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Sebastian KUROCZYCKI, Konrad GÓRNY*, Wojciech PIETROWSKI*

APPLICATION OF DEEP NEURAL NETWORK IN A MOBILE APPLICATION FOR CLASSIFYING FAILURES OF AN INDUCTION MOTOR

The article presents the use of a deep neural network to classify failures of an induction motor. Failures are related to inter-turn short-circuits occurring in the stator circuit. The classification is applied as a mobile application using the Intel Movidius Neural Compute Stick. The state assessment was made on the basis of a database containing the results of continuous wavelet analysis of the torque waveforms of the motor for a different number of shorted turns. Various database configurations for the neural network used in the application have been considered.

KEYWORDS: diagnostics of cage induction motor, intel movidius, neural networks, inter-turn short-circuits.

1. INTRODUCTION

In recent years, the use of induction motors in industry is constantly growing. Due to the improvement of the quality of materials used for their production, better constructions characterized by increased reliability and efficiency, as well as simplicity of use and relatively low production price, the general demand for modern, sometimes complex applications using induction motors is still increasing. As described in the literature [1, 2], most of the industrial factories use older generation motors that have been working for years, and often the maintenance of those machines is not carried out regularly. To avoid significant failures that could stop the production process and lead to serious financial losses, it may be helpful to apply an early failure detection system. Regular repair or replacement of electrical machines is definitely a cheaper solution than production stopping.

Based on the latest discoveries and technological solutions, new diagnostic techniques for electric motors have been developed. Many works have been devoted to the development of electrical and mechanical failures detection methods of induction motors [3, 4]. Based on the information contained in the article [5], the inter-turn short-circuits in the stator winding are one of the most common failures of induction motors. The inter-turn short-circuit is a serious

* Poznan University of Technology

fault mainly due to the aging of the winding insulation. The important fact is that most of the security systems used to detect irregularities are not able to identify this type of failure due to their initially low impact on the machine's operating parameters. This kind of issue can usually be solved by using digital processing of measurable signals. Common methods for the detection of inter-turn short-circuits are: analysis of phase current and torque with the Park's vector, phase current envelope analysis (MCSA) by use of a discrete Fourier transform or a wavelet transform.

Due to the fact that as a result of motor failure, changes in the waveforms of e.g. phase currents or torque occur, it is possible to consider the problems of diagnosis as a problem of classification. After extracting the appropriate features of the tested object, that's is possible to create a classifier that recognizes the failure of the electrical machine. The classification system can be based on algorithms related to machine learning. The most common of them are artificial neural networks [6, 7, 8]. Most algorithms of learning artificial neural networks used in diagnostics are connected with a supervised learning process requiring a large amount of data for correct training. Lack of precise test samples or a limited number of them may lead to the incorrect generalization of the solution, what is manifested by so-called overfitting or not reaching a certain error value by the neural network. Difficulties in detecting failures of induction motors arise mainly from the complexity of electromechanical processes taking place in the machine.

In the presented article, it is proposed to combine the existing fault location methods using wavelet analysis with the latest technological developments in the analysis of 2D signals from Intel Movidius based on deep neural network.

2. CLASSIFICATION ALGORITHM

The software for failures detection of the stator winding has been developed in the Python programming language. The software enables the training of a selected neural network with use of training data in the form of images depicting various degrees of failures to the stator of the induction motor. At the research the GoogLeNet network was used. General scheme for SI-based diagnostic system is shown in Fig.1.

Fig. 1. Diagram of the procedure for the development of a short-circuit detection system

Due to the non-stationary character of torque waveforms, the results of continuous wavelet transform were used to train the deep neural network. The torque waveforms were obtained on the basis of the field-circuit model of asynchronous motor.

The wavelet transform used for the *x(t)* signal can be described by the following formula:

$$\gamma(\tau,s)=\int_{-\infty}^{+\infty}x(t)\frac{1}{\sqrt{s}}\psi^{*}\left(\frac{t-\tau}{s}\right)dt \tag{1}$$

where: $\psi\left(\frac{t-\tau}{s}\right)$ is a mother wavelet, * – is a complex conjugation, s – is a scale, τ – is an offset.

