

INTERPRETATION OF GEORADAR DATA BASED ON MACHINE LEARNING TECHNOLOGIES

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Abstract

In the laboratory analysis of geological data, a number of problems arise due to the insufficient accuracy of the results. For example, different laboratories may provide different end results for the same samples, which creates a problem. This can lead to unreliable results, which can ultimately reduce the quality of the assessment.

Machine learning allows to speed up the processing of radar data, as well as avoid the above-mentioned «misunderstandings». The problem of conducting scientific research at specialized landfills for a comprehensive assessment of the possibilities of using computer technology in the interpretation of georadar profiles is urgent. This makes it possible to objectively evaluate the result of automatic interpretation of georadar data.

The several machine-learning algorithms described in the article are designed to improve the analysis and interpretation of data by incorporating various methods for optimizing georadar data processing processes. These methods include regression, classification and clustering.

By incorporating these methods of optimizing the processing of georadar data into several machine-learning algorithms, the software can provide a comprehensive analysis and interpretation of the data obtained. This allows for a better understanding of the relationships, patterns and trends in the data, which ultimately leads to more informed decision-making and improved understanding.

To improve the understanding of the results, the following quantitative indicators were obtained: correlation coefficient – 0.7072, determination coefficient – 0.5001, all these indicators correspond to these models. The deviation from the regression line is on average 22.37 units. Based on the classification results, the soil was determined to be wet. Errors in the sets do not exceed 1 %.

Keywords: georadar, geodata, interpretation, radargram, method, experiment, Bessel filter, spectrum, object, machine learning.

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1. Introduction

The georadar method is a relatively new technology used to study the geological environment in our country. Although theoretical developments have been around for a long time, it is only with the current level of technological progress that it has become possible to implement promising scientific ideas. This is due to the creation of modern equipment and computer systems for data collection and processing [1].

Despite the increasing need for georadar research in the field of construction and geocology, there is still a significant shortage of literature and specialized courses on the theory, technique, methods and geological interpretation of geo-radar data. This makes it difficult to find specialists who are able to conduct research and solve complex problems. As the demand for georadar continues to grow, there is an urgent need to increase the availability of resources and training to meet this demand.

Automation of radargram processing based on machine learning technologies is an important task in the field of radar data analysis. A radargram is an image obtained using a radar system and containing information about various objects and their properties.

Machine learning allows the development of algorithms and models that can automatically process radargrams and extract useful information from them without the need for manual

interpretation. This speeds up the data processing process and allows to solve problems such as object classification, segmentation and recognition on radargrams [2].

The most time-consuming method is still manual interpretation of data, in which a specialist works with each route separately and determines the location and amount of the boundary of the medium based on changes in the characteristics of the signal. A wide range of algorithmic solutions for signal modification and filtering has been developed for this method, simplifying the work of the interpreter. In the vast majority of modern software and hardware complexes, the initial data obtained from georadiolocation is subjected to a number of preliminary transformations (such as filtering and Fourier or wavelet transformations of each trace) with the subsequent alignment of all traces into a two-dimensional image and subsequent modifications (brightness/contrast adjustment, changing the color palette, etc.).

As a result of these transformations, the specialist receives a much clearer image, which is easier to work with. However, even the use of complex multi-stage algorithms is not a panacea, since the problem of noise from nearby objects with significantly contrasting permittivity values (such as bridge supports and large structures) or creating noise similar to the original signal (such as power cables) It still remains. At the same time, the problem of defining boundaries remains solely the responsibility of a specialist [3].

The relevance of the problem is justified in order to better understand the relationships, patterns and trends in the data, which leads to a more reasonable improvement in understanding. Therefore, research on optimizing the processing of georadar data based on machine learning technologies is relevant.

The purpose of the study is to optimize the process of analyzing georadar data based on machine learning technologies. The tasks of optimizing the processing of georadar data include a set of machine learning methods, such as:

1. Regression is a statistical technique that helps understand the relationship between one dependent variable and one or more independent variables. This allows to predict values based on observed patterns in the data. Using ensemble regression, software can identify patterns and trends in data and make predictions based on those patterns.

