1. Jakub ZIELONKA[1], 2. Tymoteusz NACZYŃSKI[2], 3. Maciej SUŁOWICZ[3]

Cracow University of Technology, Faculty of Electrical and Computer Engineering (1)(2)(3)
ORCID: 1. 0000-0003-4672-4576; 2.0000-0003-0323-5393; 3. 0000-0001-6436-1110

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Diagnosis of a group of induction motors powered from a joint point using deep learning

***Abstract**. The article presents the application of artificial intelligence based on deep learning algorithms for diagnostics of a group of induction motors. The group of diagnosed machines consists of four squirrel cage induction motors powered from one common point. For diagnostic purposes, similarly to the MCSA method, the stator current signal and additionally the supply voltage signal were used. In the research, the structures of convolutional neural networks - CNN were developed and then the training and testing procedure was carried out. The accuracy of the assessment obtained during the experimental tests was presented using the truth matrix.*

***Streszczenie.** W artykule przedstawiono zastosowanie sztucznej inteligencji opartej o algorytmy uczenia głębokiego do diagnostyki grupy silników indukcyjnych. Grupa diagnozowanych maszyn składa się z czterech silników indukcyjnych klatkowych zasilanych z jednego wspólnego punktu. Do celów diagnostycznych, podobnie jak w metodzie MCSA, posłużył sygnał prądu stojana i dodatkowo sygnał napięcia zasilania. W badaniach opracowano struktury konwolucyjnych sieci neuronowych - CNN a następnie przeprowadzono procedurę treningu i testowania. Uzyskana podczas badań eksperymentalnych dokładność oceny przedstawiona została za pomocą macierzy prawdy (**Diagnozowanie grupy silników indukcyjnych zasilanych ze wspólnego punktu z wykorzystaniem sieci neuronowych o uczeniu głębokim**).*

Keywords: squirrel cage induction motor, electrical machine diagnostics, convolutional neural networks, deep learning, MSCA.
Słowa kluczowe: silnik indukcyjny klatkowy, diagnostyka maszyn elektrycznych, konwolucyjne sieci neuronowe, uczenie głębokie, MSCA.

Introduction

Maintaining electric motors in the best possible technical condition is a key task in the context of the economic efficiency of a given industry using electric machines. In addition to the financial aspect, the risk of endangering the health and life of people in the vicinity of the working machine in the event of its improper use should also be taken into account.

Diagnostics of electric motors can be done in two ways, which are commonly referred to as online [1-2] and offline [3]. The first method does not require the diagnostic team to shut down the machine for measurement and diagnostics. Examples of this are diagnostics using current signals - MCSA (Motor Current Signature Analysis) [4-7], vibroacoustic measurements [8] or thermal diagnostics [9-10]. They allow non-invasive detection of electric motor defects such as cage bar failures, eccentricity, winding short circuits, lack of symmetry, motor unbalance, bearing damage. Offline diagnostic methods, on the other hand, require the machine to stop running. This is necessary in order to install the appropriate sensors or perform diagnostics while the electric motor is stopped. As an example of offline diagnostics, tests to verify the insulation condition of the machine windings can be given [11]. Based on the above, conclusions can be made about the pros and cons of each of the two diagnostic approaches mentioned. What diagnostic method will be used, what specific algorithms will be implemented depends largely on the financial capabilities of the owner of the object under study, physical capabilities, i.e. where the object is located and what access to it is, finishing with time and quality aspects depending on the needs of the principal or the standards set by law.

Today, squirrel-cage induction motors account for about 90% of all machinery operating in the broader industrial and power generation sectors. They owe their popularity to their low operating costs, diversity in the way they are powered, and ease in the context of controlling them in drive or other systems [12]. This, in turn, shows how important it is becoming to diagnose squirrel-cage induction motors and detect damage to their components at the earliest possible stage.

