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Application of the regression neural network for the analysis of the results of ultrasonic testing

Abstract. Conducting a study on this topic becomes relevant due to the great importance of the safety of critical infrastructure facilities and the presence of operational defects in equipment elements and pipelines, which poses serious threats, including the possibility of equipment destruction and negative environmental impact. The purpose of this work is to study the possibility of using the diffraction-time technique of ultrasonic non-destructive testing together with a deep convolutional neural network to accurately determine the numerical value of the height of an operational crack. The methods used include the analytical method, classification method, functional method, statistical method, synthesis method, and others. The study found that an automated approach to measuring crack height, based on diffraction signals and the use of neural networks, significantly improved the quality and accuracy of non-destructive testing. Ultrasonic testing is one of the most common inspection methods for detecting service cracks and is considered to be the most effective. It allows for reliable detection of defects and determination of their size without destroying the product. The results of the study emphasize the high potential and efficiency of the method in analysing the data obtained and provide confirmation of its applicability for determining the condition of objects during ultrasonic inspection. The paper emphasizes that these technologies are particularly important and effective. It is noted that their widespread use

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in various industries, such as medicine, aviation, and machine learning, demonstrates their power in solving complex problems. The practical significance of the work lies in the development of advanced approaches that provide new insights and methods to improve the efficiency of analysing the results, which can be applied in industry to improve the quality of control and reliability of technical facilities

Keywords: non-destructive testing; operational defects; diagnostic efficiency; Data Processing; automation of procedures; industrial monitoring

INTRODUCTION

The use of regression neural networks significantly improves the efficiency of ultrasonic data analysis, helping to detect operational defects, thereby ensuring safety and reliability. Automated analysis enables faster defect detection, reducing inspection and maintenance time and costs. Deep neural networks provide high accuracy in detecting even small defects, contributing to reliable diagnostics. The study of this topic promotes the use of innovative technologies in the security of critical facilities and contributes to progress in science and technology. All this is aimed at ensuring more efficient and safer monitoring of the condition of infrastructure facilities. The challenge of this study is the difficulty of detecting operational defects, in particular cracks, which may be hidden or invisible using traditional inspection methods. In addition, the challenge is to develop ultrasonic inspection methods that effectively detect defects and guarantee reliability and accuracy to avoid potential errors and incorrect results.

According to D.V. Pronyaev & V.V. Melnyk (2022), artificial neural networks have provided unique opportunities to improve healthcare systems and increase the effectiveness of medical education. They have been introduced into the training process of medical specialists to simulate real-life clinical scenarios. This has allowed students to gain practical experience in a safe environment and develop diagnostic and treatment skills. However, this study did not address the security and reliability of AI algorithms in the context of medical data, which is a key aspect in the use of such technologies in sensitive areas.

The purpose of the study by A. Atamanchuk (2022) was to develop and test a method for detecting and identifying an unmanned aerial vehicle (UAV) based on neural networks, aimed at improving the efficiency and accuracy of the recognition process. An effective method has been developed that can be used to detect and identify UAVs with high accuracy. The results obtained have practical applications in various industries where they detect and recognize unmanned aerial vehicles. However, this work did not take into account the possible challenges and threats associated with the analysis of unmanned aerial vehicles, which may raise questions about the protection and confidentiality of the information revealed.

In their study, O.M. Berezsky *et al.* (2021) apply the linear regression method to analyse the quantitative characteristics of cytological images in order to obtain objective indicators and improve diagnostic capabilities. The use of linear regression in the analysis of cytological images simplified the interpretation of quantitative data and allowed for objective comparisons between different cellular structures. The research is aimed at improving the methods of analysing cytological images, which is essential for the development of modern medicine. The application of the linear regression method is an important step in improving the objectivity and speed of diagnosis based on cytological data. However, the study did not conduct a comparative analysis with other machine learning methods to determine the advantages and disadvantages of using linear regression.

In their study, O. Burlieiev *et al.* (2021) determine the level of efficiency and benefits of using artificial neural networks in various sectors of the economy, including market analysis, forecasting economic indicators, and financial management. The study highlights the high potential and efficiency of using artificial neural networks in the economy, with the ability to analyse complex relationships and make accurate forecasts, making them a key tool for solving the problems of the modern economic environment. However, the authors did not consider all aspects and specific cases of application of artificial neural networks.

In their paper, N.V. Kuznietsova & Z.S. Chernysh (2020) analyse the use of regression models in the financial analysis of enterprises and determine their effectiveness in predicting financial performance indicators. As a result, the use of regression models has allowed enterprises to more accurately analyse and forecast financial performance indicators, which, in turn, will help improve management strategies and make informed decisions. However, the study lacked additional analysis, which could include a comparison of the effectiveness of regression models with other methods, such as time series analysis or machine learning methods.

