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The Method of Diagnostics of Radio-Electronic Means Based on the Analysis of Shock Effects by Means of Machine Learning Algorithms

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***Abstract*— The content of the article focuses on the problem of insufficient effectiveness of existing methods of diagnostics of radio-electronic means, in particular, aimed at identifying structural defects. The defects of mechanical nature are not given sufficient attention, so the development of a diagnostic system aimed at identifying structural defects is an urgent task of practical significance. To solve this problem, it is proposed to use modern information technologies, including machine learning algorithms, which in turn will be implemented in the developed methodology for diagnosing radio-electronic means based on the analysis of impact impacts and which in turn will involve artificial neural networks based on the recognition of images of structural defects obtained after mechanical impacts. The paper describes in detail the specified diagnostic method, determines the configuration of the artificial neural network and calculates its accuracy, which in turn allows us to conclude that the chosen approach is promising. The paper presents a project of an automated system for diagnosing radio-electronic means based on the analysis of shock effects using neural networks, defines its architecture, designs the main modules, and determines the types of software.**

Keywords— technical diagnostics, radio-electronic means, impact effects, defects, neural network, machine learning, automated system.

I. Introduction

The active development of technologies for the production of radio-electronic products, the constant desire to ensure their high quality and reliability, contribute to the emergence of more and more advanced methods for monitoring and diagnosing various defects that inevitably manifest themselves in the production of any complexity.

Since any defect in a product negatively affects its operational parameters and can even lead to serious accidents, science and production are always looking for ways to improve such an indicator as reliability. One of the ways to improve the reliability of systems in general and electronic equipment in particular is technical diagnostics.

Although a significant proportion of defects in radio-electronic means (REM) have a mechanical nature [1], today the processes of monitoring and diagnosing these products are primarily associated with tracking their electrical characteristics. The importance of conducting tests on the mechanical impact of REM is also that the detection of certain design flaws, as a rule, is possible only within the framework of acceptance control, while electrical or thermal parameters are easier to detect during operation.

Due to the high significance of the above-mentioned processes for diagnosing REM, including at the stage of checking structural elements, the task of creating a more effective method for diagnosing electronic devices is constantly relevant.

As mentioned earlier, most of the methods of monitoring and diagnosing are aimed at analyzing REM from the point of view of the flow of electrical processes. Nevertheless, scientific publications related to the detection of structural defects through thermal or mechanical action also remain an important part of the theory of technical diagnostics in general.

A serious drawback of the available research is the fact that at the moment the complexity and diversity of REM does not allow to identify and identify all the defects of the device using any one method. In the study, the hypothesis, which is that the existence of the defect in the design of REM can be detected as a function of system response to input impulse, for example, a single shot. That is, the presence of any of the defects will affect the output characteristic of the structure itself, so that the fault can be identified by the type and parameters of this characteristic.

Studies have shown that the greatest influence on the electronic means is a combination of vibration effects and single shocks [2–4]. For this reason, these types of tests have

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the highest priority, while the remaining loads can be attributed to additional ones. We will describe in more detail the impact effects, the reaction to which acts as the initial data used in the implementation of diagnostics in the ongoing study [5–7].

In mechanics, a shock is a short-term jump-like process. During the impact, large but instantaneous forces arise at the point of contact of the solid bodies, causing some finite momentum. The electronic means and objects for diagnostics within the scope of this study are printed node (PN). The main idea of the developed technique is to analyze such shock effects on the printing units. In this case, the neural network (NN) will be engaged in this analysis [8].

II. Methods of Diagnostics of Radio-Electronic Means

To solve the above problems, the methods of REM diagnostics, the theory of artificial neural networks (ANN), and pattern recognition are used. In the process of work, the TensorFlow software library, created specifically for machine learning, is used. The SolidWorks software package was used to simulate the impact [9].

We will describe a similar method of diagnosing electronic means in the form of a sequence of actions that need to be performed.

1) The test PN is placed on the test impact stand.

2) The PN is subjected to a mechanical impact in the form of a single impact with a triangular pulse.