One of the most popular diagnostic methods is the MCSA already mentioned in this article. It involves measuring current signals and analysing them. The genesis of this method comes from the need to diagnose hard-to-reach machinery on oil rigs [13-14]. Thanks to funding from the British government, it was possible to conduct research on the development of this method. With the passage of time, the method proved to be very effective in the context of electric motor diagnostics. Of course, in addition to measuring the current signal, it is necessary to process it properly. The MCSA method uses FFT (Fast Fourier Transform) analysis to process diagnostic signals for the extraction of relevant features. STFT (Short Fast Fourier Transform) analysis or Wavelet Transform are also most commonly used in diagnostic methods. Digital signal processing using these transforms makes it possible to extract from the signal waveforms diagnostic symptoms indicating the occurrence of machine damage in the frequency domain or in the time-frequency domain.

Modern diagnostics of electrical machinery is, of course, different from classical diagnostic methods [15-16]. Many methods used today are based on past achievements and developed mathematical foundations. Advances in technology have increased the computing power of computers and improved the quality and accuracy of measuring devices and transducers.

The development of digital and machine signal processing contributed to the growing interest in AI (Artificial Intelligence) issues. In the 20th century, the first AI algorithms were developed [17], the so-called classical methods. NN (Neural Network) neural networks were based on connecting inputs to its outputs. The simplest way to think of it is as *n* inputs and *m* outputs between which there are dependencies. These dependencies are very elaborate and arise at the NN learning stage in accordance with the programmed structure. As a result, we can obtain an algorithm capable of independently analysing the results (NN inputs) and making diagnoses based on them (NN outputs). Classical methods [18-19], however, required the user to provide information - in other words, the characteristics that the NN should pay attention to during the learning stage. On the basis of these characteristics, dependencies are formed and what further results in the quality of the responses to the outputs that the developed network generates. Such solutions appear in the literature under the name ML (Machine Learning). In the last few years, networks named as Deep Learning (DL) have gained considerable popularity. These types of algorithms no longer require the user to perform significant digital processing of diagnostic signals or point out characteristic features of a given fault [20]. DL networks in their nature are designed to find patterns and features on their own during the training stage. This can cause some anxiety, since we are not sure what signal features the DL network will pay attention to. On the other hand, however, DL networks surpass human perception capabilities, so they can see such a set of features in the input data that are invisible to the human eye. This accounts for the great potential and popularity of DL networks these days [21-32].

Fig.1 illustrates schematically the differences between classical neural networks and those based on deep learning algorithms.

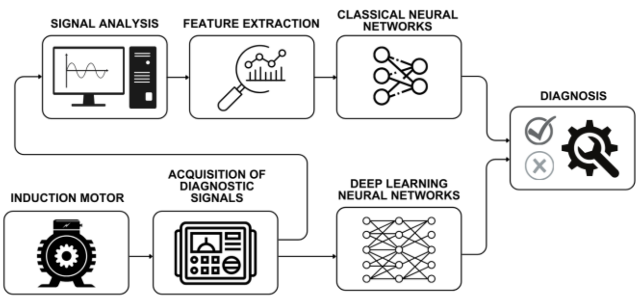

Fig.1. Block diagram representing the differences between classical neural networks and those based on deep learning algorithms

The article presented here is the beginning of the authors' research into a diagnostic solution for a group of machines from a central power point. The first step, however, is a study to identify whether there are symptoms from a faulty machine in the sample. For this purpose, the capabilities of Convolution Neural Networks (CNN) were used. Networks of this type dominate the fields of image analysis [33-35]. In the following part of the article, the adopted research methodology will be presented along with the digital processing of the signals and the CNN structures used.

Concept for diagnosing a group of induction motors powered from a joint point

Nowadays, industry encounters assemblies of machines working together, often in a single drive system. Diagnostics of individual motors would therefore require metering each motor and conducting separate diagnostic analyses. This, in turn, translates into increased costs due to the cost of additional sensors or maintenance work and the need to store much more information from the diagnostic tests performed.

Therefore, the idea of diagnosing a group of motors based on joint signals was born. It is still important in the development of diagnostic research to continue the search for new solutions or the use of well-known methods with the support of new technologies and computer programs. In this study, the authors try to answer the question of whether it is possible to obtain the correct diagnosis about the state of a machine working in a machine complex based only on joint signals - measured at the input of the power supply system. Therefore, to begin with, the current signal and the supply voltage were measured. The tests were carried out in different operating configurations of individual machines.