The purpose of this study is to determine the feasibility of using the diffraction-time technique of ultrasonic non-destructive testing in combination with a deep convolutional neural network to accurately determine the numerical value of crack height.

MATERIALS AND METHODS

This study was carried out by applying methods that reveal the theoretical and practical content of the object, providing a comprehensive view of innovative approaches to the use of a regression neural network for analysing ultrasonic inspection results. The analytical method in this study was used to thoroughly review the theoretical aspects of regression neural networks used for the analysis of ultrasonic inspection results. This method made it possible to understand and describe the mathematical foundations of the functioning of neural networks in the context of studying ultrasonic inspection. The analysis of the mathematical foundations of regression neural networks in the context of ultrasonic control contributed to the understanding of their potential in accurate analysis and processing of results.

The classification method made it possible to systematize different types of ultrasonic data and define their categories for the needs of applying regression neural networks. The classification results helped to determine the optimal network parameters for specific data classes. The application of this method made it possible to identify different types of ultrasound images and to distinguish their main categories, depending on the needs of regression neural network analysis. This method made it possible to adapt the structure and parameters of regression neural networks to different types of information, which increased their efficiency and accuracy of analysis of the results.

The functional method considered the existing capabilities of regression neural networks and their application to analyse the results of ultrasonic testing. This method considered how the regression neural network performed specific tasks and solved problems related to ultrasonic inspection. The functional method determined the effectiveness and efficiency of regression neural networks in solving specific ultrasonic data analysis tasks. This method made it possible to determine how the neural network adapts to various conditions and identifies key functions during information processing, which provides important guidance for further improvement of its performance.

The statistical method allowed combining the data obtained, and identifying statistical patterns and risks associated with the use of regression neural networks in the context of ultrasound inspection, which is important for assessing the reliability and validity of the results. The synthesis method in this study was used to create and optimize regression neural networks for ultrasound data analysis. This includes the synthesis of network parameters, structure, and weights to achieve optimal performance.

In the study, ultrasonic data obtained using diffraction time-of-flight technique was collected. The data was carefully processed and prepared for further use in the neural network. A deep convolutional neural network was tuned and trained using the ultrasound data. A regression approach was used to accurately determine the crack parameters. The results were validated and analysed to determine the effectiveness of the regression neural network for analysing ultrasonic data and determining crack heights. The results of the regression neural network application were compared with other approaches and methods of ultrasonic inspection to determine the advantages and disadvantages.

A thorough review and analysis of the diffraction-time technique used to measure crack parameters in materials was carried out. Different approaches and techniques that use ultrasound for defect detection are considered. The paper uses a deep convolutional neural network to analyse and process the received diffraction signals. The application of a regression neural network allows accurately determining the height of cracks in materials based on the obtained ultrasonic data.

In this work, a convolutional neural network for image recognition was developed and used to reduce errors in determining the height of the defect. To train a neural network, it is necessary to have so-called labelled data, i.e. data for which the correct answer is known in advance, in this case, the height of the crack. For this purpose, the training data were modelled using the CIVA software. Experimental measurements with real defects would have been more efficient, but this would have required ultrasonic equipment, transducers, and a huge number of samples with real defects. CIVA is a platform for non-destructive testing tasks consisting of modules: modelling, visualization, and analysis. In this study, the software was used to model rectangular defects with different heights, lengths, and defect angles (Table 1). In the end, the artificial crack database consisted of 3 sets: test, validation, and training. In total, the database contains approximately 100 images and took about 30 hours to generate.

Table 1. Parameters of the training model

Model parameters	
Sample form	Rectangular
Material	Steel
Length	200 mm
Thickness	100 mm
Height	30 mm
Converter parameters	
Type	Contact
Emitter shape	Disk
Diameter	6.35 mm
Angle of refraction	60°
Angle of incidence	23.165°

Continued Table 1.

Model parameters	
Scanning scheme	
Location	Symmetrical
Distance between centres	38 mm
Initial position	71×37 mm
Scan move	along the axis
Step (x-axis)	0.5 mm
Number of steps (on the x-axis)	120
Simulated defect	
Height	0-30 mm
Length	30 mm, 40 mm
Angle of inclination of the crack	0°, 2°, 4°

Source: created by the authors

The structural similarity index (SSIM) was used to quantify the structural similarity between images, which allows determining the degree of correspondence between the structures and content between them. In this study, a convolutional neural network (CNN) was developed to solve the problem of determining the height of cracks using the Keras library, TensorFlow framework. The training process of this neural network was performed on an Intel Core i5-7300HQ CPU. Despite the fact that the CPU training speed is less efficient compared to using graphics cards, it was sufficient in this case. This is due to the small number of parameters in the neural network structure and the size of the training set, which contained only 52 images. In general, the training process for 100 epochs usually takes from 10 to 30 minutes.

