Artificial Intelligence Evolution
http://ojs.wiserpub.com/index.php/AIE/

Research Article

Application of Model Data for Training the Classifier of Defects in Rail Bolt Holes in Ultrasonic Diagnostics

Aleksei Kaliuzhnyi

Department of Applied Information Technologies, Yuri Gagarin State Technical University of Saratov, Saratov, Russia
Email: kaazdes@gmail.com

Received: 12 January 2023; **Revised:** 28 March 2023; **Accepted:** 4 April 2023

Abstract: The task of searching for defects on defectograms of ultrasonic inspection of rails using machine learning methods is considered difficult due to the lack of a sufficient representative training data set. In this study, on the example of defects in bolt holes of rails, the possibility of synthesizing an effective classifier trained on artificial data obtained by mathematical modeling is shown. Experiments have shown a high accuracy of predicting samples of real (not model) data exceeding 99%.

***Keywords*:** non-destructive ultrasonic inspection of rails, flaw detection, artificial data set, deep learning, neural networks, automatic defectogram analysis

1. Introduction

To ensure traffic safety in railway transport, non-destructive inspection of rails is regularly carried out using various approaches and methods. One of the main approaches to determining the operational state of railway rails is ultrasonic non-destructive testing [1]. Assessment of the testing results depends on the flaw inspector, which leads to the risk of missing out on defects and the possibility of accidents in railway transport. The need to increase the efficiency of the process of analyzing ultrasonic inspection data and its independence from the action of subjective factors of the flaw inspector makes the task of creating an automated system relevant. One of the actively developing approaches to pattern recognition of ultrasonic testing defects is the use of artificial neural networks. However, the main reason for the unsatisfactory accuracy of their recognition is the impossibility of high-quality training of neural networks in the absence of a representative training set of data that cannot be obtained by traditional methods.

The purpose of this work is to show the necessity, possibility, and effectiveness of applying the results of mathematical modeling for creating a training set of neural network data for searching for rail defects in their ultrasonic diagnostics.

2. Subject area analysis

When a flaw detector equipped with piezoelectric transducers (PZT) travels along a railway track, ultrasonic pulses

DOI: https://doi.org/10.37256/aie.4120232339

are emitted into the rail within a specified period. At the same time, receiving the PZT register reflected waves. The detection of defects by the ultrasonic method is based on the principle of reflecting waves from metal inhomogeneities, since cracks, including other inhomogeneities, differ in their acoustic resistance from the rest of the metal [1-2].

During ultrasonic scanning of rails, their structural elements and defects have acoustic responses, which are displayed on the defectogram in the form of characteristic graphic images (scans). Figure 1 shows an example of a defectogram in the form of a B-scan («Bright-scan») of a rail section with a bolted connection.

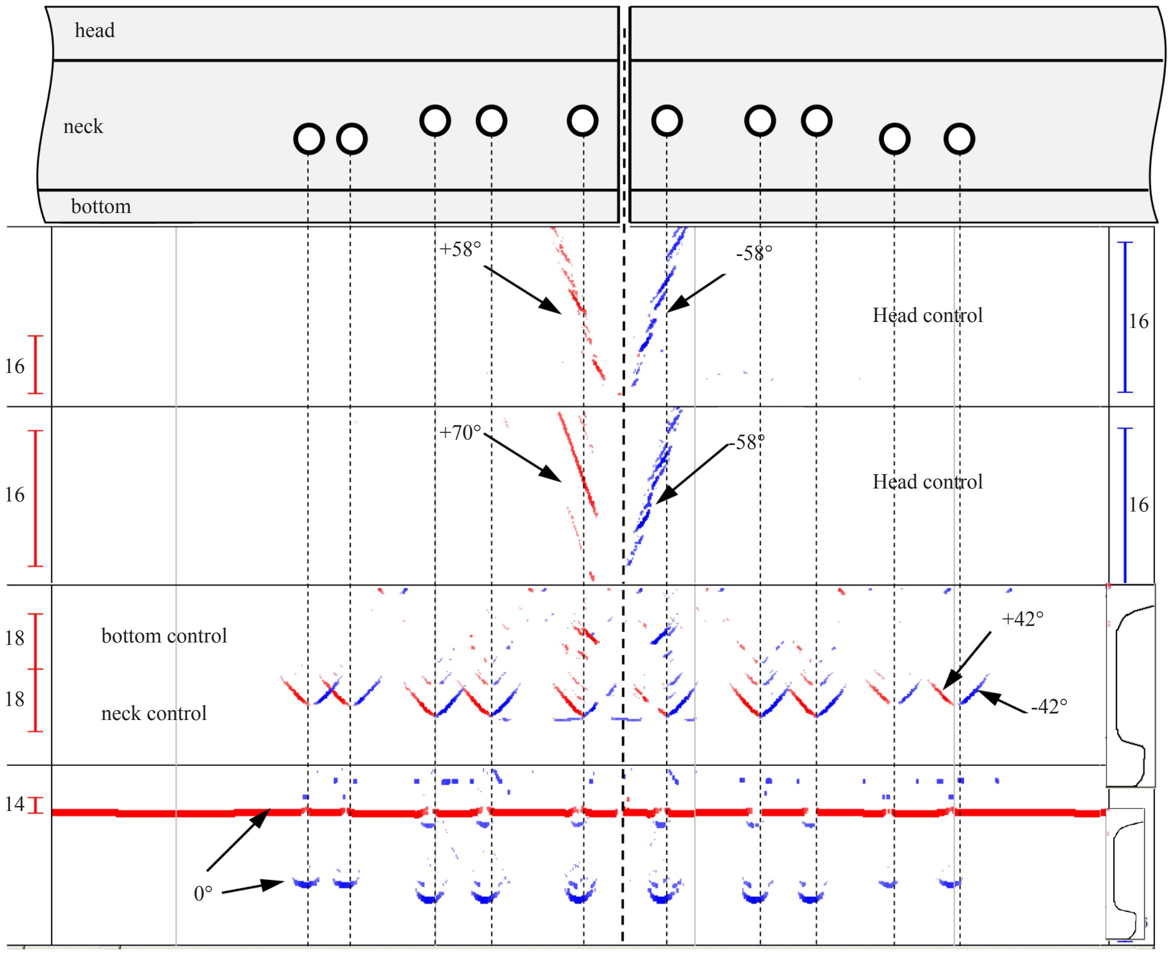


Figure 1. Example of the defectogram section of the bolt joint of the rail obtained by scanning with Avicon-11 ultrasonic equipment

2.1 *Decoding of defectograms*

The main purpose of the analysis (decoding) of the defectogram is to reliably find and highlight the graphic images of defects against the background of possible interference and images of structural elements. For the visual search for defects on the B-scan and A-scan, the cognitive functions of the involved experts-flaw detector operators are used.

Currently, the problem of searching for and recognizing defects is entirely assigned to the flaw detector operator [1, 3-6]. As a result of this, the human factor influences the quality and speed of the defectogram analysis. The small size of graphical images of defects, against the background of a significant length of the entire defectogram, measured in tens of kilometers of the railway track, significantly increases the psycho-emotional load on the flaw detector operator and increases the likelihood of missing defects [1, 3, 7-10], which increases the risk of accidents in railway transport. Therefore, an important direction is the creation of automatic defect recognition and expert systems.