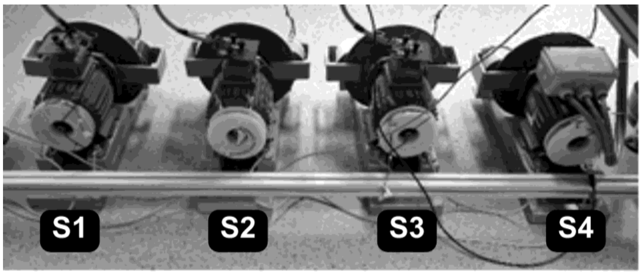

Fig.2 Laboratory station

Laboratory station and signal acquisition

For the purpose of the study, a stand was set up as shown in Fig.2. The stand consists of four low-power squirrel-cage induction motors manufactured by TAMEL SZJe 14a with the following nominal parameters: P_N = 0.8 *kW*, U_N = 380 *V*, I_N = 2,2 *A*, n_N = 1400 *rpm*, $\cos\varphi_N$ = 0,74. One machine is marked as healthy, and therefore with no damage. The other three engines had damage to 1, 2 and 3 rotor cage bars, respectively. For further consideration, the following motor designations were adopted:

- S1 – damaged 1 rotor cage bars,
- S2 – damaged 2 rotor cage bars,
- S3 – damaged 3 rotor cage bars,
- S4 – healthy.

Damage to motor rotors was introduced manually by cutting a cage bar on one of the shorting rings. A sufficient number of bars were cut off to simulate the damage as listed above.

On the laboratory station, shown in Fig.2, it is possible to carry out diagnostic tests on a group of engines in many operating configurations. The article presents the first phase of testing. The current in the joint supply line and, in addition, the voltage supplying the group of motors was selected as the diagnostic signal. The power supply scheme is shown in Figure 3. The measurement was carried out using an NI USB-6259 measurement card and a computer with MATLAB environment. The recorded signals were sampled at a frequency of 100 *kHz*.

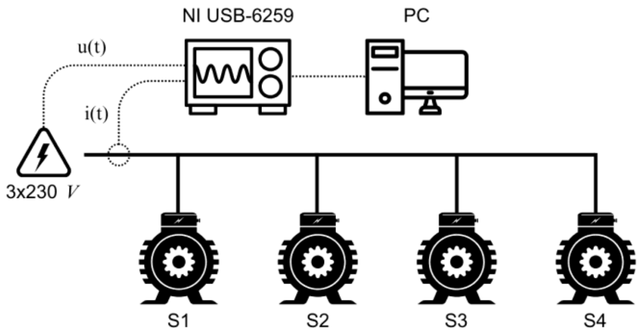

Fig.3. Scheme of laboratory station

It should be noted that research on induction motor diagnostics has been carried out for many years. It is still important in the development of diagnostic research to continue the search for new solutions or the use of well-known methods with the support of new technologies and computer programs. In their study, the authors try to answer the question of whether it is possible to obtain the correct diagnosis about the state of a machine operating in a machine complex based only on joint signals - measured at the input of the power system. Therefore, to begin with, the current signal and the supply voltage were measured. The tests were carried out in different operating configurations of individual machines.

Digital processing of the measured signals

The focus of the research presented here is on the use of CNN to identify patterns characteristic of the damage under study. Before discussing the selected set of studies, it is necessary to explain the operation of CNN. These networks belong to the group of DL algorithms, which independently search for patterns based on a catalogued set of data [36-37]. The predominant achievements of CNN are observed in image analysis. The first question that arises is how to represent the measured signal in the form of an image? Probably the first thing that comes to mind is to save, such a signal waveform or its transform in the frequency domain, as an image file with popular extensions such as *jpg* or *png*. This type of situation is very common if we recognize with CNN what is in a given image. The situation becomes much more complicated in the case of electrical signals. Of course, in the case of thermal diagnostics, the analysis of thermograms with DL networks poses no problem, and such solutions are currently used. On the other hand, analysis of images using DL requires considerable attention mainly because of the possibility of losing a lot of key information contained in the measured signal as shown in Figure 4.