In order to compose the signal, the Inverse Wavelet Transform should be used, which is defined as follows:

$$x(t)=\int\gamma(\tau,s)\cdot\psi\left(\frac{t-\tau}{s}\right)d\tau ds \tag{2}$$

The analysis results include the transformation for nine different wavelets (db1-db9) in case of two different machine load: T = 0 Nm and T = 15 Nm. The training database is composed of the results of mentioned analysis for a different numbers of shorted-turns in one phase of the stator winding, successively 0, 1, 2, 3, 10, 20, 30, 40, 50, 55 where 55 means a short circuit of the entire coil of a phase winding. The number of 180 different images were used in the learning process. The Figures 2–4 show selected waveforms of torque subjected to continuous wavelet transform (CWT) as well as results of their transformation by CWT.

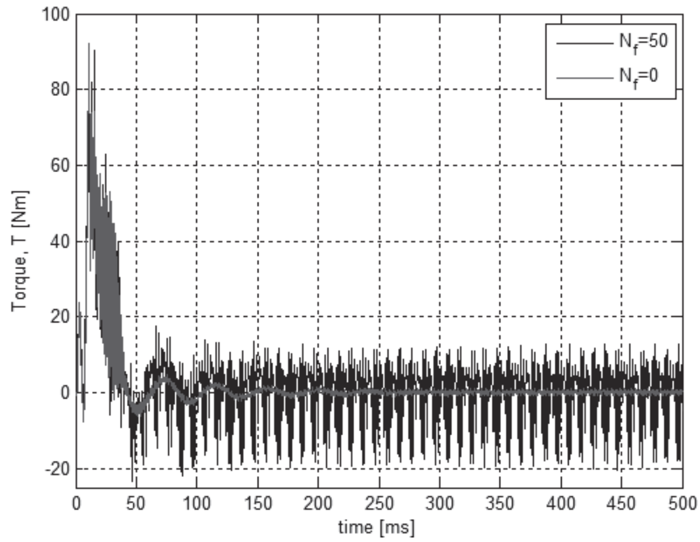

Fig. 2. Torque waveforms for load T = 0 Nm

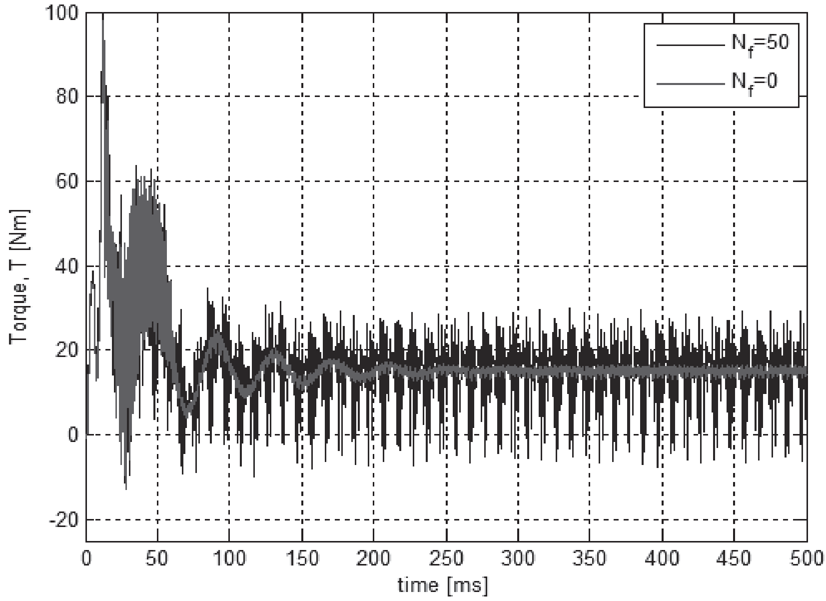

Fig. 3. Torque waveforms for load T = 15 Nm

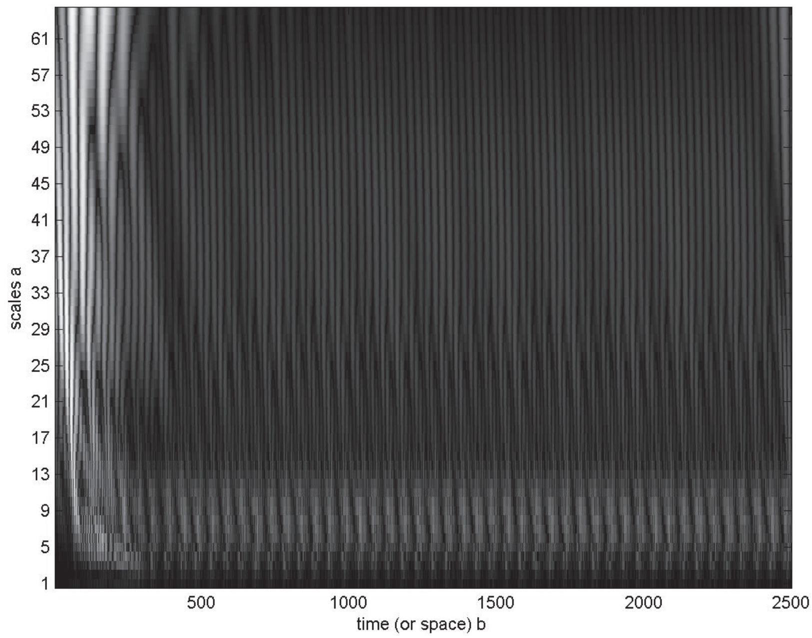

Fig. 4. The image from the database representing the CWT analysis with the db8 wavelet - 8 shorted turns