2.2 *Problems of creating automated decryption systems*

The used flaw detector measuring systems have lumped parameters, they register, process, and save the received data, while the three-dimensional picture of the propagation of ultrasonic waves is reduced to a two-dimensional picture of the graphic image. This leads to a reduction in information about the object of study. Therefore, the efforts of manufacturers of flaw detection equipment are associated with the constant search for system parameters, sounding schemes, settings, and their combinations and are aimed at obtaining and storing the most important information about the object of study in terms of detecting defects. This approach changes the graphical appearance of defectograms and leads to the need to accumulate empirical knowledge on their analysis (decoding) for each type of flaw detector.

The methods of automatic decryption of data used in commercial software products often use the amplitude criterion, applying the principles of statistics to data analysis. However, many years of experience in using this approach did not solve the problem of automating the decoding of defectograms [1, 3, 9, 11-12].

With the development in the field of machine learning and its successful application in terms of simulating human cognitive functions for pattern recognition, companies, engineers, and researchers have focused their efforts on the application of artificial neural network algorithms to the problems of finding defects in the ultrasonic inspection of rails. [4-5, 9, 13-17]. In these studies, there are some successful attempts to create such systems, but the forecast accuracy of the created networks is not sufficient for their practical use, which is confirmed by the lack of commercial software products in the ultrasonic inspection market. The analysis and conclusions formulated in the work of most researchers [5-9, 12, 15-20] showed that the main reason for the low efficiency of neural networks is the insufficient amount of training data set.

2.2.1 *Dataset creation problem*

Despite the application of the general principle of ultrasonic testing of rails, manufacturers of flaw detection equipment compete with each other by using various:

-design features of the input and registration of pulses,

-sound schemes,

-data pre-processing methods,

-ways of filtering and presenting signals on defectograms.

Differences in the obtained control data and the competition of equipment manufacturers do not allow the creation of a common and open data set (Dataset) for training neural networks, which would most likely allow overcoming the barrier to using modern pattern recognition algorithms that exist in the field of flaw detection. The task of creating a training set of data for one or more of the same type of flaw detectors of one manufacturer is hindered by:

-rare detection of each class of defects on railway tracks during their routine diagnostics (approximately 1 defect per 100 km of track [10]),

-large variations in the graphic image of defects within the same class.

At the same time, the accumulated data set does not contain the same number of samples of each class of defects, that is, it is characterized by its imbalance, since most of it is made up of frequently occurring images of structural elements with no defects. This imbalance of the data set when using deep learning algorithms as a leading approach in the field of pattern recognition leads to a decrease in the forecast accuracy of synthesized neural networks for classes with defects [14, 16, 20]. Increasing the data set using field experiments with artificially created physical models of defects in rails is notable for its laboriousness and high cost. In the practice of flaw detection, such sections of the rail track are called test sections and serve to adjust flaw detectors and compare their performance.

The use of pre-trained neural network techniques and data extension (augmentation), considered during the work [16], showed their low efficiency.

One of the possible ways to solve this problem is to create an artificial data set based on mathematical modeling of the process of ultrasonic inspection of rails.

3. Methodology for solving the problem

3.1 *Application of mathematical modeling*

The possibility of using the results of mathematical modeling of the propagation of ultrasonic waves for creating an automated system for decoding defectograms is mentioned in the work [21], where the software is based on a deterministic mathematical model developed on the basis of existing theoretical knowledge in the field of ultrasonic location. In the work [21], it is proposed to use simulation results to assess the technical potential efficiency of sounding schemes, to assess the detection of defects of various sizes, to calculate echo signals and trajectories of ultrasonic waves, to develop new methods and means of monitoring, to compare analysis and to optimize sounding schemes.

Simplifications in the given model and its determinism do not allow to reflect on the results of its modeling the stochasticity of the measurement process during non-destructive inspection of rails associated with random:

-fluctuations in the degree of acoustic contact between the transducer and the rail surface,

-changes in geometric dimensions of the investigated rails along their length,

-deviations of input angles and other PZT parameters from the set ones,

-changes in the alignment of the PZT,

-changes in the acoustic properties of the metal of rails of different manufacturers and years of production, forms of defects,

-deviations of structural reflector shapes,

-fluctuations of reflecting properties of rail surfaces and defects,

-values of parameters of the measuring system setting,

-the noise of measuring equipment,

-conditions for the input of ultrasonic vibrations into the rail.

These reasons do not allow the proposed model to obtain an artificially created data set, which should reflect the variety of possible combinations of the listed factors for effective training of the neural network [8-9, 13-17, 22].

3.2 *Application of phenomenological models*

To achieve the goal of creating a generalized data set, the models used should reflect the variability in the process of diagnostic examination of rails, the structure and geometry of the object of study with the possibility of a quick and simple mechanism for setting their parameters. Therefore, this paper proposes to consider the use of phenomenological models with individual probability of change in each parameter (hereinafter referred to as models). It is assumed that the relative simplicity of their task for stochastic modeling will provide a representative set of data.

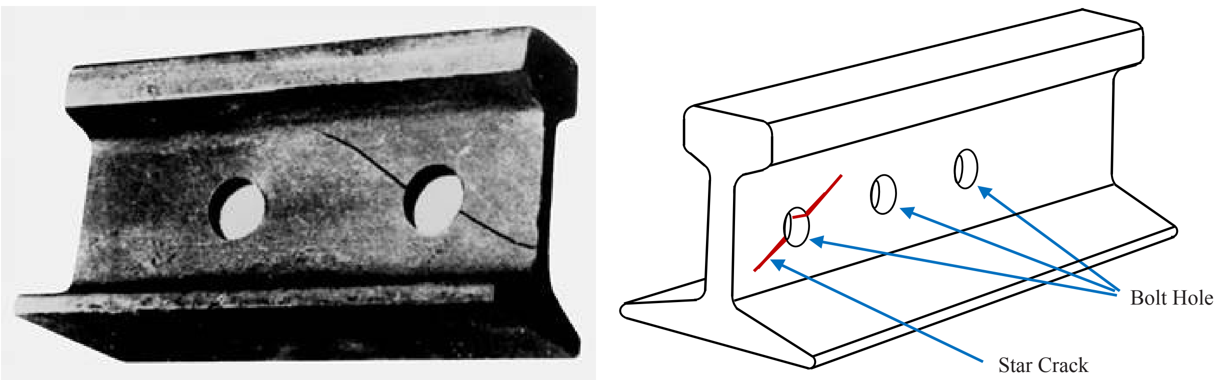


Figure 2. Example of star crack of bolt hole

To test the proposed approach, a model was created describing the process of reflecting and recording ultrasonic waves from structural reflectors of rails in the form of bolt holes and their radial cracks. This defect is referred to in the literature as «Star Crack» and is detected by a flaw detector channel with a preferred central angle of ultrasound input in the range of 38°-45° [2-3]. In most cases, radial cracks develop in the bolt holes and run along the rail neck at an angle of 45° to the longitudinal axis of the rail (Figure 2). The orientation of fatigue cracks in the neck is determined by the variety of combinations of deviations in the sizes of pads and rails from the nominal value [3]. Despite the systematic introduction of a seamless track on the railway network, the diagnosis of bolt holes is an important task [3].