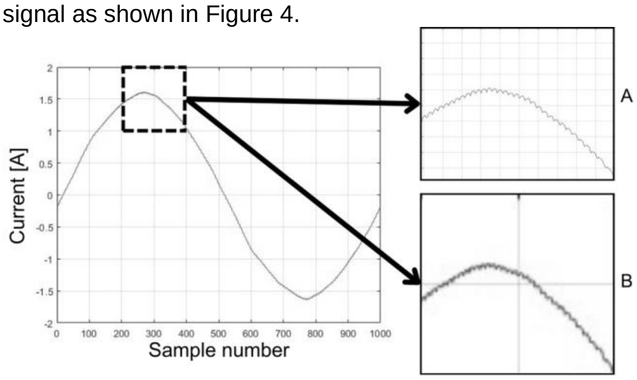

Fig.4 Comparison of data resolution: A - data in matrix form; B - data saved as an image file.

In the rest of the article, the data under consideration will be referred to as signal images. However, at this stage it is necessary to explain what a image is. For a human, it is a graphical form of representation of something. For a computer, on the other hand, it is a matrix of numbers. For colour images, it is a 3D matrix and for black and white photos, the matrix has a dimension of 1D. In this study, the authors assumed that the image means data in the form of a matrix.

The measured signals of both current and voltage are represented by a vector. Thus, in order to obtain a matrix representing a given signal, a transformation from vector to matrix must be performed. The selection of the size of such a matrix is also an important element. Each individual element of the matrix represents one input of the neural network. For example, a matrix of size 10x10 will require as many as 100 NN inputs. The same will be the case with the dimension of a graphic image, where the size is given in pixels - one pixel is one input.

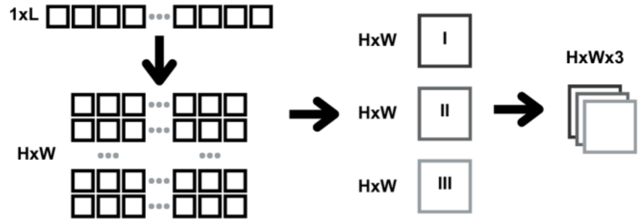

Fig.5. Diagram of signal conversion from the form of a vector to a matrix and finally to an image. L, H, W - dimensions of the vector and matrix; I, II, III - layer number.

Figure 5. illustrates how the measured signal is converted from vector to matrix form. The size of the matrix was chosen empirically, although the main criterion was that a single matrix should cover at least one full period of the signal. In our case, 1000 samples were sufficient to capture one period of the signal. Accordingly, the dimensions *H* and *W* of the matrix had to be found in divisors of the number 1000. Of course, it is possible to use more samples in the input. However, it should be borne in mind that this approach will affect the duration of the NN learning stage. The final adopted dimension of the input matrices was 25x40.

Figure 5 also shows further conversion to a 3D matrix. The three layers indicated can be interpreted as 3 different signals. Suppose we measure current, voltage and instantaneous power simultaneously. Each signal is one layer. The combination of the 3 layers is interpreted by the computer as a single image. Of course, a one-dimensional matrix can be generated too.

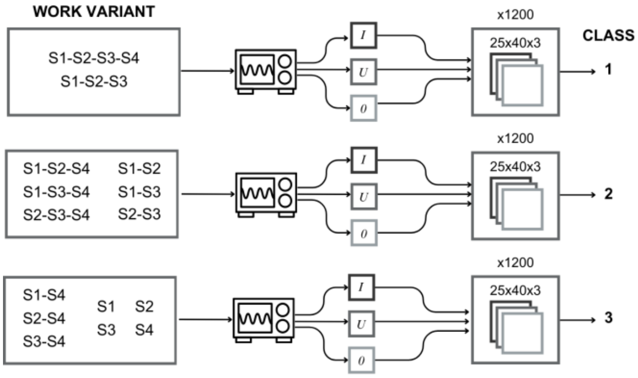

Fig.6. Diagram showing the process of creating a data set for CNN analysis

Figure 6. shows the methodology adopted in the process of creating data sets. The assumption of the research was that the final neural network should be able to assign data to the following classes:

1. 3 induction motors with damage are working,
2. 2 induction motors with damage are working,
3. 1 induction motor with damage is working.