2. Classification is another data management technique used in the ensemble. It involves categorizing data into different groups or classes based on specific features or characteristics. By applying classification algorithms, the software can assign data points to predefined categories, allowing for deeper understanding and interpretation of the data.

3. Clustering is a technique that groups similar data points together based on their similarity or distance from each other. This helps identify patterns and structures in the data and can be useful in discovering relationships and patterns that are not obvious. By incorporating clustering algorithms into the ensemble, the software can analyze data and group similar data points together, allowing similar data to be compared and interpreted.

2. Materials and methods

2.1. The object and hypothesis of the study

The georadiolocation method is one of the most promising methods for studying the internal structure of underground environments – from soil profiles to concrete structures and the bottom of reservoirs. The popularity of georadar is explained by a combination of factors. Firstly, the method is relatively inexpensive, since it requires only one piece of equipment. Other methods, such as drilling and seismic exploration, are much more expensive and time-consuming. Secondly, georadar is a non-destructive method of obtaining information about the subsurface; an electromagnetic pulse is emitted into the ground, and reflected waves are recorded by the receiver. Thirdly, the frequency of the signal can vary depending on the specific application, which allows to select the required resolution and depth of sensing.

Despite its advantages, ground-penetrating radar is not without drawbacks. The most significant of them is the difficulty of interpreting the data obtained. This is due to the unique characteristics of the received radar image – a two-dimensional graph of the dependence of the amplitude of the reflected signal on the time of its arrival.

2. 2. Retrieving a dataset

At the newly built laboratory site, at the «Zher» test site, a number of experimental studies were carrying out using the Zond-12e ground penetrating radar with a 300 MHz antenna. The object «Copper cable» was considering for the study. The copper cable is buried at a depth of 122 cm, pit length 319 cm, width 73 cm.

The results obtained were processed using the «Prism 2» program, intended for use in field conditions as part of the Zond-12e georadar. The data is downloaded as a text file (**Table 1**).

Table 1

Real georadar data of the «Copper cable» object

Trace	0	1	2	3	4	5	6	7	8	9	10
The value of the amplitude of the signals	-145	-142	-140	-155	-182	-214	-243	-310	-440	-651	-913
Trace	11	12	13	14	15	...	238	239	240	241	242
The value of the amplitude of the signals	-1110	-1103	-866	-644	-854	...	-157	-151	-144	-138	-132

One of the most common ways of signal processing is filtering. The purpose of filtering is usually to separate useful signals from mixtures of other signals and noise. There are filters that do not change the phase of the signal. Such filters are called linear phase filters. This means that even if the phase of the signal changes, it happens in such a way that all harmonics of the signal are shifted in time by the same amount. Therefore, linear phase filters do not distort the phase of the signal, but only shift the entire signal in time. One of the filters is the Bessel filter, which provides maximum smooth response with a delay. The advantage of Bessel filters is an optimal and very low transient response with positive emission [4]. The filter can be described by a function of the form:

$$H(S) = \frac{d_0}{\sum_{k=0}^n d_k S^k}. \quad (1)$$

The coefficients of the Bessel filter are determined by the expression:

$$d_k = \frac{(2n-k)!}{2^{n-k} k!(n-k)!}, \quad (2)$$

n – order of the filter, k – order of degree S^n . To process the data from noise, a linear Bessel filter was used. As a result, it is possible to obtain processed data presented in **Table 2**.

Table 2

Processed data after noise removal

Trace	0	1	2	3	4	5	6	7	8	9	10
The value of the amplitude of the signals	-31	-49	-62	-71	-76	-79	-90	-126	-213	-349	-486
Trace	11	12	13	14	15	...	238	239	240	241	242
The value of the amplitude of the signals	-546	-486	-366	-334	-517	...	-352	-316	-292	-280	-256

Fig. 1 shows the processed radargram of the «Copper cable» object.

The radargram clearly identifies an object with a length of 200 cm. The beginning of the object is located at a picket of 87.5 cm, the end at a picket of 287.5 cm, which corresponds to the model. Below, **Fig. 2** shows route and spectrum of the «Copper cable» object.

A radargram is an ultra-wideband radio signal. As can be seen from the graphs, the main spectral components of the radargram that affect the signal amplitude are the georadar antennas located around the central frequency. The basic information about the underground environment lies in the amplitude of the signal corresponding to the time of reception of the signal.