The constructed model is focused on data synthesis for one of the flaw detectors available on the market. The appearance of the model defectogram for channels +/-40° is shown in Figure 3.

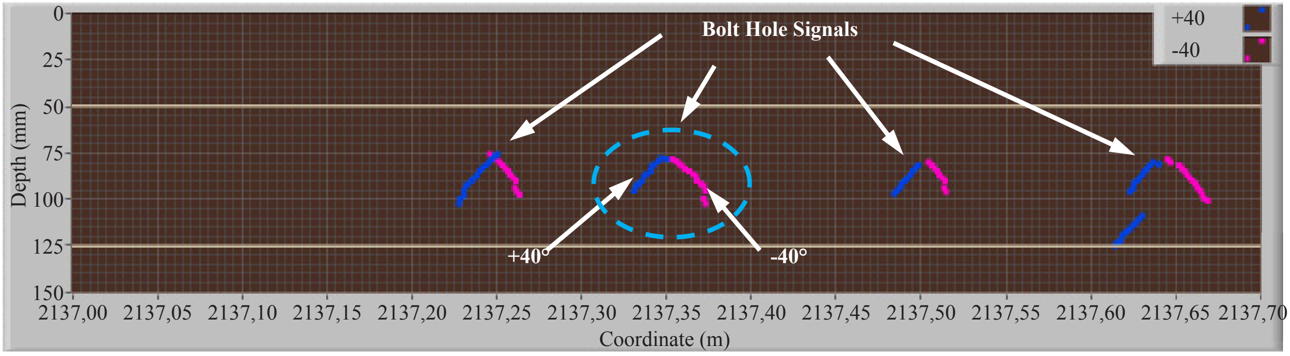


Figure 3. Model defectogram of a rail section with bolt holes

4. Building a neural network and evaluating its effectiveness

4.1 *Construction of information features*

The considered principles for obtaining defectograms and their interpretation allow us to propose the following data for analysis by a neural network, containing information signs of defects:

-A-scan data for each coordinate,

-B-scan data of a given size along the length of the rail,

-selected B-scan areas with images of individual bolt holes.

The use of A-scan to build a neural network was considered in paper [17]. However, its use in the search for radial cracks is a complex multi-connected task and is not considered in this work.

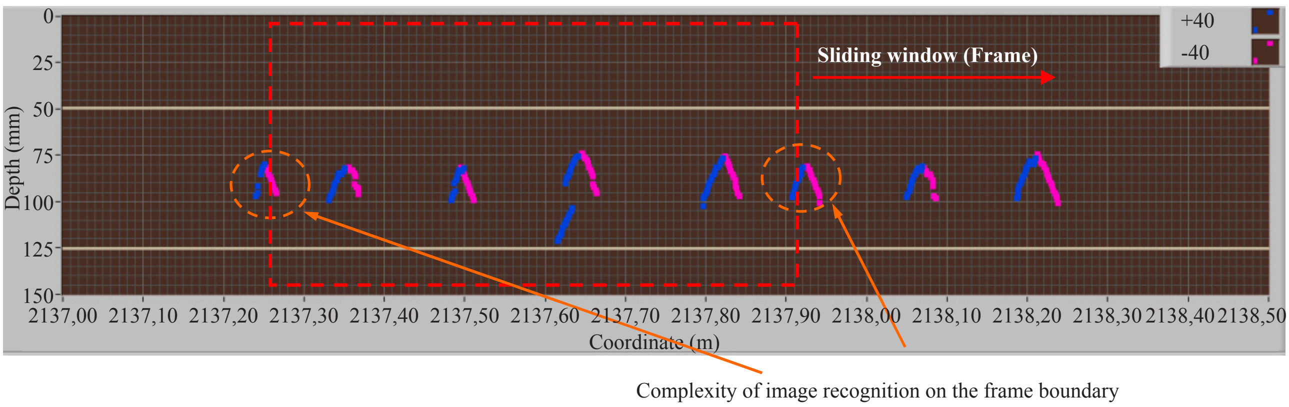


Figure 4. Selection of frame from B-scan by sliding window

The most promising may be the construction of a neural network trained to determine the defect directly on the B-scan, which is also natural for a decryption expert. Training a neural network and its subsequent work involves the use of small size of each data instance compared to the size of the entire defectogram. Therefore, for its full analysis, it is necessary to sequentially select fragments with a sliding window (Figure 4) and submit them to the input of the neural network, obtaining at the output a corresponding forecast of the presence of a defect in each selected frame. This approach is complicated by:

-selection of the effective size of the sliding window along the length of the rail, which affects the size and performance of the neural network,

-loss of information signs of defects in cases of the presence of a sliding window boundary on the signal from the bolt hole (Figure 4),

-selection of the displacement value of the sliding window along the length of the rail.

The task of bolt-hole crack recognition can be solved most simply by using an approach based on the selection of small B-scan areas with images of individual bolt-holes (Figure 5a). At the same time, information features of both the bolt holes themselves and their defects are concentrated in a selected small frame (Frame), which significantly reduces the size of the neural network and improves its performance. It is this approach in constructing information features of data instances that was chosen in this paper. In the practical use of a neural network, the location of each analyzed frame along the length of the rail is determined on the defectogram by the amplitude criterion. Figure 5b shows a spline interpolation of the time series, each point of which is defined as the sum of the amplitudes of the A-scan time series at each coordinate of the B-scan defectogram. The threshold values of the obtained time series were used to estimate the coordinates of the bolt hole along the length of the rail (Figure 5c).

