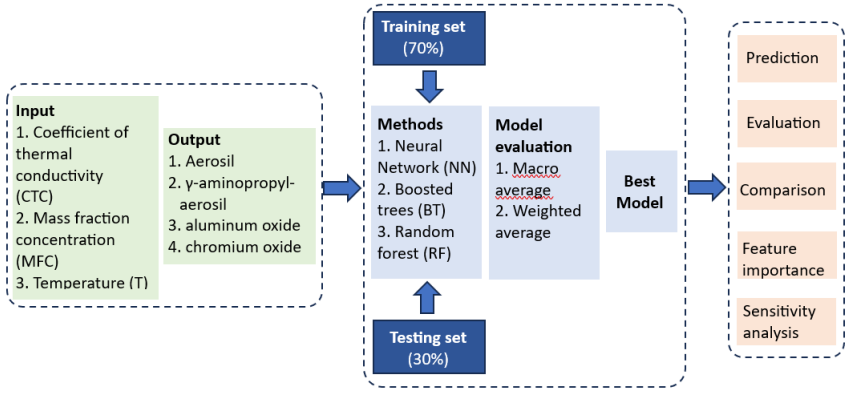

Figure 4. Technological path of machine learning methods for classifying epoxy polymers

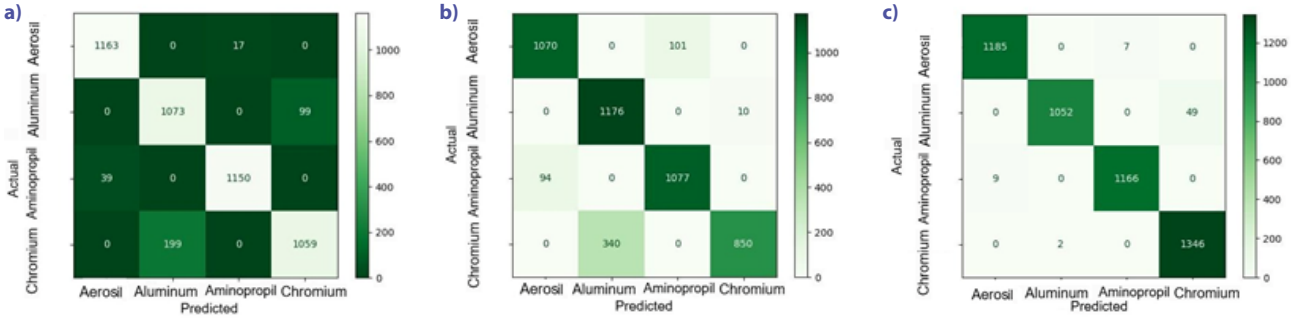

Figure 5. Confusion matrices of absolute values obtained by various machine learning methods: a) boosted trees, b) random forests, and c) neural networks

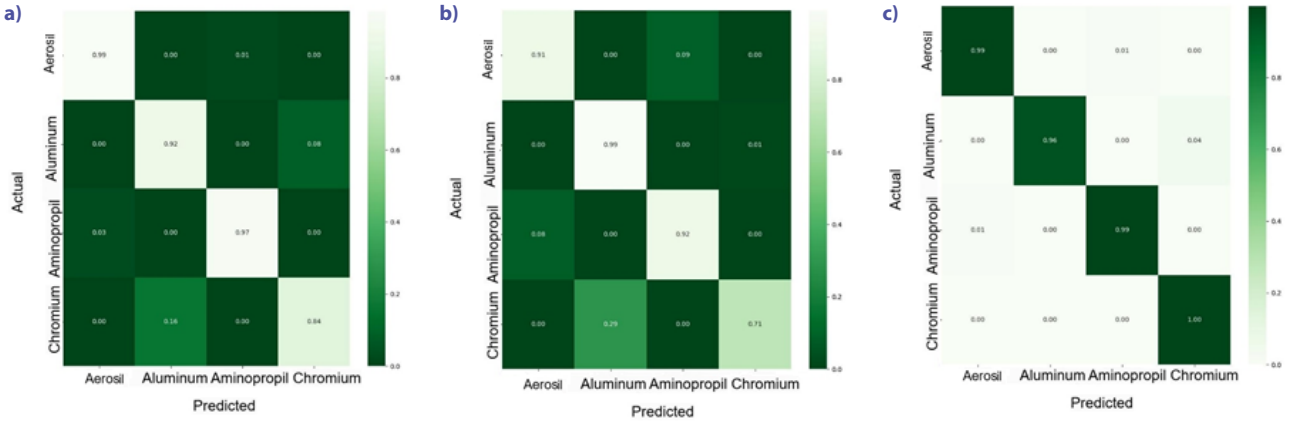

Figure 6. Normalized confusion matrices of obtained by various machine learning methods: a) boosted trees, b) random forests, and c) neural networks

