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MACHINE LEARNING AND PREDICTIVE ALGORITHMS FOR DIAGNOSING ANOMALIES IN ELECTRIC MACHINES

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Abstract: *Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) are of particular importance in electric motors. "Artificial Intelligence" refers to the competence of a machine to resolve certain actions autonomously (without human involvement), such as recognizing certain patterns, predictive maintenance, optimizing the performance of the electric motor. By using AI, electric motors could be supervised and adjusted in real time, making them more efficient and safer.*
The focus of this study is to bring to our attention the most important means of Artificial Neural Networks for the detection of these issues that appear in the functionality of the electrical motors.
Key words: *Predictive maintenance, Machine learning, Fault detection, Electrical machines.*

1. INTRODUCTION

Electric machines are the heart of most industrial production processes. The occurrence of a defect or even the shutdown of such electrical equipment can have negative effects not only on the equipment, but also on the entire technological process, and this results in significant economic losses, the risk of human accidents, negative environmental impacts and numerous other risks. Thus, comprehensive research on intelligent methods for detecting failures in electric machines is a topic of critical importance.

Traditional methods for identifying faults cannot cope with the diagnostic requirements in the context of large data volumes, diversity, fast flow and low information density, all of which are due to the dynamic and complex development of electric motors.

2. GENERAL CONCEPTS

The advancement of current technologies (AI, ML, DL) based on artificial intelligence, stimulates the evolution of fault diagnosis methods. The notion of artificial neural networks was first used in the 1980s. They can learn the characteristics of a device/system adaptively, without the need for precise mathematical models. However, these intelligent networks have certain disadvantages that must be considered:

- The problem of gradient vanishing consists in the exponential decrease of gradients in the process of their transition back into the layers of a deep network during the learning process. The described phenomenon can significantly hinder the convergence of the network, resulting in the inability to learn complex models and representations.
- Overfitting, also known as overlearning, appears when the network learns all the details, even the noise in the signal. Being included in the learning process, it has a negative impact on learning performance.
- Local minima or "local minima" are those points within an interval for which the given function has a value smaller than the values in its immediate vicinity, but not necessarily the smallest possible value in the entire function (corresponding to global minima or "global minima").
- The need for a large amount of information.

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According to groundbreaking studies conducted in 2006 [22], which developed the notion of “Deep Learning”, it was demonstrated that the properties of data created by a multilayer network model can more precisely illustrate the original data, resulting in lowering the complexity of the training process. This scientific discovery resulted in a rapid increase in studies related to deep learning, such as the use of unsupervised layer-wise training (Unsupervised greedy layer-wise training) or the use of an error backpropagation technique (Error backpropagation), with the same goal of optimizing their parameters and improving the generalization capacity of the network.[23][24]

Currently, the most well-known deep learning models are:

- Deep Belief Network – DBN;
- Autoencoders – AE;
- Convolutional Neural Network – CNN;
- Recurrent Neural Network – RNN.

3. FUNDAMENTALS OF ARTIFICIAL NEURAL NETWORKS

3.1 DBN (Deep Belief Network) is considered as a multi-layer neural network built from "Restricted Boltzmann Machines" (RBM) and a classifier. It transforms raw data from the lower level into a more abstract representation at the higher levels. The base layer reflects the original data, while the upper layers learn to group and classify the features of this data.

The concept of "Restricted Boltzmann Machines" – RBM is equivalent to a two-layer recurrent neural network that underlies DBN. This is composed of a visible layer and a hidden layer. Every single layer has m visible units $v = v_1, v_2, \ldots, v_m$ and n hidden units $h = h_1, h_2, \ldots, h_n$ (where v and h are binary variables). The neurons of the visible layer and those of the hidden layer are connected to each other by the weight w, as can be seen in figure RBM is a model characterized by the “energy function”. It is considered that the system is convergent if the energy function is smaller. Being a low energy, the network parameters will be easier to find through training. Therefore, the energy function of RBM can be expressed as [30]:1.

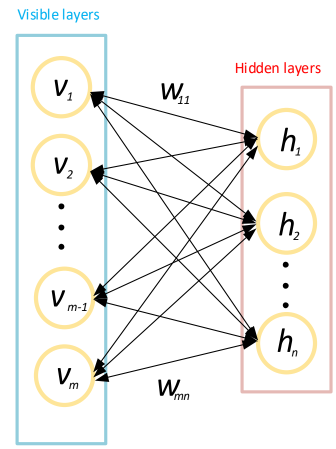

Fig. 1. Restricted Boltzmann Machine – RBM diagram (Adapted from [27])

$$E(v,h) = -\sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j - \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij} v_i h_j \ [27] \tag{1}$$

- a_i – bias (displacement value) of visible layers v_i;
- v_i – state of neuron *i* in the visible layer;
- b_j – bias (displacement value) of hidden layers h_j;
- h_j – state of neuron *j* in the hidden layer;
- w_{ij} – weight between the visible components v_i and the hidden ones h_j;

Figure 2 represents the structure of a DBN which is composed by *n* RBMs and a classifier.