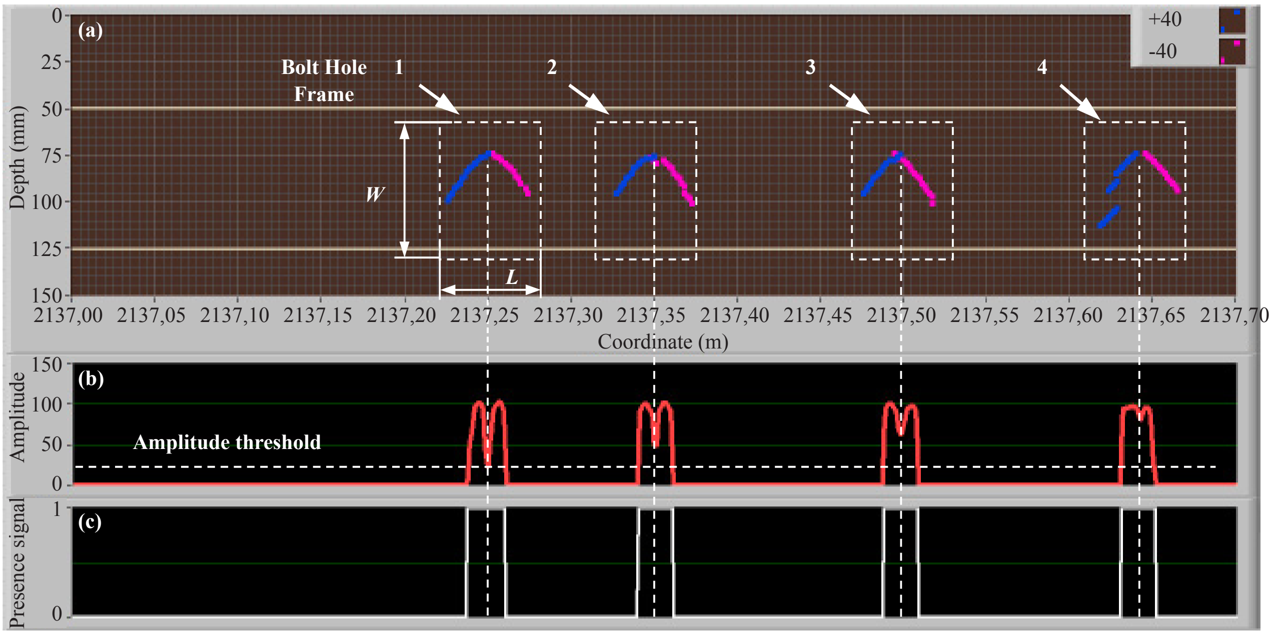
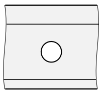
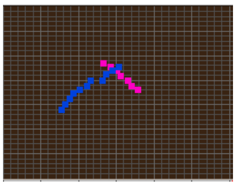
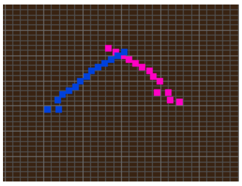
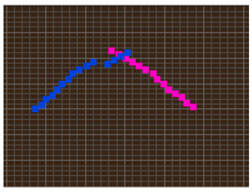
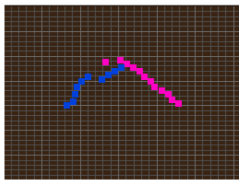
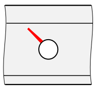
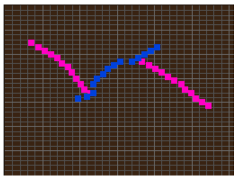
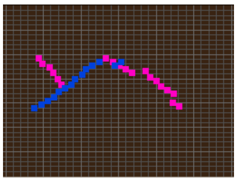
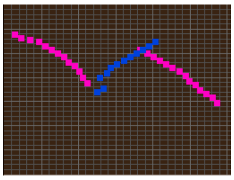
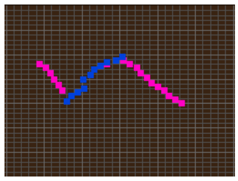
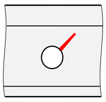
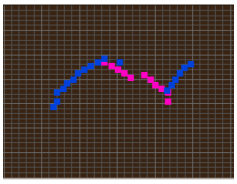
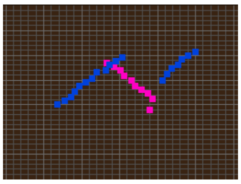
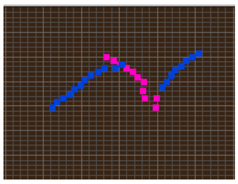
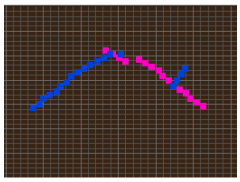
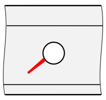
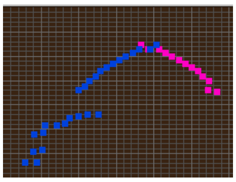
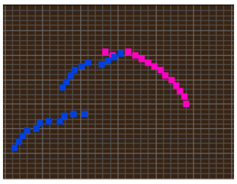
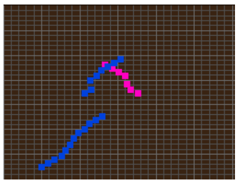
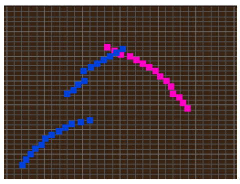
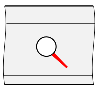
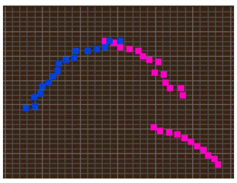
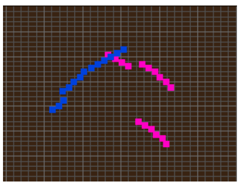
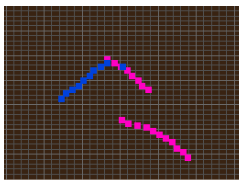
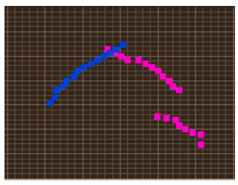
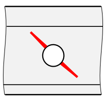
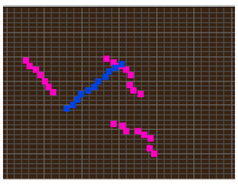
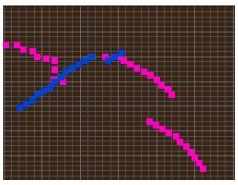
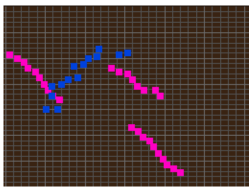
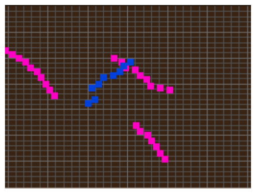
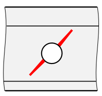
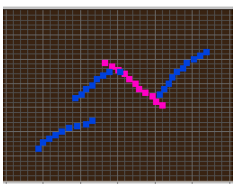
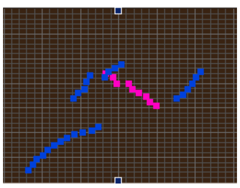
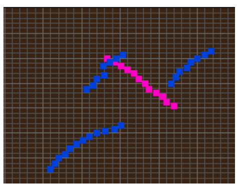
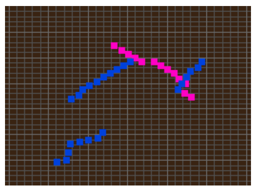


Figure 5. Selection of B-scan frames for individual bolt holes

The coordinate of the beginning of the frame along the depth of the rail is fixed since the bolt holes are located in the area of the rail neck with a small spread. The width W and the length L of each of the frames are the same (Figure 5a) and are selected on the basis of the maximum possible dimensions of the signaling of the bolt holes and their defects.

4.2 *Classification of bolt-hole defects*

Table 1. Examples of graphic images of bolt holes on B-scan (model data)

Class/Image	Example 1	Example 2	Example 3	Example 4
0 				
1 				
2 				
3 				
4 				
5 				
6 				

Based on information about the characteristic location of radial cracks in bolt holes, a classification of 7 classes was introduced, each of which was assigned a symbolic graphic designation (Table 1). In the practice of binary classification, it is generally accepted to assign class «1» to rarer outcomes or a state of interest, and class «0» to a common state. With regard to the detection of defects, we define the common and often encountered in practice defect-free state-class «0», and defective states «1»-«6». Despite the fact that during the operation of the railway track, the presence or absence of a defect (binary classification) is of decisive importance, we will consider the possibilities of the classification algorithm and quantify which types of defects are more likely to be ly classified as defect-free, which is a dangerous case in the diagnosis of rails.