RESULTS

A crack is one of the most dangerous operational defects, which, depending on its size, particularly its height, can lead to equipment failure. Non-destructive testing tasks play a key role in ensuring the safety, reliability, and efficiency of NPP equipment. Non-destructive testing is the inspection of the quality of products using various fields or radiation. The ultrasonic inspection method is based on the ability of high-frequency vibrations to penetrate the material and reflect scratches from the surface.

Time-of-flight diffraction (TOFD) technology, in turn, is used to record diffraction signals that occur at the edges of a defect using two sensors (Fig. 1). This technique makes it possible to establish the coordinates of cracks quite accurately (Hecht, 1997). The system of this method contains a transmitter and a receiver of ultrasonic waves, which are directed to a single point inside the welded joint. If no defect is present, then after the compression wave is emitted from the transmitter, the first signal to reach the receiver is a side wave representing the outer surface, and the second signal to reach the receiver is an echo from the back wall representing the inner surface. If a defect is present, the diffraction signal is generated at the top of the defect and arrives before the signal generated at the bottom of the defect.

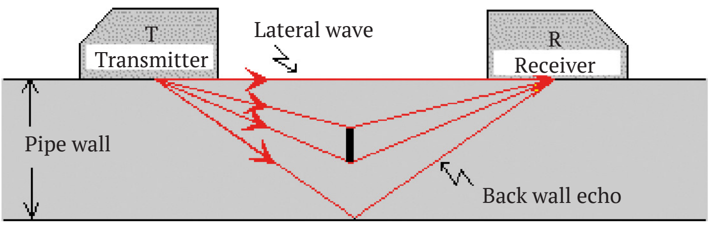

Figure 1. The working principle of TOFD technology

Source: created by the authors

Simple geometric considerations can be used to estimate the height of a crack, knowing the scan angle, the difference in the arrival time of the two signals, and a constant, the speed of sound propagation in the material. However, in reality, the signals are very difficult to recognize (Fig. 2).

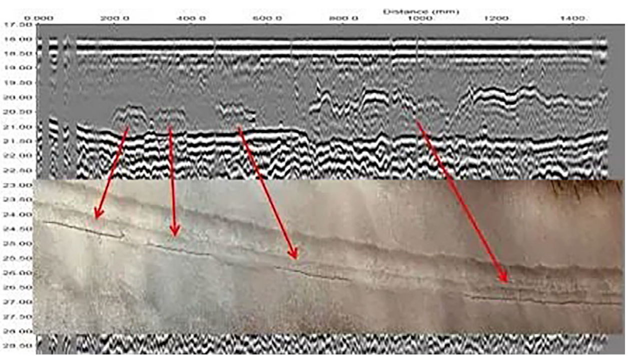

Figure 2. Real TOFD signal

Source: created by the authors

Deep learning is a machine learning technique that is one of the best for solving problems of processing large amounts of data, processing speed, and reducing error. Deep learning models are often called deep neural networks because they consist of a multi-layered architecture. Each layer of the network receives input and performs a certain operation before passing the results to the next layer. As mentioned earlier, a convolutional neural network specializes in image analysis. The peculiarity of this architecture is that it highlights the features of images and at the same time reduces the amount of information by identifying the most informative part of it. In fact, each convolutional layer of a neural network is a set of digital filters whose kernels are optimized during training (Protsenko, 2022). Examples of modelling control results are shown in Figure 3. It is possible to see a slight difference between the results, but calculating the height of the defect without significant errors is a task beyond the reach of humans. Therefore, computer processing is used in this work (Bowles, 2015; Yousefi *et al.*, 2018; Lee *et al.*, 2023).

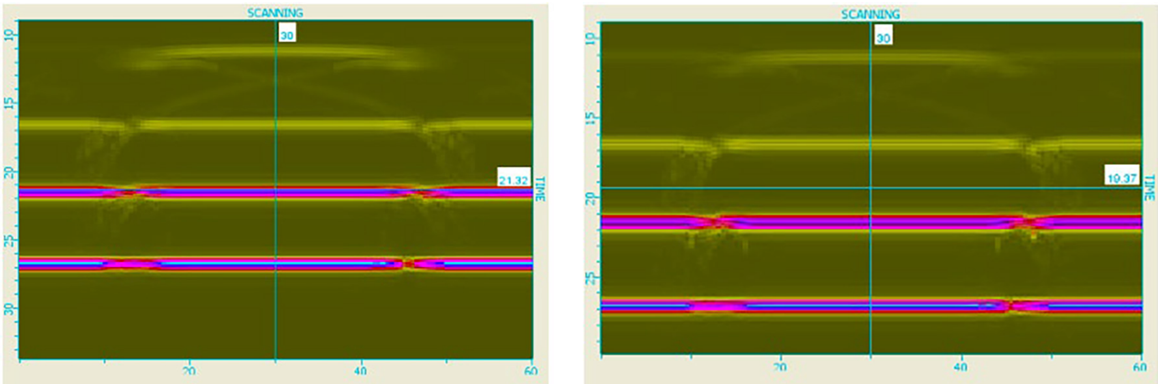

Figure 3. The result of ultrasonic control in the form of an amplitude image for defects with a height of 3 mm and 4 mm, respectively