The learning process of neural network was carried out via the Caffe framework, duration of the learning process depended on the compute power of processing unit and ranged from 6 hours in the case of the Nvidia GeForce GTX 1080 graphics unit to few weeks in the case of the i7 920 CPU. The artificial neural network was compiled into a form compatible with the requirements of the Intel Movidius Neural Compute Stick device via the NCSDK API. By use of the application developed in Python programing language and the pre-learned neural network, the inference was carried out. The application was launched on the platform Raspberry Pi 3 model B + on a Linux system.

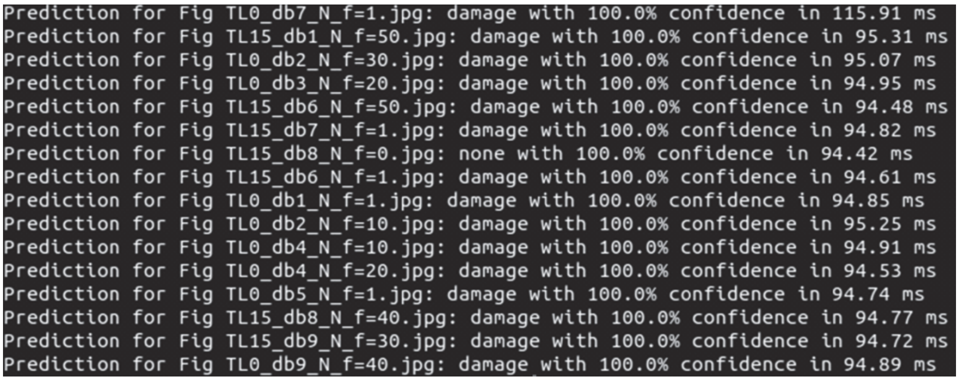

Fig. 5. Sample results of inference

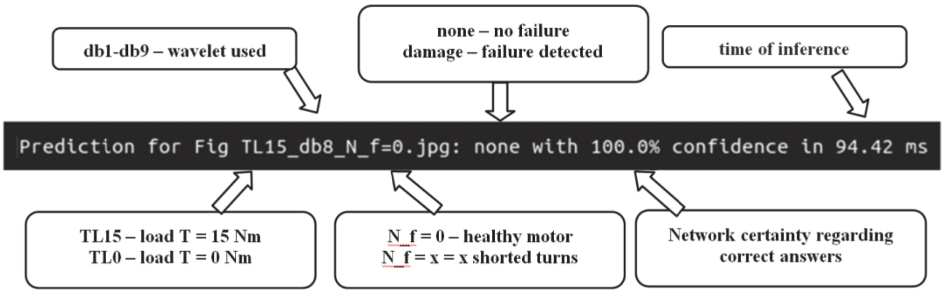

Fig. 6. Interpretation of program results

Fig.5 presents examples of inference results. The interpretation of the results is shown in Fig. 6. As shown in Fig 6, the software displays information about:
– the name of the input data that was subjected to classification;
– machine status;
– percentage of certainty of the decision;
– the time of inference of the artificial neural network.

The mobile application using the Intel Movidius neural network accelerator is shown in Fig.7.