Each defect class is displayed on the defectogram in the form of a characteristic graphic image, which is distinguishable for experts in the process of data decoding. Different forms of a crack, its location, and the reflective properties of the surface lead to changing graphical images, examples of which are presented in Table 1.

Each highlighted graphic frame is a matrix for the +40° and -40° ultrasound input channels, where each number is a signal amplitude value, and the indices of each array element represent the location along the length and depth of the rail. In this paper, the problem of searching for defects in a selected frame is reduced to the problem of pattern recognition. To do this, each fragment is converted into a graphic image of 60 × 75 pixels in grayscale with the loss of information belonging to the ultrasound input channel (Figure 6).

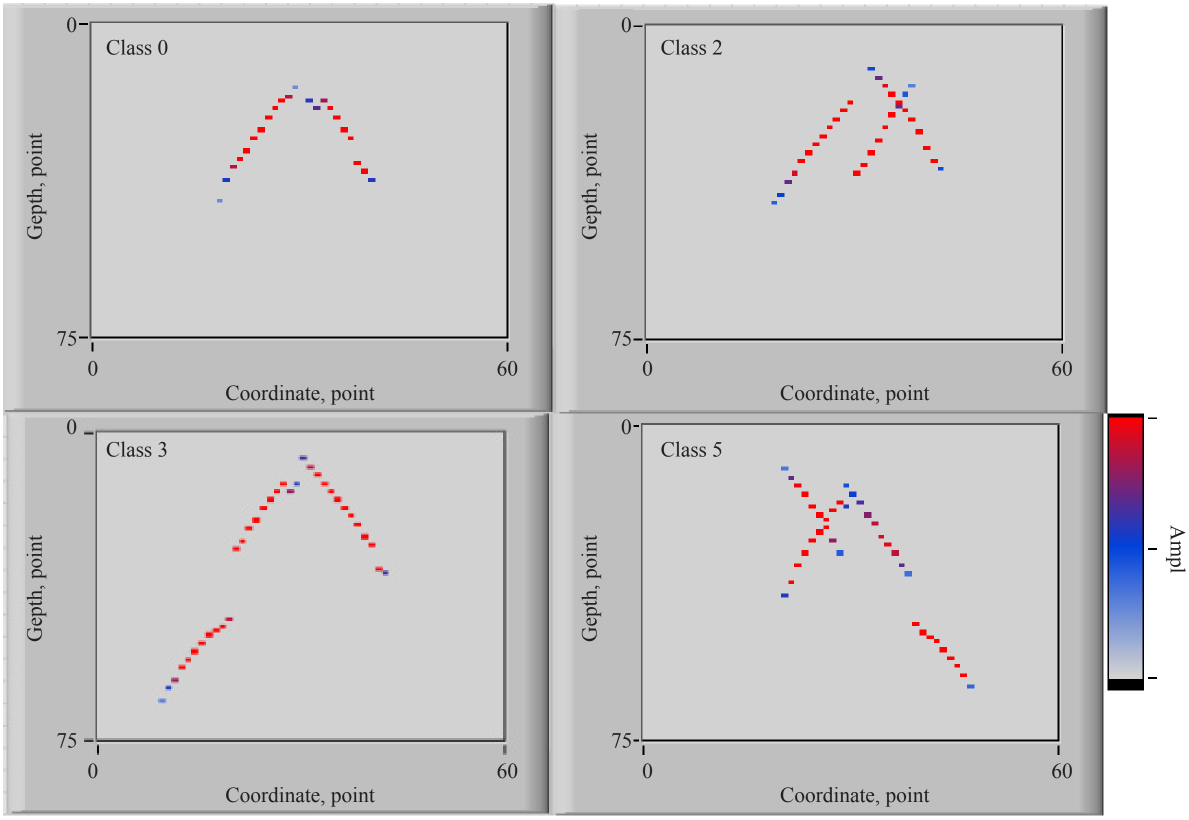


Figure 6. Examples of graphic images of the accepted classes of bolt holes

4.3 *Formation of data sets*

A balanced dataset containing 280,000 samples for seven classes of images of bolt holes with Star Crack defects was used as a data set (Table 1). This set was obtained on the basis of mathematical modeling of the developed phenomenological models describing the process of reflection and registration of ultrasonic waves from constructive rail reflectors in the form of bolt holes and their radial cracks.

The data were divided into three parts. The first part is the training data set, which contains 200,000 samples (70% of the total) and is used directly for training the network. The second part refers to the validation data, which contains 40,000 samples (15%) and is used to evaluate the accuracy and overfitting (over-optimization) of the network model at each training epoch. The third part refers to the test data, contains 40,000 samples (15%), and is used to assess the quality of the prediction of the resulting model.

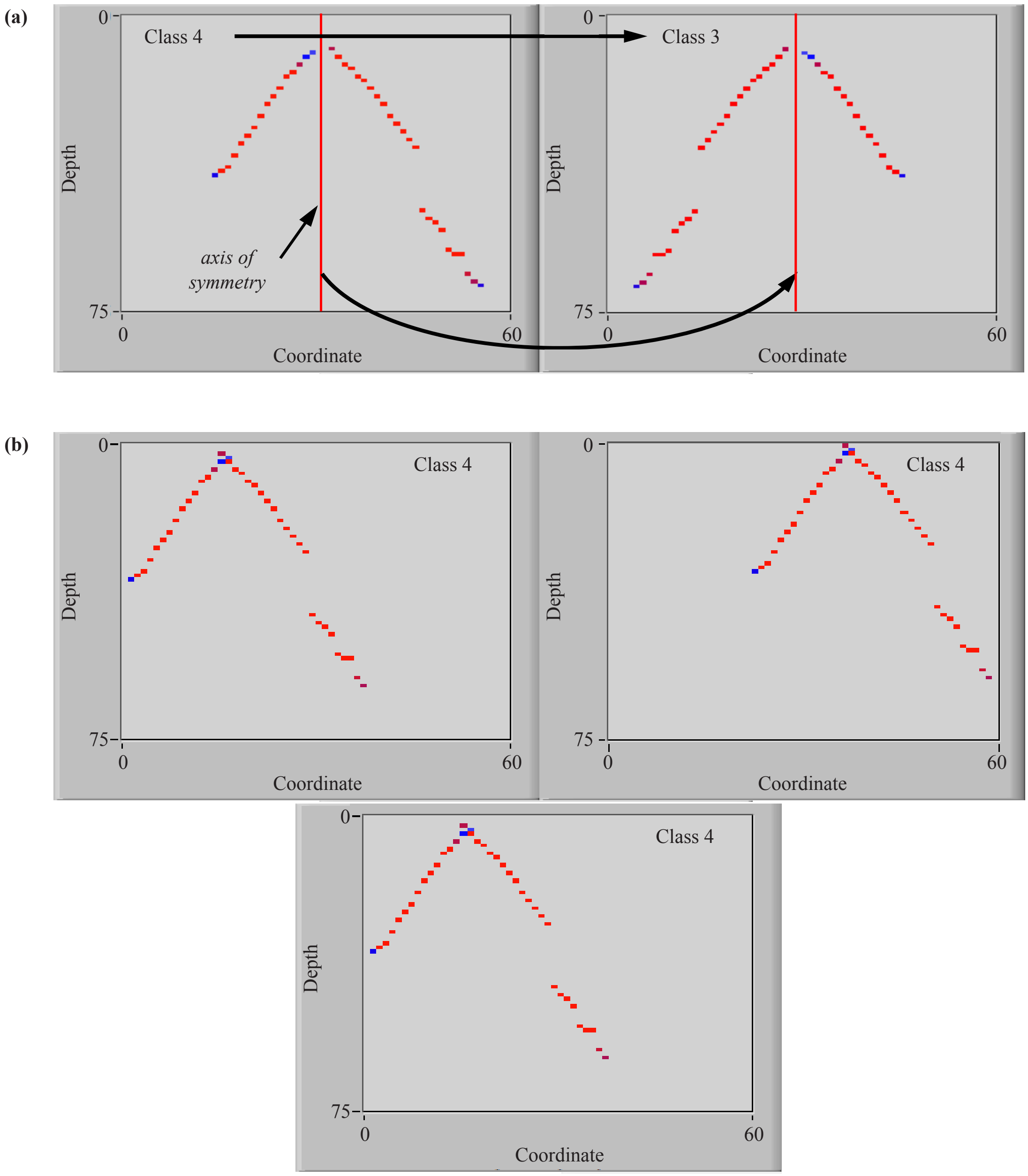
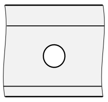
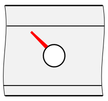
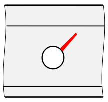
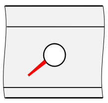
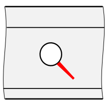
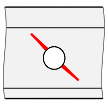
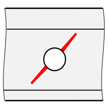