In each class, all possible combinations of motor operation under rated load were studied. The combinations were labelled as operation variants in Figure 6. The current and supply voltage signals labelled I and U were selected as diagnostic signals. The third layer, labelled 0, is an empty matrix serving as a complement to the input 3D matrix, which does not affect the output of the CNN in any way. In this way, data sets were obtained for later analysis using the CNN network.

CNN Structures

Building the structure of the CNN network was done empirically. There are no general and universal rules for building CNN structures. However, it is possible on the basis of the experience of other researchers to draw confident conclusions about the rules for building structures, but in principle there is no general set of rules.

In practice, ready-made network structures are also available. These are structures with a huge number of parameters that have undergone a training process on datasets of thousands or even millions of cases. Such structures can be used for diagnostic purposes. However, the question arises whether this is optimal? Is the use of a structure with millions of parameters necessary for diagnostic issues that do not need the ability to verify thousands of cases just four or five? Examples of structures from the *Pretrained Deep Neural Networks* group are these (the number of parameters in millions is given in parentheses):

- SqueezeeNet (1,24),
- GoogLeNet (7),
- ResNet-18 (11,7),
- ResNet-50 (25,6),
- NASNetLArge (88,9),
- DarkNet-19 (20,8).

These are just a selection of the structures available in the MATLAB DeepLearning Toolbox. The number of parameters determines the capabilities of a given structure. It can be said that a larger number of them results in better data recognition and classification skills. However, too many parameters increase the time the network takes in the learning stage.

In the development of the CNN's own network structure, the MATLAB environment with appropriate tools was used. Fig. 7 shows a preliminary schematic of the structure with listed blocks necessary for the correct operation of convolutional neural networks.

Below, a brief characterization of the individual layers:

- INPUT – input layer, in which the size of the data is declared,
- CONVOLUTION – layer that performs mathematical splicing operations on matrices,
- BATH NORMALIZATION – a layer that performs mathematical splicing operations on matrices A layer that normalizes the learning data set to reduce sensitivity to the initial network parameters,
- MAX POOLING – layer to reduce the size of the input data,
- ReLu – activation function,
- FULLY CONNECTED – layer that performs data multiplication before the corresponding weights,
- SOFTMAX – calculation layer based on *softmax* function,
- CLASSIFICATION – output layer, which classifies the input data into the appropriate classes.

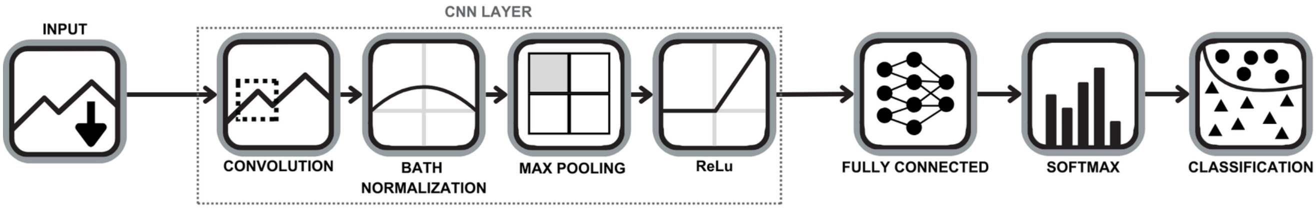

Fig.7. Base diagram of the developed convolutional neural network in MATLAB software

Building the structure consisted of modifying the layer labelled CNN LAYER. The other elements remained unchanged. The authors sought the best structure by adding more CNN LAYER in a serial way. Structures containing 3,4,5 and 6 CNN LAYER were tested. Each trial consisted of changes in the number of CONVOLUTION layer filters.