3) The response of the node is monitored using a sensor attached to it for 1 second at a frequency of 1000 Hz.

4) The obtained dependence of the oscillation amplitude on time is stored on a digital medium in the form of pairs of XY values.

5) The stored impact result is fed to the input of the ANN model.

6) The result of the ANN model is a numerical value indicating that the device under study belongs to one of the classes under consideration.

7) Based on the obtained value, a conclusion is made about the presence or absence of a defect in the PN.

The main element in the method described above is the ANN. The elements that are somehow related to it, whether it is the choice of the network architecture or the volume of input data and their representation, largely determine the accuracy of the diagnosis, and hence the effectiveness of the methodology as a whole.

As part of the first practical tests, the results of modeling impacts on printed components in the SolidWorks software package were used as data for NN training [9]. An example of impact modeling is shown in Fig. 1. At the same time, the simulation was performed under the following states of the PN.

- The printing node is deformed.
- The printed node has an incorrect layout of elements.
- The wrong material was used in the node.
- There is a foreign element in the node.
- The node has no defects.
- There is a crack in the node.
- The fastener was loosened in the node.
- The node is missing one of the components.

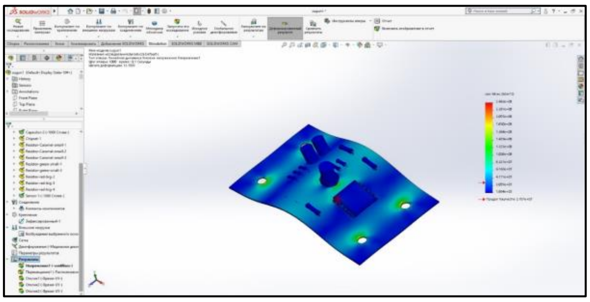

Fig. 1. Example of impact modeling in SolidWorks

A total of 1008 impact results were obtained on the printed node with 126 data sets for each node state described above, respectively. In the future, both the total number of results and the number of classes will be increased.

III. Choosing a Neural Network Architecture

Two variants were considered as the neural network architecture.

1) Classic multilayer perceptron.

2) Convolutional neural network.

A multilayer perceptron (MP) is an architecture of a forward propagation neural network that includes at least 3 layers: input, hidden, and output [10]. The *ReLU* function (1) is used as the activation function in all layers except the last one.

$$f(x) = \begin{cases} 0, x < 0 \\ x, x > 0 \end{cases}, \quad (1)$$

where x - is the value coming to the output of the neuron.

The *softmax* function (2) was used to output the final result as a set of probability estimates that give a total of one.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}, \quad (2)$$

where z - is the original vector of dimension K, e - is the exponent.

The compiled model after 5 training epochs gives an accuracy below 15%, as shown in Fig. 2.

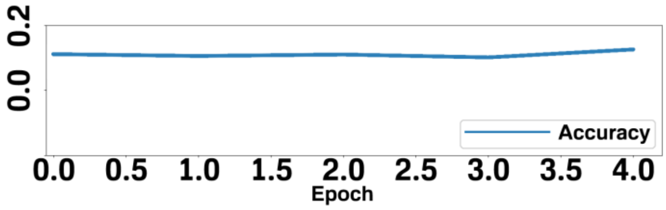

Fig. 2. Classification accuracy of the multilayer perceptron

The result obtained is not acceptable, but the accuracy can be improved by increasing the number of epochs or by reconfiguring the layers. An alternative to the multilayer perceptron is the convolutional neural network (CNN) [11, 12]. This architecture is primarily designed for image recognition and classification, which is not a hindrance, since the results of shock effects are easily displayed in the form of graphs.

Having the results of impact impacts in the form of a set of points (*X*, *Y*), you can build images of graphs that can only be submitted to the input of the NN model, but there is a more efficient approach for classifying such initial data. If you look at the left part of Fig. 3, reflecting schedule impact on PN, we can see that a significant amount of space in the image is the emptiness, not containing information, and decreasing the size of the image lost detail most curve on the chart.