Figure 7. Application of symmetry (a) and displacement (b) of images to increase the data set

To assess the possibility of using a neural network trained on model data to recognize images of real bolt holes and their defects, a fourth set was formed-«real measured data». It was obtained by scanning rails with test defects on a railroad test track (RTT). The total number of available samples was 53 unit; their distribution by class is presented in Table 2 (columns a, b, c). For a more reliable check of the quality of the neural network, this set was increased by applying the principles of symmetry (Figure 7a) and moving images (Figure 7b), which made it possible to increase the set to 40,000 units (Table 2).

Table 2. Distribution of the «real measured data» set by class

Class	Graphical symbol	Initial number of samples	Increase in the number of samples	
			due to symmetry	due to displacement
a	b	c	d	e
0		19	19 + 19 = 38	38 + 14,400 = 14,438
1		8	8 + 6 = 14	14 + 5,200 = 5,214
2		6	6 + 8 = 14	14 + 5,094 = 5,108
3		5	5 + 12 = 17	17 + 6,400 = 6,417
4		12	12 + 5 = 17	17 + 6,400 = 6,417
5		0	0 + 3 = 3	3 + 1,200 = 1,203
6		3	3 + 0 = 3	3 + 1,200 = 1,203
Total		53	106	40,000

4.4 *Neural network architecture selection*

Training a neural network in order to increase the accuracy of the forecast is cyclic in nature with a finite enumeration of possible options for its structure and hyperparameter values. The initial network architecture is often set based on the applied network-building practices in the considered subject area [8-9, 13-17, 19]. The similarity and possibility of comparing the task posed in the work with the well-known task of recognizing images of handwritten digits from the Modified National Institute of Standards and Technology (MNIST) set [22] made it possible to propose a similar architecture for the first variant in the form of a Convolutional Neural Network (CNN) from sequentially connected layers Figure 8a.

4.4.1 *Activation functions*

The *RELU* (rectified linear unit) function was used as the activation function for the neurons of the inner convolutional layers of the network. For an output fully connected layer, the normalized exponential function softmax was used, at which the sum of the values of all output neurons is equal to one.

4.4.2 *Loss function*

As a function of learning losses, a measure of the error characteristics of multi-class classification problems was used in the form of the distance between the probability distributions of actual data and their prediction (cross-entropy).

4.4.3 *Optimizer*

The presented network was trained using the stochastic gradient descent algorithm in the Root Mean Squared Propagation (RMSProp) modification [6, 19, 22].

4.4.4 *Metrics*

The class balance allows us to choose an accuracy indicator as a measure of success in training the algorithm as a value equal to the ratio of the number of correctly classified instances to their total number. A single metric cannot evaluate all aspects of the applicability of the model to the situation, so the test phase uses a confusion matrix, precision, and completeness measures for each class classifier.

4.5 *Network training and results analysis*

Neural network synthesis and training were carried out in the interactive cloud service «Collaboratory» in Python 3.8 using the Keras library.

The search for the optimal classifier structure was performed using the Keras_tuner tool. The final version of the network in the form of a linear stack of layers is shown in Figure 8a. The mutual arrangement of convergent accuracy dependencies at 99.5% at the training and validation stages shows the lack of retraining effect and sufficient model complexity (Figure 8b). The lack of regularization layers is due to the large size of the training data.

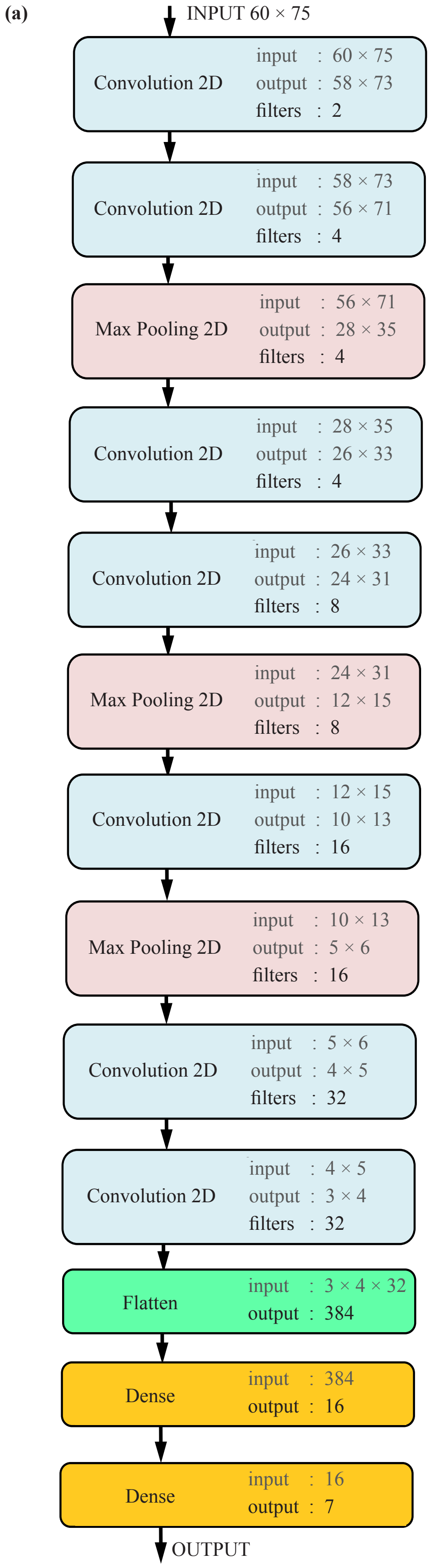
The assessment of the quality of the trained neural network was carried out on the prepared «test data» set using the scikit-learn library with the calculation of characteristic indicators of Figure 8c and the confusion matrix-Figure 8d.