Source: created by the authors

As a result of the modelling in the CIVA software, a dataset was obtained that contained 118 images, each of which was uniquely indexed (labelled), i.e. had unique parameters of the crack for which the signal was modelled. The modelling itself is manual and contains many procedures and processes involving humans, so errors are possible when generating, naming result files. Therefore, to exclude their influence on the study, all photos were analysed for uniqueness by comparing each photo with all others using a code. In the process, only 52 images were found to be unique. Since the rest of the photos had at least one duplicate (the same photo), but with different indexing, none of them could be used, as it was no longer possible to establish which indexing was correct. Therefore, all non-unique images were excluded from the database that would be used to train and test the neural network.

For the selected 52 images, Figure 4 shows the so-called heat similarity matrix – how similar one photo is to another. The Structural Similarity Index (SSIM) is then used to quantify the similarity between the photos, which allows finding out the degree of correspondence between the structure and content between them. Usually, in such cases, it is possible to use a comparison by calculating the mean square error (MSE), but this means only a pixel-by-pixel comparison of images with complete disregard for the structures on it. Unlike MSE, SSIM gives more weight to structures than to the colour of a single pixel pair. That is, this similarity assessment is better at recognizing similar photos that are similar to the human eye than MSE, i.e. it calculates the so-called perceived similarity (Wang *et al.*, 2004; Wang & Bovik, 2009). According to the obtained SSIM index, a cell on the similarity matrix is coloured. Red indicates full similarity, and blue indicates the least similarity of all. Ideally, only the main diagonal should be red, i.e. the photo should be similar only to itself. In the matrix above, it is possible to see other red cells, but the similarity coefficient is different, which means that the data is not identical.