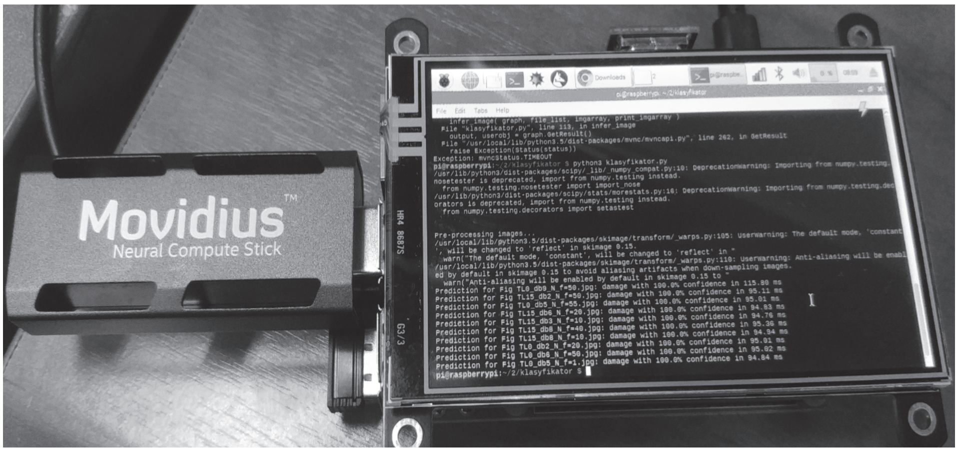

Fig. 7. Implementation of the software on Raspberry Pi 3

3. SELECTED RESULTS

Tests of artificial neural network were performed for six different database configurations:

– for a different database sizes: a full database, 3/4 base, 1/2 base, 1/4 base,
– for an incomplete database, without images for 10 and 55 shorted turns.

The overall percentage of valid network responses for different database configurations was checked. In addition, the percentage of correct responses of artificial neural network with a distinction to the number of shorted turns is specified.

The results presented in Fig. 8 show that with the increase of database size the correctness of the classification of the artificial neural network is increasing. In the case of network training process based on the entire available database, the result was obtained at the 99.4%. Decreasing the size of the database results in a deterioration of the precision of the artificial neural network.

Problems with correct image interpretation are only in cases, where failure is at a very early-stage, i.e. when one or two turns are shorted or when the machine is healthy as shown in Fig.9. A particularly troublesome case is the recognition of a short-circuit for healthy motor for a small training dataset.