To solve this problem, instead of using a graph, it is necessary to obtain an image of the *GAF*-matrix or the angular Gram matrix, the use of which for time series analysis already gives high classification accuracy on popular classical data sets [13].

Formulas for obtaining the angular Gram matrix – normalization of the series in the segment [-1, 1] (3), conversion of values to the polar coordinate system (4), calculation of the elements of the *GAF*-matrix (5):

$$\widehat{y_i} = \frac{(y_i - \max(Y)) + (y_i - \min(Y))}{\max(Y) - \min(Y)}, \qquad (3)$$

where Y - is the set of all available points$y$, y_i – i-th point Y, $\widehat{y_i}$ – the normalized value of y_i;

$$\varphi_i = \arccos(y_i), \qquad (4)$$

where φ_i – is the polar angle for the point y_i;

$$G = \begin{bmatrix} \cos(\varphi_1 + \varphi_1) & \cdots & \cos(\varphi_1 + \varphi_n) \\ \vdots & \ddots & \vdots \\ \cos(\varphi_n + \varphi_1) & \cdots & \cos(\varphi_n + \varphi_n) \end{bmatrix}, \qquad (5)$$

where G – is the angular Gram matrix (*GAF*-matrix).

All the formulas described above were embedded in a Python script that reads the *Y*-column of each experiment and generates the corresponding matrix image. The transition from the graph to the matrix is shown in Fig. 3.

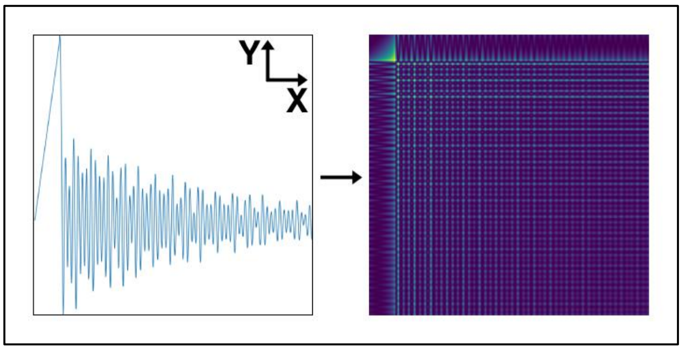

Fig. 3. Transition from the graph image (*X*, *Y*) to the angular Gram matrix

The final configuration of the neural network used for training is shown in Fig. 4 [14, 15].