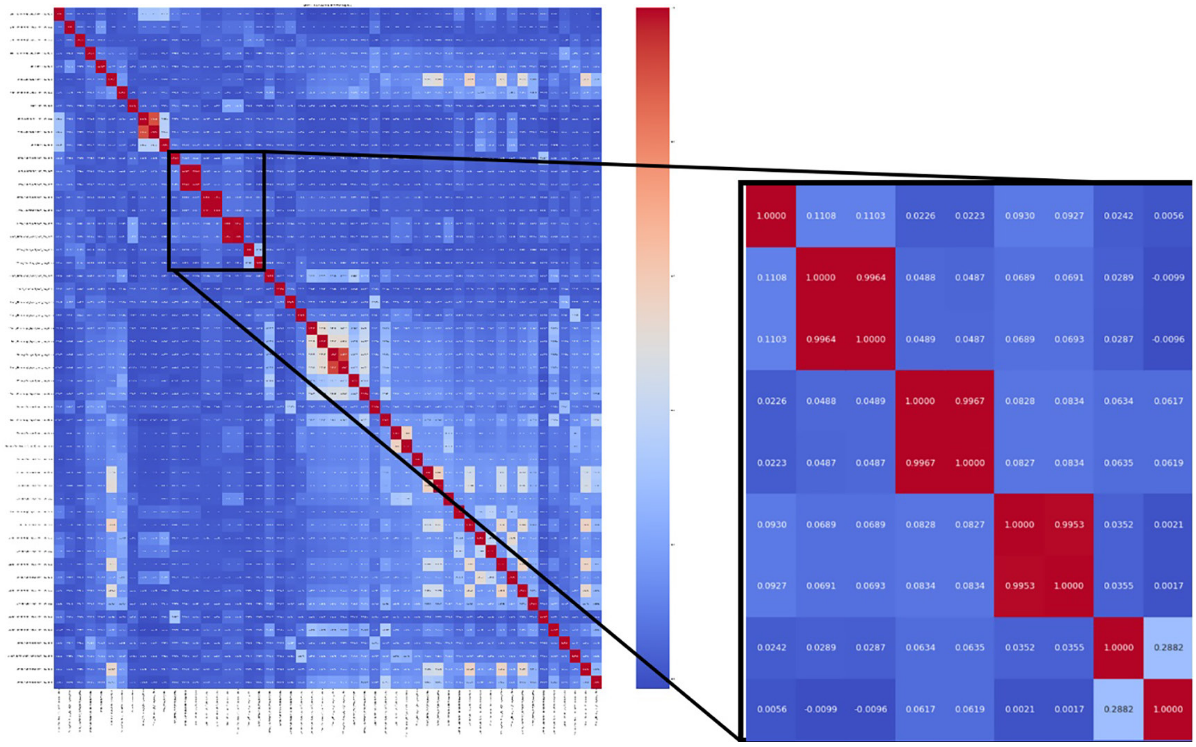

Figure 4. Thermal similarity matrix of the used data set

Source: created by the authors

The dataset was divided into three smaller datasets: a training dataset of 39 images, a validation dataset of 7 images, and a test dataset of 6 images. The training set is used to train the neural network, the validation set is used to evaluate the trained models and compare them with each other to select the best hyperparameters, and the test set is used to evaluate the final neural network with the hyperparameters already selected. To train the neural network, it was decided not to use any augmentation, i.e. artificially expanding the database by enlarging/decreasing, shifting, rotating the image. Despite the small dataset, augmentation would not be very correct in this case. In contrast to object classification tasks, where augmentation is almost always a standard approach and can be applied to object images without losing their essence, this task analyses an ultrasound signal (Wong *et al.*, 2016). Any manipulation of the data can lead to signal distortion, which in turn can affect the accuracy of its analysis. This data-driven approach ensures that the network training is based on original, untouched data, and thus maximizes its accuracy in recognizing ultrasound signals.

Modern machine learning methods make heavy use of frameworks such as TensorFlow, which provide powerful tools for developing and training neural networks. Achieving optimal results required careful selection of hyperparameters. This included determining the optimal number of Conv2D and MaxPooling2D convolutional layers, adjusting the number of filters and kernel sizes for each Conv2D layer, defining the parameters of fully connected layers, dropout values, and batch sizes. After that, the best configuration was selected based on the results of testing on the validation dataset. The structure of the best neural network is shown in Table 2 and schematically depicted in Figure 5.

Table 2. Architecture of classification convolutional neural network

Layer	Activation function	Characteristics
Conv2D	ReLU	The number of filters – 64 The core size – 6×6
MaxPooling2D	-	The core size – 2×2
Conv2D	ReLU	The number of filters – 32 The core size is 5×5
MaxPooling2D	-	The core size – 2×2
Conv2D	ReLU	The number of filters – 32 The core size – 4×4
Flatten	-	-
Dense	ReLU	The number of neurons – 64
Dropout	-	Rate – 0.4
Dense	ReLU	The number of neurons – 32
Dropout	-	Rate – 0.4
Dense	Softmax	The number of neurons – 6
Number of parameters		3,124,390

Source: created by the authors

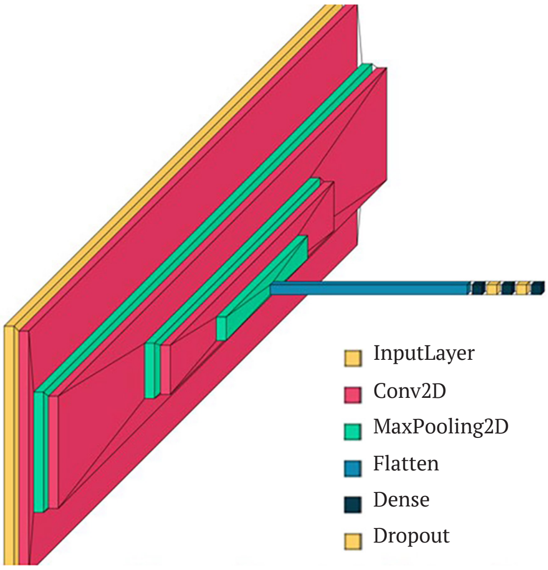

Figure 5. Classification model architecture

Source: created by the authors

The results of testing the checkpoint-preserved classification network after training for 100 epochs are shown in Table 3.

The error of the model in classifying one image, which was assigned to a class located at a distance of only 1 mm from the actual crack height, indicates the importance of further improvement and development of the system. In order to quantify the error and improve the accuracy of predictions, it is worth considering the use of a regression neural network (Fig. 6).

Table 3. Results of training the classification model

Cracked Test ID	Crack height, mm	Height class	Estimated height class	Classification result
1	3 mm	0-5 mm	0-5 mm	True
2	9 mm	5-10 mm	10-15 mm	False
3	11 mm	10-15 mm	10-15 mm	True
4	17 mm	15-20 mm	15-20 mm	True
5	19 mm	15-20 mm	15-20 mm	True
6	25 mm	25-30 mm	25-30 mm	True
7	29 mm	25-30 mm	25-30 mm	True
Precision				85.71%