The network has a small discrepancy between the completeness, accuracy, and weighted estimates of both each class classifier and the model as a whole. Such a high prediction accuracy of each class is due to the network training on a balanced sample. The overall accuracy of the model was 99.63%.

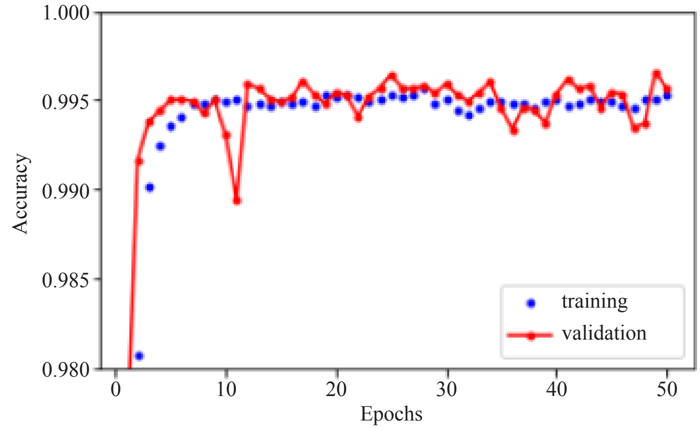
Of greatest interest is the classifier of the defect-free-zero class, which has the lowest precision index of 0.9915 (Figure 8c), which is reflected in 6 + 11 + 17 + 15 = 49 positive classified specimens with defects (Figure 8d). All 49 specimens belong to defects of classes 1-4, which have one radial crack each.

Let’s consider the possibility of applying a network trained on model data to the prediction of defects, which are obtained by direct measurement by flaw detection equipment.

(a)



(b)



(c)

	precision	recall	f1-score	support
0	0.9915	0.9993	0.9954	5,753
1	0.9944	0.9979	0.9962	5,727
2	0.9943	0.9957	0.9950	5,753
3	0.9986	0.9968	0.9977	5,621
4	0.9989	0.9961	0.9975	5,596
5	0.9986	0.9944	0.9965	5,751
6	0.9981	0.9941	0.9961	5,799
accuracy			0.9963	40,000
macro avg	0.9964	0.9963	0.9963	40,000
weighted avg	0.9963	0.9963	0.9963	40,000

(d)

True value \ Predicted value	0	1	2	3	4	5	6
0	5,749	2	1	1	0	0	0
1	6	5,715	5	0	0	1	0
2	11	3	5,728	0	0	0	11
3	17	0	0	5,603	1	0	0
4	15	0	0	0	5,574	7	0
5	0	27	0	0	5	5,719	0
6	0	0	27	7	0	0	5,765

Figure 8. Characteristics of the model: a) structure, b) change in accuracy during training and validation, c) report on the main indicators of the classification of the test data set, d) confusion matrix

4.6 *Network efficiency for measured data*

The proposed approach of using a neural network trained on model data to recognize patterns obtained by a flaw detector in the diagnosis of rails is illustrated in Figure 9.

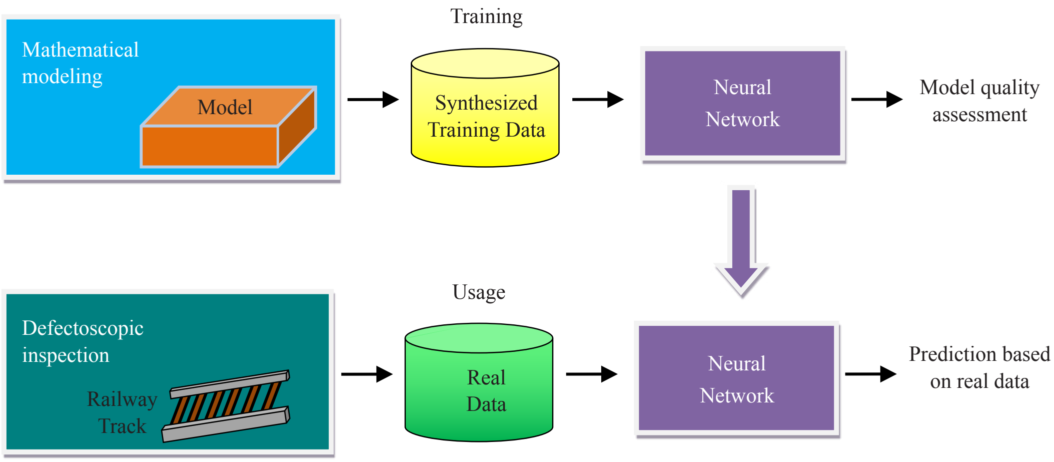


Figure 9. Application of a neural network trained on model data

To assess the quality of the selected neural network for the purpose of recognizing patterns of real bolt holes, modeling was carried out on the data set «real measured data». The accuracy of the network was 99.78% (Figure 10), which is 0.15% higher than the result shown by the network on the «test data» set, which can be explained by the lower representativeness of the «real measured data» set. It can be said that the defect images in the «real measured data» set are, in a sense, a subset of the artificially created «test data» set on which the network was trained.

	precision	recall	f1-score	support
0	1.0000	0.9976	0.9988	14,438
1	0.9945	1.0000	0.9972	5,214
2	0.9988	1.0000	0.9994	5,108
3	0.9915	1.0000	0.9957	6,417
4	1.0000	0.9914	0.9957	6,417
5	1.0000	1.0000	1.0000	1,203
6	1.0000	1.0000	1.0000	1,203
accuracy			0.9978	40,000
macro avg	0.9978	0.9984	0.9981	40,000
weighted avg	0.9978	0.9978	0.9978	40,000

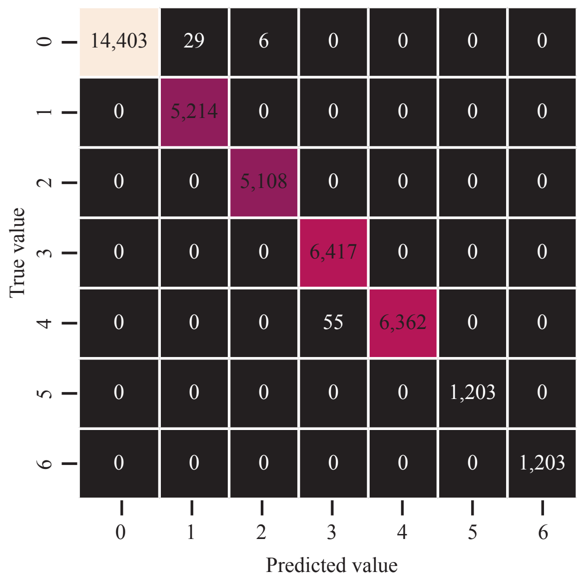


Figure 10. Main indicators of classification of option 2 model for data set-«real measured data»

The resulting similarity of model accuracy estimates on the «test data» and «real measured data» sets and their high values show the possibility and effectiveness of the proposed method of creating a data set for training a neural network.