Table 1 Selected structures developed

Structure	Number of CNN LAYER	Number of CONVOLUTION layer filters
I	3	15-12-5
II	4	60-40-20-10
III	5	60-45-30-15-5
IV	6	60-50-40-30-20-10

The structures studied had about 50-60 thousand parameters, which is a huge difference compared to the aforementioned *Pretrained Deep Neural Networks* structures. However, for a study containing only 3 classes, it does not seem necessary to use structures with such a huge number of parameters.

Results

The prepared data sets according to the scheme shown in Figure 6 were used in the process of learning convolutional neural networks. This stage requires three packages from the user, they are respectively: training package, validation package, testing package. The process of training the network involves searching for all the parameters of the structure so as to obtain the best possible match between the training data and the validation data. The prepared data set contained 1200 image samples, which can be evenly divided into three packages of 400 samples each.

Figures 9 through 12 show the truth matrices. They graphically represent the accuracy of a given structure. The values on the main diagonal represent an error-free match of the output data to the target class. The matrices on the left represent the matching of the data from the test suite and therefore the suite that was considered in the CNN learning process. In each case, the accuracy was more than 99%, which is an optimistic result, but the research cannot end there.

In the field concerning artificial intelligence, there is a phenomenon called network overlearning or learning by heart. This means that a learned network structure can only analyse and classify data locally - within what it has learned. The idea behind AI is that it should be able to look at a problem globally.

Therefore, a new data set prepared in accordance with the covered methodology was used for the following tests. The new data set was obtained in another measurement a few days later. It can be inferred that this measurement, which took place under the same conditions, would achieve accuracy at an equally high level. Unfortunately, an average match of 60%-62% was obtained at the testing stage. This shows how important it is to test developed structures on data that are not known to her. This type of approach ultimately allows us to determine whether the structure can analyse a given issue.

Right side of the Fig. 9 to Fig. 12 contain the truth matrices obtained when testing the developed structures using the new set. We can see the significant amount of wrong answers the structure gave compared to how it answered based on the learning set.

Table 2 Summary of the accuracy of each structure

Structure	Testing –. learning set	Testing –. unknown set
I	100 %	65,33 %
II	100 %	57,75 %
III	100 %	66,75 %
IV	100 %	64,69 %