They are constructed using machine learning methods. The confusion matrix is commonly used to solve classification tasks. It can be applied to both binary and multi-class classification. Confusion matrices contain counts of the predicted and actual values. Using neural networks, epoxy polymers filled with chromium oxide were detected to an accuracy of 100%. The accuracy of detecting epoxy polymers filled with aluminum oxide and γ-aminopropyl aerosil was 99%, and that of detecting epoxy polymers filled with aerosil was 96%. Epoxy polymers filled with chromium oxide were often misclassified by the boosted tree method as polymers filled with γ-aminopropyl aerosil (about 16% of cases). The same is valid for the random forest classifier, which misclassified 29% of epoxy polymers filled with chromium oxide as those filled with γ-aminopropyl aerosil.

The use of machine learning to classify epoxy composites with fillers allowed us to achieve high accuracy for each model, in particular, neural networks (99%), which is the highest result among the methods used, confirming their ability to accurately model complex, nonlinear

dependencies; boosted trees (93%) are less accurate than neural networks, but showed good results due to iterative focus on the errors of previous iterations; random forests (88%) have the lowest accuracy among the methods used, but their resistance to overfitting and noise makes them a useful tool for working with large and heterogeneous data sets.

In general, the study was conducted with a limited amount of experimental data. Neural networks, due to their architecture, performed well even with such a sample, but in real-world conditions, their accuracy may decrease if the database is not expanded. Boosted tree and random forest methods showed stable performance with a limited sample, which confirms their suitability for such tasks.

The greatest impact on the accuracy of the models was the mass fraction of filler, which is a key factor that determines the properties of epoxy composites, as well as temperature, which is an important parameter that affects the behavior of fillers in the matrix and the thermal conductivity coefficient, as it correlates with the type of filler, which allows the models to effectively distinguish between epoxy composites.

Overall, the results of the study confirmed the effectiveness of using machine learning methods to classify epoxy composites, as the algorithms reduce the dependence on lengthy physical experiments. In addition, the models are integrated into production lines to monitor the properties of epoxy composites in real time. Additionally, the proposed methodology is adapted to other types of materials and technologies.

Classification metrics were obtained for each method used. Parameters such as precision, recall, F1 scores, and support were defined. Tables 2–4 contain classification metrics (precision, recall, F1 scores, and support) for each class and the whole dataset. In particular, the precision, which determines the proportion of correctly classified samples among all samples, was calculated. It is the most common metric for evaluating classification models. The macro average was also calculated, which evaluates the model performance for each class separately, giving the same weight to each class. In addition, the weighted average was obtained, which considers the frequency of each class, making this metric more suitable for processing unbalanced datasets.

Table 2. Neural networks

Filler class	Precision Metric	Recall Metric	F1 Score Metric	Support
Aerosil	0.99	0.99	0.99	1192
γ-aminopropyl aerosil	0.99	0.99	0.99	1175
Aluminum oxide	1.00	0.96	0.98	1101
Chromium oxide	0.96	1.00	0.98	1348
Accuracy		0.99		4816
Macro average	0.99	0.99	0.99	4816
Weighted average	0.99	0.99	0.99	4816

Table 3. Boosted trees

Filler class	Precision Metric	Recall Metric	F1 Score Metric	Support
aerosil	0.97	0.99	0.98	1180
γ-aminopropyl aerosil	0.99	0.97	0.98	1189
aluminum oxide	0.84	0.92	0.88	1172
chromium oxide	0.91	0.84	0.88	1258
Accuracy		0.93		4799
Macro average	0.93	0.93	0.93	4799
Weighted average	0.93	0.93	0.93	4799

Table 4. Random forests

Filler class	Precision Metric	Recall Metric	F1 Score Metric	Support
aerosil	0.92	0.91	0.92	1171
γ-aminopropylaerosil	0.91	0.92	0.92	1171
aluminum oxide	0.78	0.99	0.87	1186
chromium oxide	0.99	0.71	0.83	1190
Accuracy		0.88		4718
Macro average	0.90	0.88	0.88	4718
Weighted average	0.90	0.88	0.88	4718