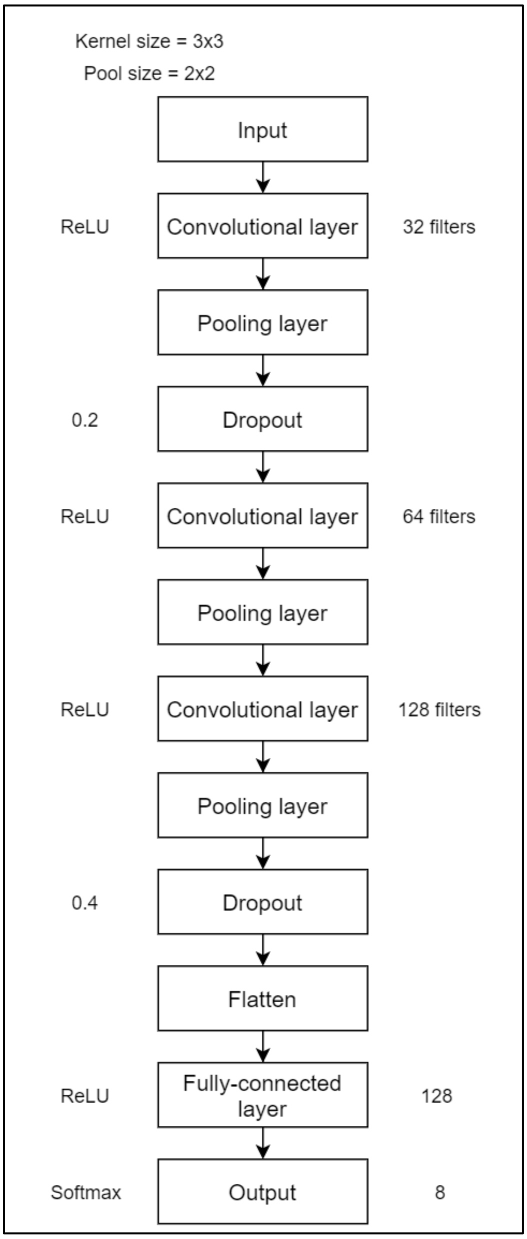

Fig. 4. Final configuration for CNN

The compiled CNN model provides 98% accuracy on the training data, as shown in Fig. 5.

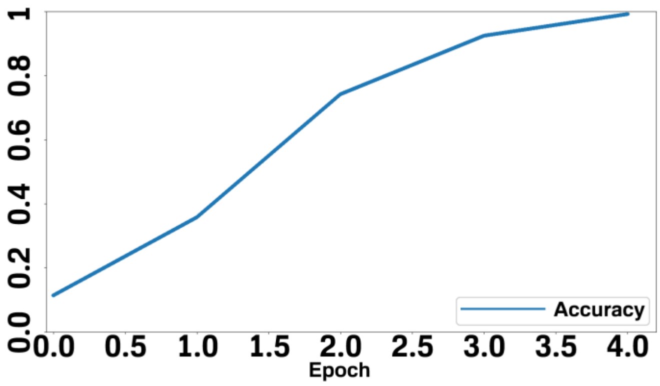

Fig. 5. CNN classification accuracy

The same result is achieved when testing the network on 10% of images selected from the original data set with matrices that did not participate in the training process.

Thus, we can say that the architecture of the convolutional neural network showed excellent results, ahead of the MP classification accuracy. Together with the information density-efficient data representation, the CNN shows an accuracy of 98% versus 12% for the MP for the same number of training iterations.

IV. DESIGNING AN AUTOMATED SYSTEM

The paper also presents the main stages of designing and developing a software tool [16], an automated system (AS) that implements the proposed method for diagnosing radio-electronic means.

At the initial stage, a functional model was implemented, designed to study the features of the AS operation and its relationship with internal and external elements, the development was carried out in an application for modeling diagrams and flowcharts "Draw.io". The functional model contains two types of diagrams: contextual (generalized) diagram; decomposition diagram. The context diagram shows one block - AS diagnostics of radio-electronic means based on the analysis of shock effects.

The input data for this speaker is: the impact results; the name of the printing unit; additional information. The output is: an entry for the host; the diagnosis; the current state of the node; schedule impact. The control data is: information about malfunctions (design defects). The mechanisms are: a user (a design engineer working in the field of development and maintenance of REM); a computer.

Next, a detailed diagram of the functional model was implemented, representing the work of the developed AS in the form of a set of functional blocks. The diagram highlights five main blocks: getting a diagnostic request; plotting and getting an image of the Gram matrix; image processing: data extraction and normalization; image analysis in a neural network and class definition; output of results.

The relationship between the blocks is as follows: the input block "prompted the diagnosis" do the results of impact on the study of printed knot in a text file with format ".CSV" and the name of the REM input by a user via the keyboard. At the output of the block, a corresponding record is created in the database (DB) based on the name of the REM, and a set of points on the coordinate plane is extracted from the downloaded file, reflecting the node's reaction to the impact.

The set of points is sent to the block "Plotting and obtaining the image of the Gram matrix", where the values of the *GAF*-matrix are calculated from the obtained points, after which the image of the graph and the resulting matrix is generated using a special library. These images are sent to the output of this block. The resulting image with a matrix reflecting the impact on the node is fed to the input of the "Image Processing" block. Here, the image undergoes a number of transformations. In particular, the size is changed, then the image is converted to an algebraic tensor, the values of which are reduced to the range [0, 1]. Such transformations allow us to provide uniform input data that is best suited for training a neural network.