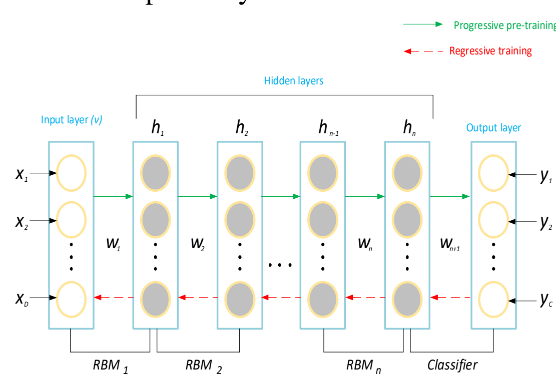

Fig. 2. Deep Belief Network structure (Adapted from [27])

The training process flow chart is shown in figure 3. The two phases of training the network are known as progressive pre-training and inverse fine-tuning. Since the pre-training stage is not capable to optimize the entire network parameters, it is necessary to use the second stage to improve the global parameters in the inverse fine-tuning phase. These parameters are modified from the upper level to the lower level in the corresponding classifier by back-propagation, then obtaining fine-tuned parameters as $\{W', a', b'\}$. This phase requires supervised training, because fine-tuning consists in learning classified information. Traditional training methods are known as not suitable for multi-layer networks, although the DBN semi-supervised training method successfully overcomes this matter.

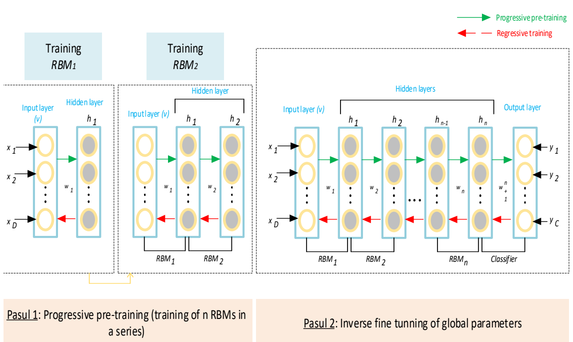

Fig. 3. Deep Belief Network training flow-chart (Adapted from [27])

3.2 Autoencoders represent a common, three-layered, unsupervised feature learning model. With the help of adaptive learning features, the output is restored to the input as accurately as possible. This model has evolved according to the standards that define the main features, for example: sparse feature (refers to values that appear sporadically in a data set, and most of these values are zeros), noise reduction, constraints (it is defined as a restriction of a possible combination in the process of assigning variables), etc. The most used features are “Sparse autoencoding network” and “Denoising autoencoding network”. The multilayer structure of a deep autoencoding network is created by overlaying several autoencoding networks (stacked autoencoder – “stacked AE”).

Structurally, a self-encoding network consists of:

1. The input layer
2. The hidden layer
3. The output layer.

These layers delimit the encoder and decoder components. The encoder has the input and hidden layers, whereas the decoder has the hidden and output layers. The encoder converts the original data, then the hidden layer collects the output vector of the network features and the decoder uses this vector to adjust the system response as accurately as possible.

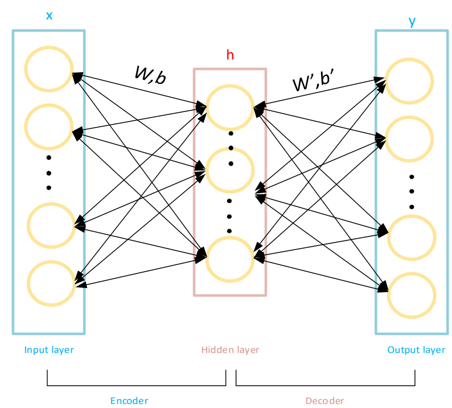

Fig. 4. Autoencoders structure (Adapted from [27])

Encoding can be defined as a process of using an input *x* that follows a clearly defined path, initially arriving at the encoder to result in an output h, where $h = f_{(W,b)}(x) = s_f(WX + b)$, W is the matrix weight, b is the matrix bias and s_f is the activation function used in the encoder. Decoding consists of using the output *h* resulting from encoding to "reconstruct" the output *y* using the decoder, where $y = g_{(W`,b`)}(h) = s_g(W`h + b`)$, $W`$ represents the connection between the hidden layer and the output layer, $b`$ is the bias between the hidden layer and the output layer and s_g is the function which activates of the decoder. The auto-encoder network is searching for the most suitable parameters (W, W`, b, b`) to obtain the best output *y* as close as possible in value to the input *x*.