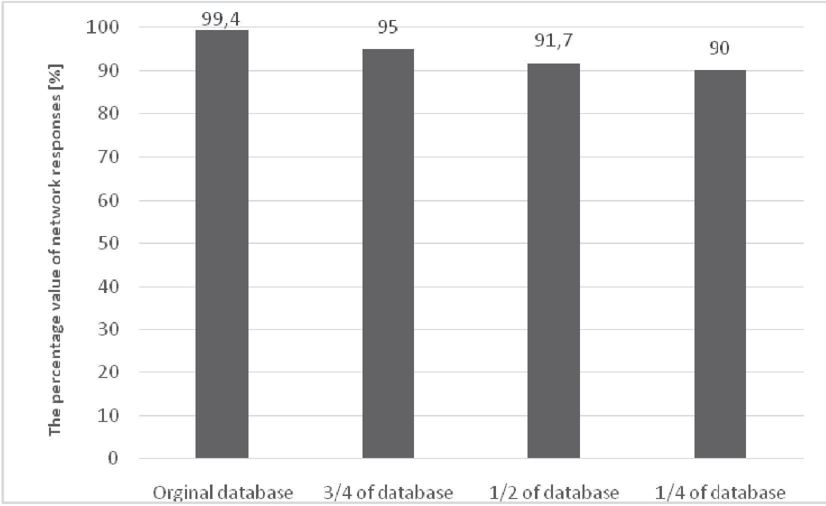

Fig. 8. Percentage of network responses for a different number of training pairs

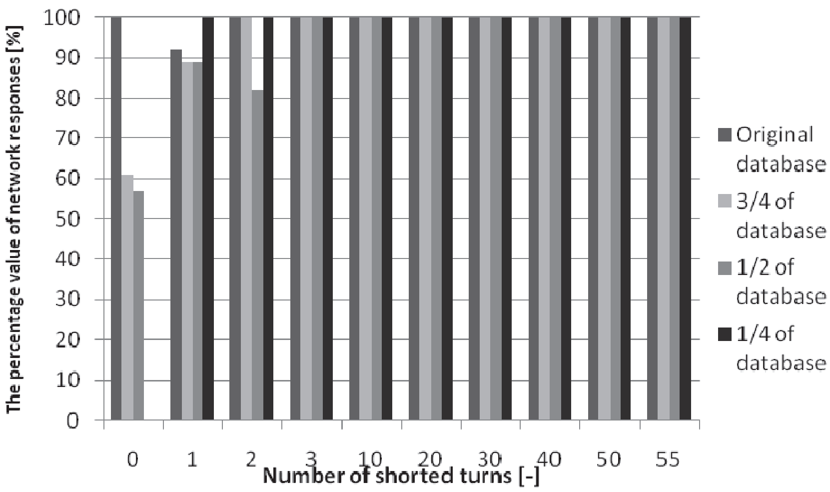

Fig. 9. Percentage of network responses for a different number of shorted turns

Limitation the database to 1/4 of its original size causes that the percentage of correctness of response in the case of an healthy motor is equal to 0. In order to present the results of network inference better, it is necessary to limit of received results to cases in which the network commits the most errors. The results for the healthy motor and for one and two shorted turns are shown in Fig.10.

As can be seen in Fig. 10, in the case of the neural network was learned with use of the entire available database, except for an isolated case, the confidence of the answer is always above 98%. A neural networks which was trained with the

75% and 50% of the database are characterized by a 75% surety of the response for the correct response, and in the range of 0-20% for incorrect interpretation. The results of the neural network that was trained on the most-reduced database are characterized by extreme values of inference certainty. Therefore, it can be considered that the network was not trained correctly in this case.

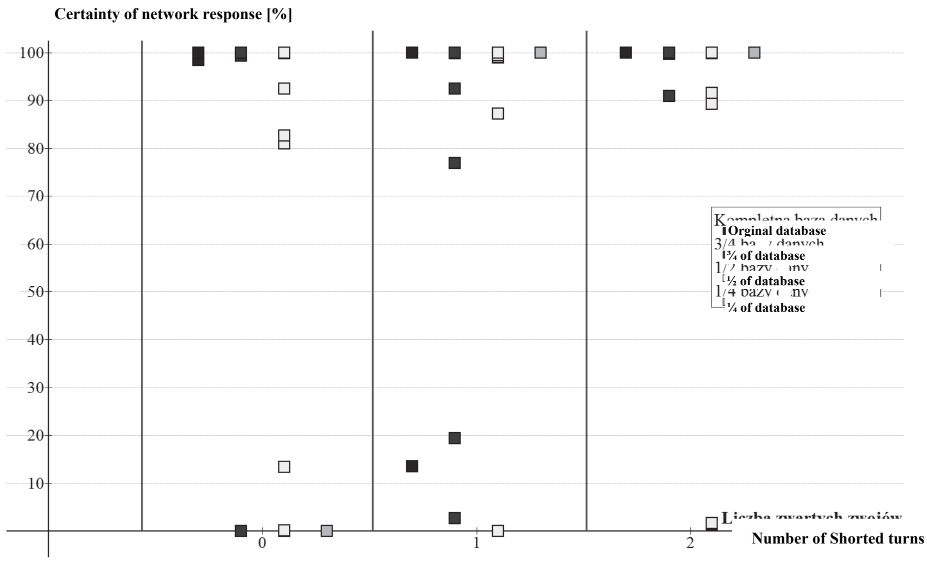

Fig. 10. Response of the artificial neural network response for different training database size configurations

The result of inference for databases without results for 10 and 55 shorted turns are presented in Fig.11 and Fig.12.