5. Conclusion

1. Based on the analysis of the subject area, it was revealed that the main reason for the lack of effective defect detection systems using machine learning algorithms on the defectograms of ultrasonic diagnostics of rails is the impossibility of high-quality training of neural networks due to the difficulty of obtaining a representative training data set by traditional methods.
2. The feasibility and possibility of creating a training data set by stochastic mathematical modeling of the developed phenomenological model describing the process of reflection and registration of ultrasonic waves from structural rail reflectors in the form of bolt holes and their radial cracks are substantiated.
3. A variant of the structure of the convolutional neural network was proposed and substantiated, and its training was carried out on the data set obtained as a result of modeling.
4. The obtained qualitative assessments of the network operation confirmed the feasibility of using the chosen architecture and the hypothesis of the possibility of classifying based on the proposed information features in the form of a B-scan of individual bolt holes.
5. The efficiency of using a neural network trained on model data to recognize images of real rail defects on the example of radial cracks in bolt holes has been confirmed.
6. The results obtained allow us to propose the use of mathematical modeling to generate a data set of other types of defects in order to create a prototype of an automated system for finding rail defects during ultrasonic testing.

Conflict of interest

The author declares that there are no personal or organizational conflict of interest.

References

[1] Shishkin VV, Stenyushkin DI, Bron MG. Mathematical models and methods for real-time analysis of railway rails ultrasonic defectograms. *Automation of Control Processes*. 2014; 4(38): 61-67. Available from: http://apu.npomars.com/images/pdf/38_2.pdf [Accessed 14th March 2023].

[2] Markov AA, Mosyagin VV, Shilov MN, Fedorenko DV. AVICON-11: New flaw-detector for one hundred percent inspection of rails. *NDT World Review.* 2006; 2(32): 75-78. Available from: http://www.radioavionica.ru/activities/sistemy-nerazrushayushchego-kontrolya/articles/files/razrab/33.zip [Accessed 14th March 2023].

[3] Markov AA, Kuznetsova EA. Rail flaw detection. *Formation and analysis of signals. Book 2. Decoding of defectograms*. Saint Petersburg: Ultra Print; 2014.

[4] Kuzmin EV, Gorbunov OE, Plotnikov PO, Tyukin VA, Bashkin VA. Application of neural networks for recognizing rail structural elements in magnetic and eddy current defectograms. *Modeling and Analysis of Information Systems*. 2018; 25(6): 667-679. Available from: doi:10.18255/1818-1015-2018-6-667-679.

[5] Bettayeb F, Benbartaoui H, Raouraou B. The reliability of the ultrasonic characterization of welds by the artificial neural network. *17th World Conference on Nondestructive Testing*. Shanghai, China; 2008. Available from: https://www.ndt.net/article/wcndt2008/papers/215.pdf [Accessed 14th March 2023].

[6] Cha Y-J, Choi W, Büyüköztürk O. Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*. 2017; 32(5): 361-378. Available from: doi: 10.1111/mice.12263.

[7] Nakhaee MC, Hiemstra D, Stoelinga M, van Noort M. The recent applications of machine learning in rail track maintenance: A survey. In: Collart-Dutilleul S, Lecomte T, Romanovsky A. (eds.) *Reliability, Safety, and Security of Railway Systems. Modelling, Analysis, Verification, and Certification. RSSRail 2019. Lecture Notes in Computer Science (LNPSE, vol 11495)*. Springer, Cham; 2019. p.91-105. Available from: doi: 10.1007/978-3-030-18744-6_6.

[8] Jiaxing Y, Shunya I, Nobuyuki T. Computerized ultrasonic imaging inspection: From shallow to deep learning. *Sensors*. 2018; 18(11): 3820. Available from: doi:10.3390/s18113820.
[9] Cantero-Chinchilla S, Wilcox PD, Croxford AJ. Deep learning in automated ultrasonic NDE-developments, axioms and opportunities. 2022; 131: 102703. Available from: https://doi.org/10.1016/j.ndteint.2022.102703.
[10] Shilov MN. *Methodical, algorithmic and software for registration and analysis of defectograms during ultrasonic testing of rails [dissertation]*. [Saint-Petersburg]: Saint-Petersburg State University of Aerospace Instrumentation; 2007. p.153. Available from: https://www.dissercat.com/content/metodicheskoe-algoritmicheskoe-i-programmnoe-obespechenie-registratsii-i-analiza-defektogram.
[11] Heckel T, Kreutzbruck M, Rühe S. High speed non-destructive rail testing with advanced ultrasound and eddy-current testing techniques. *5th International workshop of NDT experts-NDT in progress 2009 (Proceeding)*. 2009; 5: 101-109. Available from: https://www.researchgate.net/publication/228901588 [Accessed 14th March 2023].
[12] Rizzo P, Coccia S, Bartoli I, Fateh M. Non-contact ultrasonic inspection of rails and signal processing for automatic defect detection and classification. *Insight*. 2005; 47(6): 346-353. Available from: doi: 10.1784/insi.47.6.346.66449.
[13] Cantero-Chinchilla S, Wilcox PD, Croxford AJ. A deep learning based methodology for artefact identification and suppression with application to ultrasonic images. *NDT & E International*. 2021; 126: 102575. Available from: doi: 10.1016/j.ndteint.2021.102575.
[14] Chapon A, Pereira D, Toewsb M, Belanger P. Deconvolution of ultrasonic signals using a convolutional neural network. *Ultrasonics*. 2021; 111: 106312. Available from: doi: 10.1016/j.ultras.2020.106312.
[15] Medak D, Posilović L, Subasic M, Budimir M. Automated defect detection from ultrasonic images using deep learning. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*. 2021; 68(10): 3126-3134. Available from: doi: 10.1109/TUFFC.2021.3081750.
[16] Virkkunen I, Koskinen T. Augmented ultrasonic data for machine learning. *Journal of Nondestructive Evaluation*. 2021; 40: 1-11. Available from: doi:10.1007/s10921-020-00739-5.
[17] Veiga JLBC, Carvalho AA, Silva IC. The use of artificial neural network in the classification of pulse-echo and TOFD ultra-sonic signals. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*. 2005; 27(4): 394-398. Available from: doi:10.1590/S1678-58782005000400007.
[18] Papaelias M, Kerkyras S, Papaelias F, Graham K. The future of rail inspection technology and the INTERAIL FP7 project. *51st Annual Conference of the British Institute of Non-Destructive Testing 2012, NDT 2012*. 2012. Available from: https://www.researchgate.net/publication/289469062 [Accessed 14th March 2023].
[19] Ye JX, Toyama N. Benchmarking deep learning models for automatic ultrasonic imaging inspection. *IEEE Access*. 2021; 9: 36986-36994. Available from: doi:10.1109/ACCESS.2021.3062860.
[20] Posilovića L, Medaka D, Subašića M, Budimirb M, Lončarića S. Generative adversarial network with object detector discriminator for enhanced defect detection on ultrasonic B-scans. *Neurocomputing*. 2021; 459: 361-369. Available from: https://doi.org/10.1016/j.neucom.2021.06.094.
[21] Markov AA, Mosyagin VV, Keskinov MV. A program for 3D simulation of signals for ultrasonic testing of specimens. *Russian Journal of Nondestructive Testing*. 2005; 41(12): 778-789. Available from: doi: 10.1007/s11181-006-0034-3.
[22] Chollet F. *Deep learning with python*. Shelter Island: Manning Publications Co.; 2018.