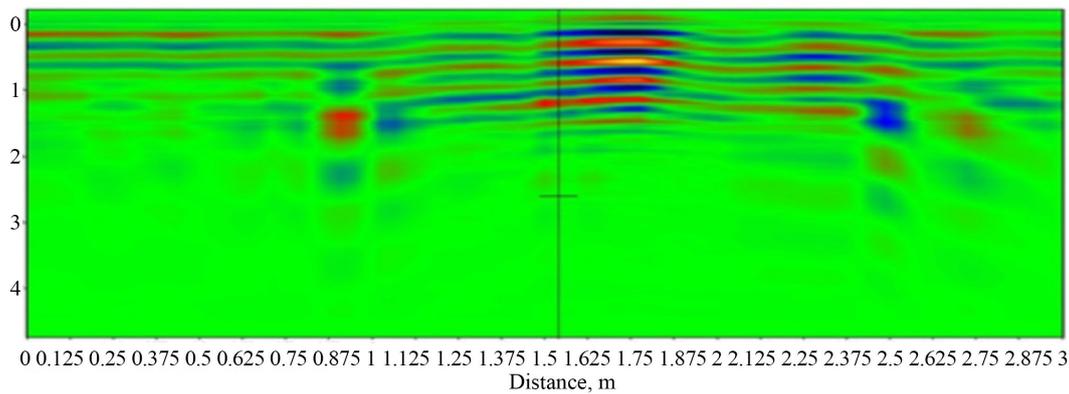


Fig. 1. «Copper cable» radargram

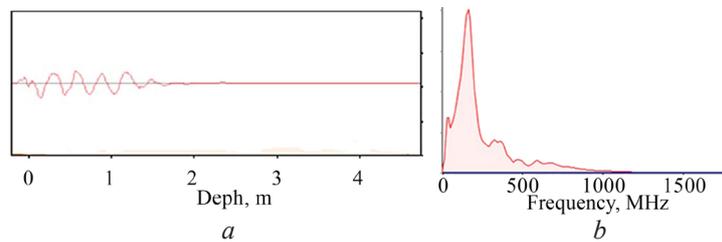


Fig. 2. «Copper cable» object: *a* – object route; *b* – object spectrum

The second object of the experimental study was «Clean Sand». The obtained data were also processed using the «Prism2» program. The data is downloaded as a text file (**Table 3**).

The received data must be cleared of various noises that hide useful data. A Bessel filter was used to remove noise, since the Bessel filter has the smoothest possible group delay. **Table 4** shows the processed georadar data.

Table 3

Real georadar data of the «Clean Sand» object

Trace	0	1	2	3	4	5	6	7	8	9	10
The value of the amplitude of the signals	2	1	5	12	14	11	1	-2	-9	-8	5
Trace	11	12	13	14	15	...	238	239	240	241	242
The value of the amplitude of the signals	32	73	127	192	272	...	202	201	204	211	226

Table 4

Processed data after noise removal

Trace	0	1	2	3	4	5	6	7	8	9	10
The value of the amplitude of the signals	105	132	174	197	258	279	347	354	441	424	507
Trace	11	12	13	14	15	...	238	239	240	241	242
The value of the amplitude of the signals	476	588	572	738	745	...	9070	9083	9371	9519	9939

Fig. 3 shows the processed radar image of the «Clean Sand» object.

The radargram shows a homogeneous, undisturbed structure of the strata, which corresponds to the model. Below, **Fig. 4** shows route and spectrum of the «Clean Sand» object.

A distinctive feature of these studies is the selection of several objects, such as clean sand and copper cable. The choice of such an environment is necessary for testing algorithms and mathematical models for determining the depth and physical properties of a localized object. One of the main challenges when measuring underground-localized features is the top of the soil that lies above the features of interest.