Source: created by the authors

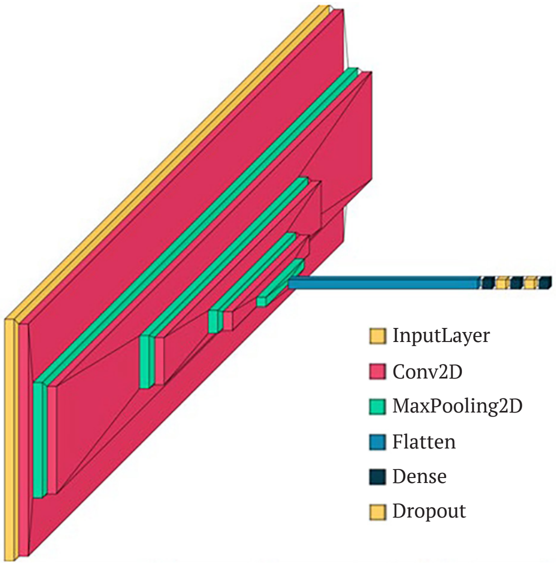

Figure 6. Architecture of the regression model

Source: created by the authors

Regression neural networks allow solving problems related to the prediction of numerical values, which in this case is ideal for determining the specific height of a crack. Compared to classification, where only two categories are possible (correct/incorrect), the regression approach provides quantitative values that determine the degree of deviation of the predicted value from the actual value. The changes in the architecture that provided for the transition from the classification to the regression model included important modifications that contributed to the solution of the problem of predicting numerical values, namely the height of a crack in the material. The original six-neuron output layer that used the softmax activation function for classification was replaced by a single output neuron without an activation function responsible for predicting the numerical value. During the hyperparameter selection, the dropout value was reduced and another convolutional layer Conv2D and MaxPooling2D were added (Table 4).

Table 4. Architecture of regression convolutional neural network

Layer	Activation function	Characteristics
Conv2D	ReLU	The number of filters – 64 The core size – 6×6
MaxPooling2D	-	The core size – 2×2
Conv2D	ReLU	The number of filters – 32 The core size – 5×5
MaxPooling2D	-	The core size – 2×2
Conv2D	ReLU	The number of filters – 32 The core size – 4×4
MaxPooling2D	-	The core size – 2×2
Conv2D	ReLU	The number of filters – 32 The core size – 4×4
Flatten	-	-
Dense	ReLU	The number of neurons – 64
Dropout	-	Rate – 0.1
Dense	ReLU	The number of neurons – 32
Dropout	-	Rate – 0.1
Dense	-	The number of neurons – 1
Number of parameters		393,745

Source: created by the authors

The results of testing the regression network stored by the checkpoint after training for 100 epochs are shown in Table 5. The average absolute error was 0.46 mm, and the average relative error was 4.86%, which indicates that this neural network is well-trained to determine the crack height, but only in the material sample specified in the simulation. Therefore, it is important to consider that the results obtained on this specimen may not be equally transferable to other specimens due to variations in the material. For a wider and more universal application of the model, it is necessary to expand the size of the training dataset and consider the variability of material properties. The findings show that the regression neural network performs well in the task of determining the crack height on a given material sample. Scaling to other materials can be achieved by expanding the training set and optimizing the network parameters.

Table 5. Results of regression model training

ID test with a crack	Height, real value, mm	Height, predicted value, mm	Absolute error, mm	Relative error, %
1	3	3.49	0.49	16.39
2	9	8.47	0.53	5.87
3	11	10.47	0.53	4.82
4	17	17.18	0.18	1.05
5	19	19.16	0.16	0.84
6	25	25.72	0.72	2.89
7	29	28.39	0.61	2.12
Average values			0.46	4.86

Source: created by the authors

In order to successfully scale the developed model to other materials and inspection conditions, two key steps are required. First, the training dataset should be expanded to include different defect shapes and sizes. This will help the model to adapt to the different nature of materials and avoid transferring sample properties to a specific material only. Second, it is important to optimize the neural network parameters. This involves experimenting with hyperparameters, such as network architecture, learning rate, and other parameters that affect its performance. These steps can be used not only to achieve high accuracy on a particular material, but also to ensure the overall adaptability of the model to different conditions and types of materials, which would make it more versatile and effective in practical applications (Erkmen & Yildirim, 2008; Qiao *et al.*, 2020). Additionally, the modelling allowed determining the optimal size of the training set to achieve maximum efficiency. Sensitivity analysis of hyperparameters, such as training speed and data set size, revealed their impact on the model's performance and identified optimal values. Validation on real data confirmed the model's adaptability to new conditions and data, which will enhance its applicability in real-world scenarios. Comparison with other methods of analysing ultrasonic inspection results also shows the high efficiency of the developed neural network. In general, the results obtained confirm the great potential and practical value of the regression neural network for analysing ultrasound data, and also indicate ways to further improve and expand its applications in various fields of technical diagnostics and control.

The paper emphasizes the importance and effectiveness of advanced deep learning and neural network technologies. It is noted that their widespread use in various fields, such as medicine, aviation, and machine learning, indicates their power in solving high-level problems. In medicine, they help automate diagnostics and develop effective treatments. In the aviation industry, these technologies ensure efficient monitoring and maintenance of aircraft, increasing safety. In machine learning, they expand the possibilities in forecasting and task classification. The paper highlights that these technologies are key to solving modern challenges in science and technology. Their widespread adoption in various industries demonstrates a deep approach and potential for solving various problems, emphasizing the importance of their application in the modern technological environment.