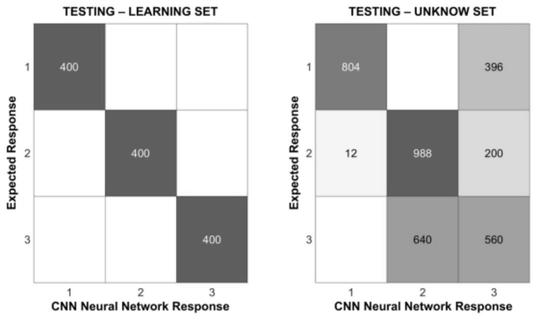

Fig.8. Truth matrices for structure I

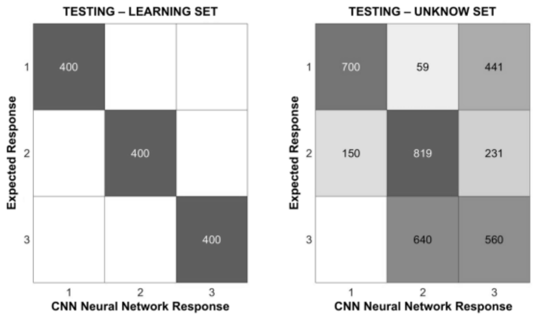

Fig.9. Truth matrices for structure II

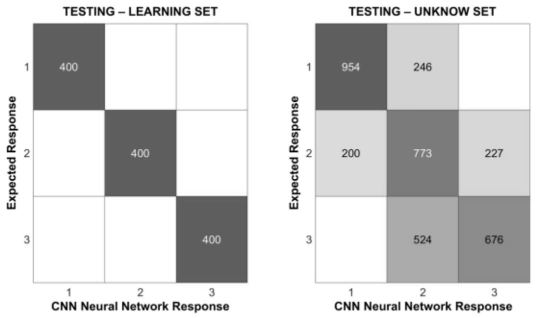

Fig.10. Truth matrices for structure III

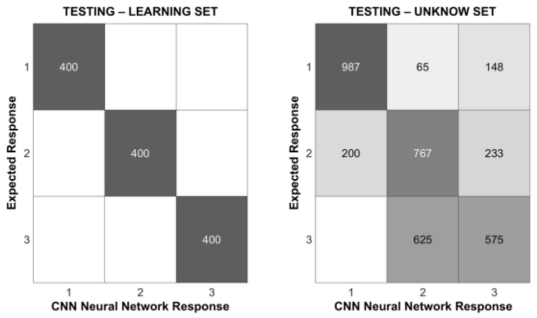

Fig.11. Truth matrices for structure IV

Table 2 summarizes the percentage of accuracy of the presented structures. The obtained values are not satisfactory enough. In the context of machine diagnostics, it is unacceptable to make a diagnosis based on such an unreliable result.

During the study, it was noted that CNN during the repeated training process with the same settings of the learning algorithm, show completely different accuracy. Sometimes higher and sometimes lower matching accuracy was obtained for unknown data. Another study was conducted to look for the highest possible match. After many attempts, a match of about 69% was obtained and eventually the CNN was able to be trained so that when tested on unknown data it could correctly classify it at a level of 73.11% - as shown in Figure 12.

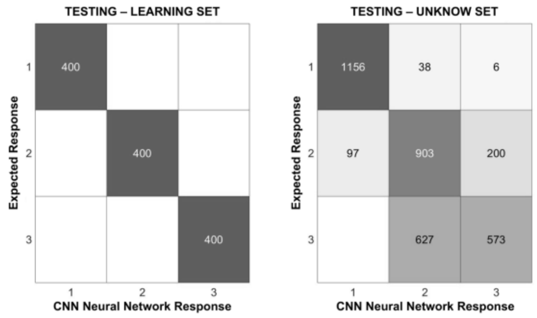

Fig.12. Truth matrices structure I - best fit (Test accuracy on learning data - 100%, test accuracy on unknown data - 73.11%)

Based on the truth matrix shown in Figure 12, it can be concluded that the CNN can almost flawlessly classify the variant of operation during which 3 motors with damage operate (1156/1200 - 96.33%). Also, it can relatively well indicate, on the basis of power signals, the variant of operation during which 2 motors with damage are working (903/1200 - 75.25 %). In contrast, the network cannot effectively classify the case in which 1 motor with damage is operating (573/1200 - 47.75 %). The conclusion that emerges is that the biggest problem is in distinguishing between class 2 and class 3.

Summary

The presented research on the diagnosis of a group of induction motors using CNNs is just the beginning. The topic should be further developed, which is not a major challenge given the continuous technological progress of digital technology devices. Thus, it is possible to implement the prepared neural networks on FPGAs and apply them in the wider industry. However, it should be remembered that such solutions must be sufficiently tested in the laboratory so that they can later be left in normal operation unattended.

Summing up the presented research, it should be considered that convolutional neural networks are for issues related to the diagnosis of electrical machines a new tool that can both assist the diagnostician and completely replace him. These networks need to be reliably developed and tested. The key to CNN is the proper selection of data. This is not to discount the capabilities that AI has, but it is important to remember that these are algorithms that are not infallible. They mimic the human learning and perception process and try to go beyond human perceptual capabilities. However, the key is what data the artificial intelligence has. If this data contains a lot of errors or is inaccurate then AI learning can be compared to human learning based on an outdated encyclopaedia.

Authors: *M.Sc. Eng. Jakub Zielonka, E-mail: jakub.zielonka@doktorant.pk.edu.pl; M.Sc. Eng. Tymoteusz Naczyński, E-mail: tymoteusz.naczynski@doktorant.pk.edu.pl; D.Sc. PhD. Eng. Maciej SUŁOWICZ, Assoc. Prof. CUT, E-mail: maciej.sulowicz@pk.edu.pl; Cracow University of Technology, Faculty of Electrical and Computer Engineering, Department of Electrical Engineering, 24 Warszawska Street 31-155 Kraków.*

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