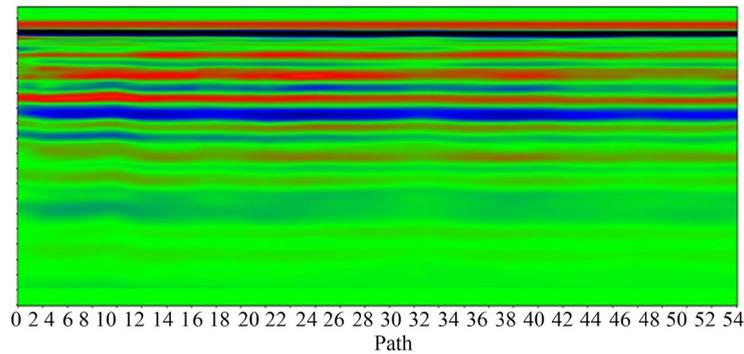


Fig. 3. Profile radargram

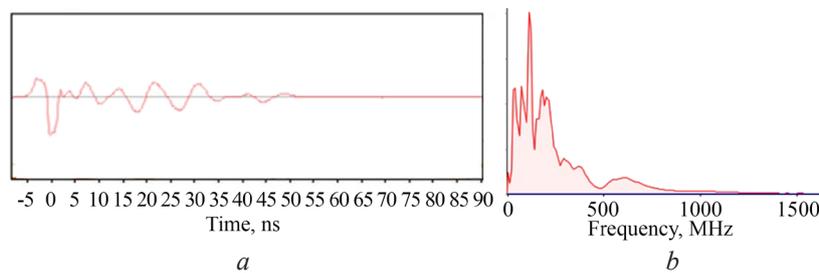


Fig. 4. «Clean Sand» object: *a* – object route; *b* – object spectrum

Passing through this area, electromagnetic waves interact with each other when reflected from different objects. The interaction can both amplify and weaken the waves.

One way to solve this problem is to extend the solution of Maxwell's equations from the surface of the earth to the location of the objects of interest. However, this expansion task is incorrect due to the attenuation of the electromagnetic field in conductive media.

Using georadar, a series of experimental studies was carried out and a set of radar images was obtained in order to analyze the collected data. In addition, a cycle of calculations was carried out to verify the compliance of the results of mathematical modeling with real data obtained from ground-penetrating radar [5].

The mathematical modeling process can be dividing into several stages. The first step is to build a georadar model of the site based on the collection of environmental data. In addition to geological information about the layers, the model should also include data on electro physical properties such as conductivity and permittivity. These properties are relating to the saturation of air and moisture, temperature and other factors. The level of detail of the model may vary depending on the capabilities of the modeling tool used. This means that some simplifications may be required, such as ignoring border irregularities and the three-dimensional nature of the section.

The use of optimization methods necessitates the introduction of iterative methods, therefore, in [6], economical methods for solving direct and inverse problems were developed.

2. 3. Model evaluation

The ensemble of machine learning methods uses several learning algorithms to achieve a higher level of efficiency than could be achieved with each individual learning algorithm. This approach aims to optimize accuracy by combining the strengths of different algorithms and using their unique capabilities [7].

Using a combination of these algorithms, the ensemble method offers a more reliable and comprehensive solution to problems in machine learning.

In general, the combined result is more reliable than the individual result because it reduces the variance.

Fig. 5 below shows the algorithm for implementing the model.

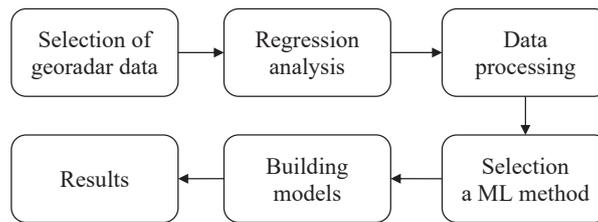


Fig. 5. The algorithm for implementing the model

Let's suppose that there is regression model that is a parametric family of functions (x, α) , where the model parameters are denoted as a vector $\alpha \in R^p$. Now it is possible to define a measure of the quality of approximation of the target dependence on the data set $X\ell$ as the sum of squared errors:

$$Q(\alpha, X\ell) = \sum_{i=1}^{\ell} (g(x_i, \alpha) - y_i)^2. \quad (3)$$

Least squares learning is the process of finding a parameter vector α^* that minimizes the mean squared error on a given training set $X\ell$. In other words, it all comes down to determining the optimal parameter values that minimize the difference between the predicted and actual values in the sample. This method plays an important role in machine learning because it provides the most accurate results of approximating the model to the original data [8]. The problem is to find parameter values such that the prediction errors are as minimal as possible:

$$\alpha^* = \arg \min_{\alpha \in R} Q(\alpha, X\ell). \quad (4)$$

In this optimization problem, a standard approach based on the necessary minimum condition can be used to find a solution. If the function $g(x, \alpha)$ has a sufficient number of derivatives that are differentiable with respect to α , then at the minimum point it is possible to obtain a system of p equations relating p unknown variables:

$$\frac{\partial Q}{\partial \alpha}(\alpha, X\ell) = 2 \sum_{i=1}^{\ell} g(x_i, \alpha - y_i) \frac{\partial g}{\partial \alpha}(x_i, \alpha) = 0. \quad (5)$$

Using machine learning libraries, (3), (5) can be implemented automatically.

3. Results and discussion

Automation of radargram processing using machine learning technologies can lead to the following results [9]:

1. Increased processing speed. Machine learning technologies make it possible to process radargrams much faster compared to manual methods. This reduces analysis time and allows for quick results.

2. Increased processing accuracy. Machine learning has extensive computing power and can detect even minor defects or changes in radargrams. This improves diagnostic accuracy and allows problems to be detected at an early stage.

3. Reduced costs. Automation of radargram processing processes helps reduce the costs of training and servicing specialists. Machine learning technologies make it possible to perform a significant part of the work, thereby reducing personnel costs.

4. Increased reliability. Machine learning allows to automatically classify and analyze radargrams, eliminating errors that may occur during manual processing. This increases the reliability of the results obtained and reduces the likelihood of missing defects.

In general, automation of radargram processing based on machine learning technologies can increase the efficiency and accuracy of defect detection, speed up the research process and reduce equipment maintenance costs [10].

Data for machine learning algorithms was obtained using experiments conducted at the «Zher» test site. One of the «Copper Cable» objects was considered for the study (Fig. 6).



Fig. 6. «Copper cable» object

The second object was sand in its pure form. Model of an undisturbed medium with a homogeneous structure. In Fig. 7, the «Clean Sand» object is shown.



Fig. 7. «Clean Sand» object and ground penetrating radar «Zond-12e»

Based on the data obtained from the «Clean Sand» object, the Fig. 8 shows one of the machine learning regression algorithms.

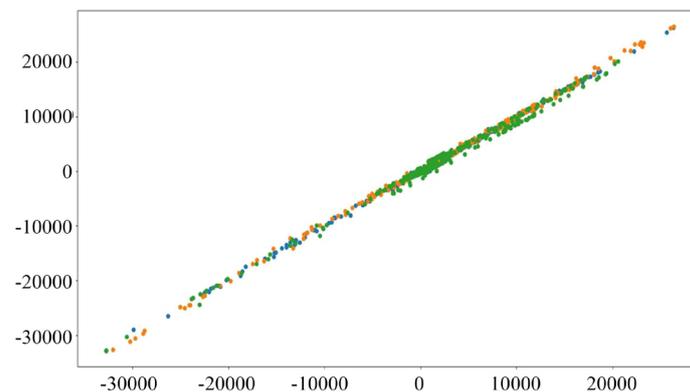


Fig. 8. Regression based on data from the «Clean sand» object

The figure shows that the theoretical regression line corresponds to the empirical regression line. According to the data obtained, the adequacy of the model and a homogeneous, undisturbed structure that corresponds to the model are visible [11]. The following Fig. 9 shows the second machine learning method clustering.

The algorithm is based on the assumption that the greater the difference or distance between parallel hyperplanes, the smaller the average classifier error will be [12]. The following Fig. 10 shows the result of clustering the «Copper cable» object.