DISCUSSION

This research article discusses a key topic in the field of non-destructive testing, namely improving the accuracy of crack height measurements using diffraction signals and the use of neural networks to optimize this process. Much emphasis was placed on analysing the methodology of using machine learning technologies, in particular neural networks, which can improve the efficiency of the inspection procedure. Specific aspects of the use of neural networks in crack height measurement were discussed in detail. The peculiarities of diffraction signals were carefully considered, and machine learning-based models were developed to accurately determine the size of cracks in materials. The regression neural network is highly effective in determining the parameters of ultrasonic inspection, which has led to a significant increase in measurement accuracy, a critical aspect for ensuring the reliability and safety of industrial facilities (Fomin *et al.*, 2023). The use of neural networks has made it possible to automate the process of analysing ultrasonic data, reducing dependence on the human factor, and speeding up the time to detect defects (Smailov *et al.*, 2023). This contributed to the efficient use of resources and optimization of production processes. The results of the study indicate that the regression neural network can be scaled up and applied to different materials and conditions. This makes it a versatile tool for solving control problems in various industries.

One of the key advantages of this study is its relevance in the modern context. In particular, measuring the height of cracks turns out to be a critical task in ensuring the safety and reliability of infrastructure facilities (Babak *et al.*, 2021). The importance of this study is emphasized by the fact that in the nuclear industry, this issue is becoming particularly relevant to prevent possible accidents. It is noted that solving the problems of crack measurement has the potential to improve safety and reliability in these strategically important industries (Ripetskyi *et al.*, 2023). The paper identifies new opportunities for applying modern technologies and studying their impact on the sustainability and safety of infrastructure systems.

In their study, O. Tymchuk *et al.* (2023) developed a model that uses recurrent neural networks to accurately estimate the value of real estate. The developed RNN model is capable of accurately predicting the value of real estate objects, considering various factors and variables, which contributes to improving real estate decision-making processes and improving the accuracy of valuations. This study is aimed at expanding the possibilities of using recurrent neural networks in the field of real estate valuation. These results are expected to improve the accuracy and objectivity of real estate pricing, which opens new prospects for market participants. The regression neural network demonstrates high efficiency in detecting and analysing defects, and the recurrent neural network is successfully used to accurately estimate the value of real estate (Shults *et al.*, 2023). Both studies harness the power of neural networks to solve important problems in their respective fields. The regression and recurrent neural networks demonstrate high accuracy and efficiency in solving the problems of ultrasonic inspection and real estate valuation, respectively.

The work by V. Gerus & S. Vitruk (2022) on the study of the effectiveness of neural networks in economics and their impact on the analysis and forecasting of economic indicators reveals significant aspects, contributing to the development of new methods and approaches in this area. As a result, the use of neural networks in the economy has led to improved forecast accuracy, increased decision-making speed and optimization of economic processes. The research of these authors focuses on the effectiveness of neural networks in economic analysis and decision-making, as well as on the accuracy of defect detection in materials. The study of the effectiveness of neural networks in economics is important for understanding the potential of these technologies in improving economic processes and making informed management decisions. The regression neural network has been shown to be effective for physical analysis of materials, while the application of neural networks in economics can improve analysis and management decision-making in the financial sector (Petchenko *et al.*, 2023).

In his study, M. Gertsiuk (2022) described the development and use of a mathematical model based on a neural network to predict the effects of river pollution. As a result, mathematical modelling based on a neural network is a promising approach for predicting the effects of river pollution, and this study aims to further develop this area in the field of water resources protection. Both studies use neural networks for different tasks, but they both demonstrate the power of these methods to solve important problems in their respective fields. The use of regression neural networks in technical applications and mathematical modelling for environmental research are promising areas of neural network use in various fields.

The study by U.M.R. Paturi *et al.* (2018) was aimed at comparing the effectiveness of regression analysis and integral numbers of microgeometry (INM) in modelling the surface roughness of AISI 52100 steel during hard turning. As a result, the regression analysis and INM proved to be effective in modelling the dependence of surface roughness on turning parameters, and INM demonstrated higher accuracy for complex nonlinear dependencies between turning parameters and roughness. The work is relevant in the context of improving turning and manufacturing technologies, which can lead to higher quality of manufactured parts and reduced production costs. Both studies are distinguished by their relevance and importance for certain industries but have differences in the areas of application and approaches to solving the relevant problems.

In their study, N. Ceryan *et al.* (2012) described the development and application of generalized regression neural networks for predicting the unconfined compressive strength of carbonate rocks. The results of this study are useful for geologists, engineers, and material manufacturers working with carbonate rocks. The model serves as a tool for fast and accurate prediction of mechanical properties of materials. The research aims to develop knowledge in the use of neural networks for predicting the mechanical properties of rocks, contributing to the further development of methods and technologies in the field of geology and mining. Both studies consider the use of regression neural networks in different areas: determining ultrasonic inspection parameters and predicting the mechanical properties of carbonate rocks. These two studies demonstrate the importance and effectiveness of using regression neural networks in solving analysis and prediction problems in various fields. They complement each other, providing a valuable contribution to the development of materials control and research methods.