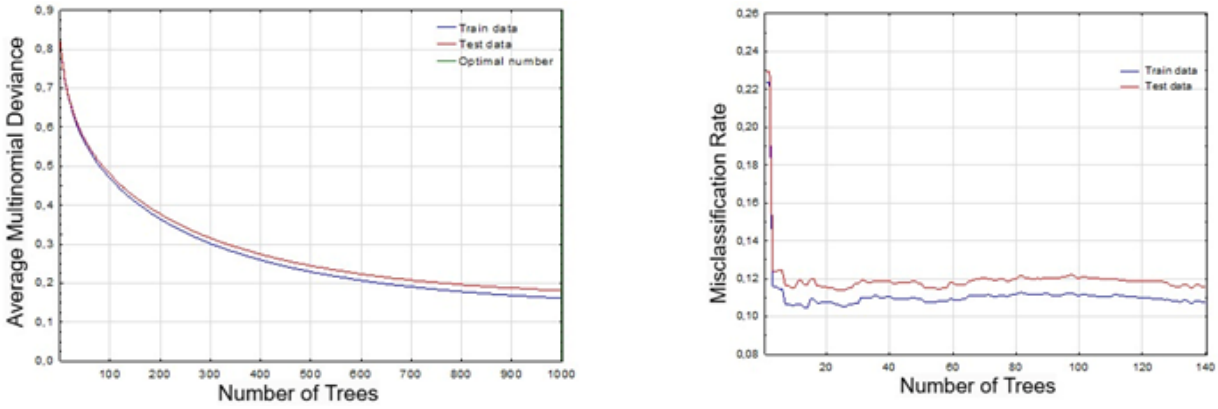

Figure 7. Performance metrics dependence on the number of trees: a – average MND in boosted trees, b – MCR in random forests

Table 5. Neural networks parameters

Neural network	Learning algorithm	Error function	Hidden activation function	Output activation function
MLP 3-9-4	BFGS	Entropy	Tanh	*Softmax*

These metrics make it possible to evaluate the model from different perspectives. This is particularly relevant for data processing, where classes are of different sizes. In general, neural networks rank first among the methods for classifying epoxy polymers.

The dependences of the average multinomial deviance (MND) on the number of trees in the boosted trees and the misclassification rate (MCR) on the number of trees in the random forests methods are crucial. It gives us a key to understanding how these models operate and how they can be improved (Figure 7). In particular, using the optimal number of trees in random forest and boosted tree methods allowed to reduce the average classification error and prevent overfitting.

In the boosted trees method, multinomial deviance is a loss function used to assess the performance of classification models with multiple classes. It measures how well the model predicts the probabilities for each class; in particular, lower deviance values indicate better model accuracy, whereas higher deviance indicates that the model's predictions are less accurate or poorly approximates the class probabilities. It is known that, in the initial stages, the plot generally shows a decrease in average deviance as the number of trees grows. This means the model is learning and increasingly distinguishing between the classes, predicting probabilities more accurately. After a certain number of trees, deviance stabilizes or reaches a minimum. This point likely represents optimal model complexity, where adding more trees no longer improves the accuracy on the training data. If deviance increases after reaching a minimum, this may indicate overfitting. In this case, the model becomes overly tailored to the training data and generalizes less effectively to new data. In general, this plot helps to choose the optimal number of trees in a boosted trees model to achieve the lowest average multinomial deviance, minimizing the risk of overfitting.

In the random forest method, the misclassification rate is the proportion of incorrectly classified examples out of the total examples. It reflects the model's accuracy: a lower misclassification rate indicates better classification performance. In the beginning, with a small number of trees, the misclassification rate is generally higher because the model doesn't have enough trees to reduce variance and random errors effectively. As the number of trees increases, the misclassification rate gradually decreases and eventually reaches a point where it stabilizes or only decreases marginally. This indicates that additional trees no longer improve model performance significantly, and the model has reached optimal generalization. Unlike some other algorithms, random forests rarely overfit as the number of trees grows. Thus, the misclassification rate usually does not increase after stabilization. In general, the plot helps to identify the optimal number of trees, after which adding more trees provides minimal or no improvement in the misclassification rate. This allows one to avoid excessive computation and enhance the model's speed without sacrificing accuracy.

Generally, the predicted data agrees with the experimental ones (Stukhlyak et al., 2000). Table 5 summarizes the parameters of the neural networks constructed.

5. Conclusions

The task of classifying basalt-reinforced epoxy composites for aircrafts filled with aerosil, γ-aminopropyl aerosil, aluminum oxide, and chromium oxide, respectively, is solved by machine learning methods, such as neural networks, boosted trees, and random forests.

A comparative analysis of the accuracy of various machine learning models for classifying epoxy composites with fillers such as aerosil, γ-aminopropyl- aerosil, aluminum oxide, and chromium oxide was performed. The model parameters were optimized, which allowed to achieve high prediction accuracy (over 88%), even with a limited amount of experimental data.

The results of the study can be integrated into the processes of automated quality control of epoxy composites for aerospace structures. These results are a significant step in the implementation of intelligent data analysis systems in materials science.

The use of neural networks provided the highest classification accuracy of 99%, which indicates their ability to model complex nonlinear relationships between the properties of epoxy composites. Boosted tree and random forest methods achieved an accuracy of 93% and 88%, respectively, providing high noise tolerance and interpretability of the results.

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