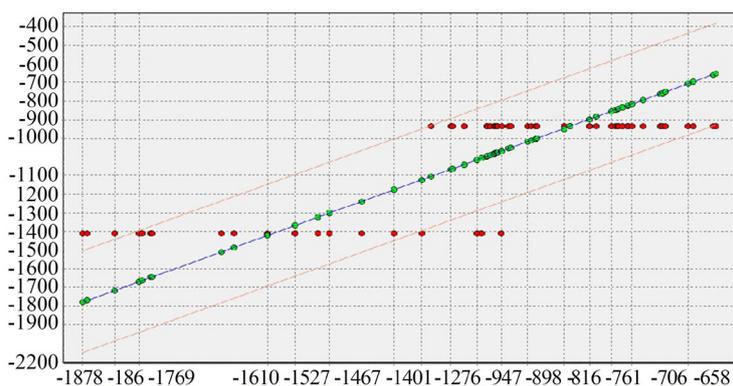


Fig. 9. Clustering based on data from the «Clean Sand» object

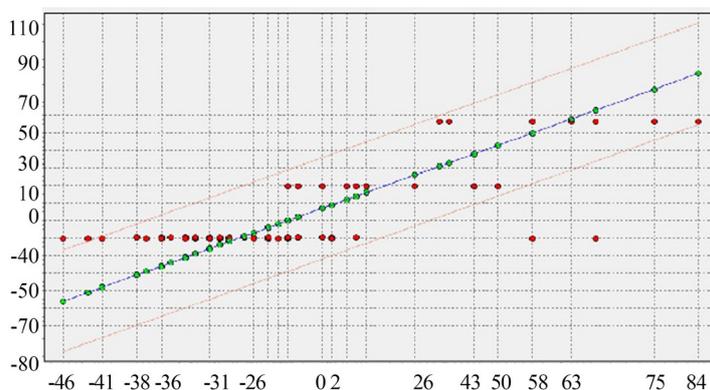


Fig. 10. Clustering according to the «Copper cable» object data

Based on the presented diagrams, it is possible to say that the two objects are different in spatial characteristics and properties. Therefore, the type of these objects and the environment in which they are located can be easily determined [13].

Experiments conducted on real data show that the proposed methods do not require special training and special data preprocessing to achieve accuracy on complex data sets [14].

There are many ways to interpret data obtained by ground penetrating radar. Currently, the most popular approaches involve chains of algorithms that undergo multiple signal transformations and filtering. This can be explained by the fact that the field was initially developed under severe computational constraints. However, the most promising direction for the development of ground penetrating radar now is the introduction of intelligent systems and increasing the level of automation of data processing, as well as lowering the threshold for the entry of new specialists. The implementation of these trends will expand the scope of application of ground penetrating radar and reduce costs, while achieving qualitatively superior results [15].

Monitoring quality indicators helps improve quantitative characteristics. When assessing a result qualitatively, it is necessary to develop an indicator that reflects the magnitude of the change.

In this section, let's analyze the scientific value of the proposed method using quantitative indicators.

The main regression results based on the georadar data of the «Clean Sand» object are presented in **Table 5**.

Table 5
Regression quantitative data of the «Clean Sand» object

Correlation coefficient	Determination coefficient	Sum of squares	Middle squares
0.7072	0.5001	12963050309243.09	27006354810.9231

The main results of clustering based on georadar data of the «Clean Sand» object are presented in **Table 6**.

The main regression results based on the georadar data of the «Copper cable» object are presented in **Table 7**.

The main results of clustering based on georadar data of the «Copper cable» object are presented in **Table 8**.

Table 6
Clustering quantitative data of the «Clean Sand» object

Middle	Min	max	Sum of squares	Sum
-889.575	-1139	-627	32453921	-35583

Table 7
Regression quantitative data of the «Copper cable» object

Sum	Sum of squares	Average value	Standard deviation
2926	149226	38	22.37

Table 8
Clustering quantitative data of the «Copper cable» object

Sum	Sum of squares	Average value	Standard deviation
-344	38184	-9.05	30.78

The following presents the classification results for the «Copper cable» object.

0	1	2	3
5			2
1		1	36
1		9	
4		3	12

Fig. 11. Results of the classification of the object «Copper cable»

Based on the classification results, it can be concluded that three matching values equal to one are a perfect match. This data reflects the exact humidity levels in known areas.

To evaluate the effectiveness of a task, it is best to use a «Comparison matrix». This matrix reflects the number of correct and incorrect predictions for each class.