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Prediction for Fig TL0_db2_N_f=10.jpg: damage with 100.0% confidence in 115.44 ms
Prediction for Fig TL0_db4_N_f=10.jpg: damage with 100.0% confidence in 95.10 ms
Prediction for Fig TL15_db1_N_f=10.jpg: damage with 100.0% confidence in 94.63 ms
Prediction for Fig TL15_db5_N_f=10.jpg: damage with 100.0% confidence in 94.78 ms
Prediction for Fig TL15_db9_N_f=10.jpg: damage with 100.0% confidence in 94.77 ms
Prediction for Fig TL15_db4_N_f=10.jpg: damage with 100.0% confidence in 95.08 ms
Prediction for Fig TL0_db5_N_f=10.jpg: damage with 100.0% confidence in 95.07 ms
Prediction for Fig TL0_db1_N_f=10.jpg: damage with 100.0% confidence in 95.06 ms
Prediction for Fig TL15_db6_N_f=10.jpg: damage with 100.0% confidence in 94.67 ms
Prediction for Fig TL0_db7_N_f=10.jpg: damage with 100.0% confidence in 94.75 ms
Prediction for Fig TL15_db2_N_f=10.jpg: damage with 100.0% confidence in 95.12 ms
Prediction for Fig TL15_db3_N_f=10.jpg: damage with 100.0% confidence in 95.03 ms
Prediction for Fig TL15_db7_N_f=10.jpg: damage with 100.0% confidence in 94.88 ms
Prediction for Fig TL15_db8_N_f=10.jpg: damage with 100.0% confidence in 95.21 ms
Prediction for Fig TL0_db6_N_f=10.jpg: damage with 100.0% confidence in 94.60 ms
Prediction for Fig TL0_db3_N_f=10.jpg: damage with 100.0% confidence in 94.97 ms
Prediction for Fig TL0_db8_N_f=10.jpg: damage with 100.0% confidence in 94.85 ms
Prediction for Fig TL0_db9_N_f=10.jpg: damage with 100.0% confidence in 94.54 ms
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Fig. 11. The results of inference in case of the number of shorted turns Nf = 10

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Prediction for Fig TL15_db2_N_f=55.jpg: damage with 100.0% confidence in 115.82 ms
Prediction for Fig TL15_db4_N_f=55.jpg: damage with 100.0% confidence in 95.04 ms
Prediction for Fig TL0_db6_N_f=55.jpg: damage with 100.0% confidence in 94.59 ms
Prediction for Fig TL0_db5_N_f=55.jpg: damage with 100.0% confidence in 94.81 ms
Prediction for Fig TL15_db3_N_f=55.jpg: damage with 100.0% confidence in 95.07 ms
Prediction for Fig TL15_db1_N_f=55.jpg: damage with 100.0% confidence in 95.09 ms
Prediction for Fig TL0_db9_N_f=55.jpg: damage with 100.0% confidence in 95.22 ms
Prediction for Fig TL0_db4_N_f=55.jpg: damage with 100.0% confidence in 94.38 ms
Prediction for Fig TL0_db8_N_f=55.jpg: damage with 100.0% confidence in 95.01 ms
Prediction for Fig TL15_db8_N_f=55.jpg: damage with 100.0% confidence in 94.99 ms
Prediction for Fig TL0_db1_N_f=55.jpg: damage with 100.0% confidence in 94.95 ms
Prediction for Fig TL0_db3_N_f=55.jpg: damage with 100.0% confidence in 94.55 ms
Prediction for Fig TL15_db6_N_f=55.jpg: damage with 100.0% confidence in 94.70 ms
Prediction for Fig TL15_db5_N_f=55.jpg: damage with 100.0% confidence in 94.62 ms
Prediction for Fig TL0_db7_N_f=55.jpg: damage with 100.0% confidence in 94.91 ms
Prediction for Fig TL15_db9_N_f=55.jpg: damage with 100.0% confidence in 95.29 ms
Prediction for Fig TL0_db2_N_f=55.jpg: damage with 100.0% confidence in 95.23 ms
Prediction for Fig TL15_db7_N_f=55.jpg: damage with 100.0% confidence in 94.96 ms
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Fig. 12 The results of inference in case of the number of shorted turns Nf = 10

The results of the research presented in Fig. 10 and Fig. 11 show that the deep neural network copes in the case of inter- and extra- polation. The results are characterized by 100% correctness and 100% results certainly.

4. SUMMARY

The article presents an algorithm for the detection of inter-turn short-circuit in the stator winding of an induction motor with the use of deep neural network and the Intel Movidius network accelerator. In addition, a mobile application that allows detecting a short-circuit based on 2D signals was presented. The software was testedbased on the database of images generated by the authors presenting the results of CWT analysis of the torque waveforms of the squirrel cage induction motor. The influence of the training database size on the network response was examined. On the basis of the obtained results, it can be concluded that the application of deep neural networks to the detection of faults was high effective in recognizing even minor failures, which promises well for potential future implementations of deep neural networks in diagnostic systems.

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