An analysis of various studies on the use of neural networks in various industries has shown that these technologies do indeed have high potential and efficiency in solving complex problems. These studies not only demonstrate the power of neural networks in their respective fields, but also point to their versatility and applicability in various contexts. These technologies have the potential to revolutionize approaches to analysis, forecasting and management in a variety of industries, from industry to the environment to finance. This article provides an understanding of how diffraction signals are generated and measured, making the findings and research methodology accessible to a wide range of readers. This approach promotes mutual understanding and popularization of the topic among specialists and researchers working in the field of non-destructive testing. An interesting aspect is the use of neural networks to analyse diffraction signals and determine the height of cracks. Automating the process and improving the accuracy of measurements using this approach may prove to be key to the further development and improvement of inspection systems. Overall, the study not only solves an urgent problem in the field of non-destructive testing, but also offers a technological approach that has the potential for widespread practical implementation and improved accuracy of crack height measurements, which can have a positive impact on safety and efficiency.

CONCLUSIONS

A study on the use of a regression neural network to analyse the results of ultrasonic testing has revealed the great potential of this technology in the field of non-destructive testing. Using advanced deep learning and neural network techniques, it was possible to significantly improve the accuracy and efficiency of determining the parameters of controlled objects. The results obtained allow concluding that the regression neural network is successful in detecting defects using ultrasonic inspection. This opens prospects for the widespread adoption of this technology in various industries, including industry, construction, and infrastructure.

In the course of the work, an ultrasonic inspection dataset was generated, analysed, and cleaned using TOFD technology and developed a convolutional neural network architecture for classifying defect heights based on ultrasonic inspection signals. The architecture and hyperparameters of the created convolutional neural network were improved to classify cracks in materials by their height. The resulting neural network showed a result of 85.61% accuracy on the test dataset. Based on the developed classification convolutional neural network, a regression model was developed to determine the exact numerical value of the crack height, which is an important aspect in non-destructive testing. After selecting the hyperparameters, testing on the test dataset showed the result: the average absolute error in determining the crack height was only 0.46 mm, the average absolute error was 4.86%.

The obtained results confirm the possibility of successfully using convolutional neural networks to determine the crack height from ultrasonic inspection signals and provide grounds for further research into the use of neural networks in the analysis of ultrasonic inspection results. To further improve the accuracy of predictions, the training dataset should be expanded and improved by adding data from different samples: different materials, different shapes, and sizes with a wider range of crack characteristics, and real ultrasonic inspection data of the corresponding TOFD technology.

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CONFLICT OF INTEREST

None.

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Застосування регресійної нейронної мережі для аналізу результатів ультразвукового контролю

Анотація. Проведення дослідження на цю тему стає актуальним у зв'язку з великим значенням безпеки об'єктів критичної інфраструктури та наявністю експлуатаційних дефектів у елементах обладнання та трубопроводах, що створює серйозні загрози, включаючи можливість руйнування обладнання та негативний вплив на навколишнє середовище. Мета даної роботи полягає у вивченні можливості використання дифракційно-часової техніки ультразвукового методу неруйнівного контролю разом з глибокою згортковою нейронною мережею для точного визначення числового значення висоти експлуатаційної тріщини. Серед використаних методів слід зазначити аналітичний метод, метод класифікації, функціональний метод, статистичний метод, метод синтезу та інші. В ході дослідження було виявлено, що автоматизований підхід до вимірювання висоти тріщин, який базується на дифракційних сигналах та використанні нейронних мереж, суттєво покращив якість та точність неруйнівного контролю. Одним з розповсюджених методів контролю для виявлення експлуатаційних тріщин є ультразвуковий контроль, який вважається найбільш ефективним. Він дозволяє надійно виявляти дефекти та визначати їхні розміри без руйнування виробу. Результати дослідження підкреслюють високий потенціал та ефективність методу в аналізі отриманих даних та надають підтвердження його застосовності для визначення стану об'єктів під час ультразвукового обстеження. Робота підкреслює, що ці технології є особливо важливими та ефективними. Зазначається, що їх широке застосування у різних галузях, таких як медицина, авіація та машинне навчання, свідчить про їх потужність у розв'язанні складних завдань. Практичне значення роботи полягає в розвиненні передових підходів, що надають нові інсайти та методи для покращення ефективності аналізу результатів, які можуть бути застосовані в промисловості для поліпшення якості контролю та надійності об'єктів технічного призначення

Ключові слова: неруйнівний контроль; експлуатаційні дефекти; ефективність діагностики; обробка даних; автоматизація процедур; індустріальний моніторинг