In the block "Image analysis by means of a neural network and class definition", the previously transformed image is received as input. The result of the block is the status code of the REM, which reflects the belonging to one of the classes of objects on which the existing NN system was trained.

The final block "Output of results", based on the received REM status code and the information contained in the database about the compliance of each such code with a specific fault, gives the current status of the diagnosed node, while the database stores information about the diagnosis.

As described earlier, the convolutional neural network was chosen as the architecture for the NN. However, to start training the NN with a teacher, data is required for its training and subsequent verification. The developed AS is a combination of a client application and a database. The program is an application that loads data from the database, visualizes it, and adds new information within the established functional model.

AS software [17] is a set of programs used for creating and further functioning of the system. So, to ensure the operation of the AS, the following set of software tools is required: the Windows 10/8 operating system; the PostgreSQL DBMS; the Npgsql database driver.

The PyCharm development environment and the TensorFlow machine learning library were used to write scripts related to the NN operation. The MatPlotLib software library was used for plotting graphs and images of matrices. The Windows Forms API and the Microsoft Visual Studio development environment were used to create the client application. The DocX library was used to generate text documents using program code.

The AS structure consists of 15 modules, Table 1 shows their name and description.

TABLE I. THE MAIN MODULES OF THE SYSTEM

Module Name	Module Description
Main menu	A module that defines the content of the main menu form. The form contains buttons for switching to other forms. This is also where the database connection is initialized. Reflects the current authorized design engineer
Authentication	A form module designed for authentication and subsequent authorization of the design engineer (AS user) by entering a login and password for the system
List of diagnostics	The form module that displays all the performed REM diagnostics in a tabular format. Search and filters by date and time of diagnostics are available
New diagnostic	A form module that allows you to start a new diagnostic for a pre-selected REM

Diagnostic information	A form module that reflects information about the diagnostics selected in the table. The information is taken by accessing the database based on the diagnostic identification number sent to the form constructor
List of REMs	A form module that displays all the REM stored in the system in a tabular format. You can search and filter by the status of the board and the presence of a file with the results of the impact
New REM	The form module by which a new REM is added to the system
REM information	A form module that provides information about the selected REM
Calculations for diagnostic	The module responsible for constructing a graphical representation of the impact, calculating the Gram matrix and constructing its subsequent image
CNN module	The module responsible for the configuration and subsequent use of the NN within the system. Receives an image of the Gram matrix as input, then performs the necessary transformations to transfer data to the network, then outputs the result of the NN operation
User settings	A form module that provides some personal settings for users. These settings include a folder for saving reports by default, as well as the ability to choose automatic saving for each diagnosis
Statistics	A form module that reflects statistics on the operation of the system as a whole. Provides an opportunity to get acquainted with both text and graphical display of data
Bar chart	A form module that displays a histogram for the selected statistics
Help	A form module containing reference information on how to use the software product
About	A form module that displays a brief description of the system and contains information about the author

The structure of the interface of the developed system is related to the described modules of the software product, this interface provides a convenient and intuitive use of the software by visually highlighting the main functional elements and sequential access to the necessary windows.

On the basis of the described structure, the project of an automated system for diagnostics of REM was implemented, using as input data the shock effects exerted on the REM, which fully performs the functional tasks defined for it. The high accuracy of neural network predictions based on simulated defects indicates the prospects of the chosen approach in the conditions of the real production cycle, and the use of modern technologies and AS development tools ensures easy scaling of the developed system in the future.

V. Conclusions

In this article, the main hypothesis is about the possibility of detecting structural defect in the REM as a function of system response to input pulse and the method of diagnosing of electronic tools based on the analysis of impacts through machine-learning algorithms, namely – ANN. The high accuracy of neural network predictions based on simulated defects indicates the prospects of the chosen approach.

The next stage in the study will be the conduct of a large number of experiments that will be aimed at identifying the stability of the ANN model, the reliability of its results when using printed circuit boards with a different element base. Within the framework of this research, the design and development of elements of an automated system that implements the proposed method for diagnosing radio-electronic means has been started.

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