0	1	2	3
5			2
1		1	36
100.00 %	38.27 %	13.24 %	27.61 %
38.27 %	100.00 %	38.93 %	63.66 %
13.24 %	38.93 %	100.00 %	41.67 %
27.61 %	63.66 %	41.67 %	100.00 %

Fig. 12. Comparison matrix of the «Clean Sand» object

24.38 %	100.00 %	51.38 %	56.75 %	36.68 %
40.67 %	51.38 %	100.00 %	69.58 %	49.57 %
51.72 %	56.75 %	69.58 %	100.00 %	47.98 %
27.40 %	36.68 %	49.57 %	47.98 %	100.00 %

Fig. 13. Comparison matrix of the «Copper cable» object

This matrix is balanced, which guarantees the proper reliability and adequacy of the initial data necessary for ranking objects.

The analysis allows to highlight the following key points:

1. The average computation time increases as the matrix size increases. It should be noted that this applies exclusively to the time spent on computer calculations.
2. The average value of the squared deviations usually increases on average due to random factors in the formation of the initial pairwise comparison matrices.
3. The average number of iterations represents the number of elements that had to be changed to improve the consistency of the matrix; this number is also small compared to other methods and the total number of elements in the matrix.

Features of the proposed method and the results obtained in comparison with existing methods:

1. Automatic learning. Significantly simplifies and speeds up the process of data analysis.
2. Greater flexibility. Allows to use various algorithms and approaches to achieve optimal results in different tasks.
3. Resistant to noise. They have built-in regularization and smoothing mechanisms.
4. Ability to work with large volumes of data. Allows to discover hidden patterns and associations that may not be available using traditional methods.

However, when optimizing georadar data processing processes based on machine learning technologies, the following limitations and problems must be taking into account:

1. Requires a significant amount of labeled data to train the model. Without enough data, the model may lack accuracy or be prone to overfitting.
2. The difficulty of interpreting the results. Some methods can be difficult to interpret, especially when using deep neural networks. This can create difficulties in explaining the results and making decisions based on the model.
3. The possibility of bias and model errors. No machine learning method is comprehensive and consistently flawless.

The results obtained are explained by the fact that optimization of radar data processing processes based on machine learning improves work efficiency, increases the accuracy and speed of data analysis, and facilitates the work of specialists in the field of radar and data processing [16].

The article discusses a set of machine learning methods, including regression, classification and clustering. Errors in the validation, test and training data sets do not exceed 1 %.

The used set of machine learning methods fully confirms the compliance of the model under study with the obtained values. In conclusion, the use of a variety of machine learning techniques has proven effective in analyzing georadar data. Traditional research does not use such a wide range of machine learning methods. This comprehensive approach to interpreting GPR data leads to successful data interpretation.

In the future, it is possible to develop several intelligent systems working in parallel to solve the problems of determining the boundaries of environments and searching for local inhomogeneities.

4. Conclusions

For the «Clean Sand» object, the theoretical regression line coincides with the empirical regression line, which indicates the adequacy of the model and a homogeneous structure. The clustering algorithm assumes that increasing the difference or distance between parallel hyperplanes leads to a decrease in the average error of the classifier. From the presented diagrams for the «Copper cable» object it follows that the two objects differ in spatial characteristics and properties. This is confirmed by previously known experimental data corresponding to this model. Based on the classification results, the soil was determined to be wet. Based on the classification results, it can be concluded that values of one reflect accurate humidity levels in known areas.

In practice, the use of these results can be successful, since a number of problems arise with the subjective interpretation of georadar data due to the insufficient accuracy of the results. Also, subjective analysis may not be enough to draw clear conclusions. A combination of machine learning technologies can provide comprehensive analysis and interpretation of the data obtained.

Based on the results presented above, the following conclusion can be drawn:

1. The correlation coefficient is 0.7072, which is typical for the area under study and corresponds to a strong direct relationship between the variables.
2. The determination coefficient is 0.5001, which corresponds to the model data.
3. The «Copper cable» object standard error is 22.37, which means that the observed values deviate from the regression line by an average of 22.37 units.
4. Based on the classification results, the soil was determined to be wet.

Machine learning can optimize the analysis process and automate the interpretation of geological survey data. The continuation of work in this direction is very promising.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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