To formulate the re-construction error, two methods are used:

- mean square error
- cross entropy

The choice between the two methods depends on the type of data [30]:

$$L_{mse}(x, y) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}||x - y||^2, \qquad (2)$$

$$L_{ce}(x,y) = \frac{1}{m}\sum_{i=1}^{m}[ylog(x) + (1-y)\log(1-x)]. \quad (3)$$

3.3 Convolutional neural networks (CNN) are commonly used for the detection and segmentation of various objects in images, for their recognition and classification. As advantages we find:

- The need for manual feature extraction is excluded (they are included in the machine learning process);
- High performance in the recognition process;
- Transfer Learning which allows relearning for new recognition and reconstruction tasks based on initial parts of the pre-trained CNN.

Structurally, a convolutional neural network consists of two components. The first component alternates neural layers with local convolutional connections and maximum or average pooling (max pooling / average pooling) with dimensionality reduction (subsampling) [27]. The concept of "convolutional" refers to the automatic extraction of specific features from the input data. The second part consists of one or more fully connected multilayer perceptron layers that perform the classification task by using the outputs (the outputs of the initial convolutional part) as input data. Thus, the first component focuses on the process of transforming the raw image applied to the CNN input into a feature vector, which will in turn be applied as input to the final multilayer perceptron classifier.

The mathematical model of the convolutional layer is given by the mathematical expression[30]:

$$x_j^l = f(\sum_{i\in M_j} x_i^{(l-1)} \cdot K_{ij}^l + b_j^l) \quad (4)$$

- M_j – the input characteristic
- l – the "l" layer of the network
- K – the convolutional kernel
- b – the bias
- x_j^l – the output of the layer "l"
- $x_i^{(l-1)}$ – the input of the *l-1* layer or the input for the layer "l"

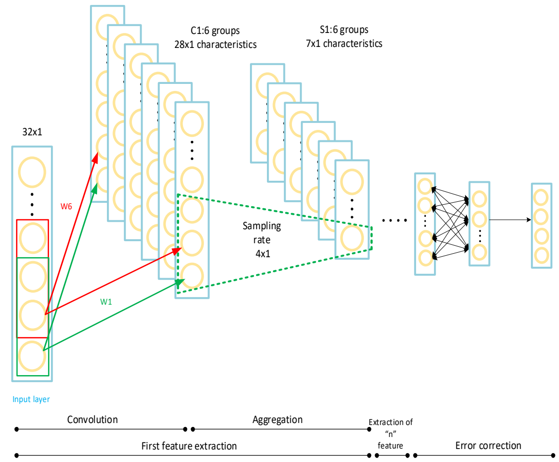

Fig. 5. Convolutional Neural Network training flow-chart (Adapted from [27])

3.4 Recurrent Neural Network (RNN): the neural networks exemplified above (DBN, AE and CNN) start with the assumption that all their input/output elements are independent of each other. The output of a RNN depends on the active input and memory, thus connecting the components in the same layer to build an oriented recurrent neural network.

The hidden layer component receives the output of the hidden layer at the previous time so it can memorize information from previous times. The mathematical model of the recurrent network is given by the expressions [30]:

$$S_t = f(WS_{t-1} + Ux_t) \quad (5)$$

$$y_t = g(VS) \quad (6)$$

- x_{t-1}, x_t and x_{t+1} – the inputs for the time *t-1, t* and *t+1*
- S_{t-1}, S_t and S_{t+1} – the inputs of the hidden layer for the time *t-1, t* and *t+1*
- y_{t-1}, y_t and y_{t+1} – the inputs for the time *t-1, t* and *t+1*
- *f* and *g* – the activation functions
- *U, V, W* – the weights

4. DEEP LEARNING IN DIAGNOSING ELECTRIC MOTOR FAULTS

Electric motors are prone to several faults, including bearing, stator and rotor problems, rotor eccentricity, etc. In the case of traditional fault identification methods, signal processing plays an essential role, being very often accompanied by classification algorithms ("Support Vector Machine" – SVM, "Decision Trees", "K closest neighbors"). These methods aim to classify and identify the type of fault. The decision to choose the signal processing method depends very much on the type of the problem to be identified.

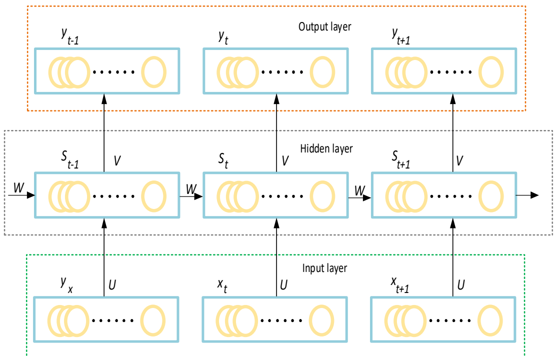

Fig. 6. Recurrent Neural Network structure (Adapted from [27])

For example, in the case of a motor bearing fault, vibration signals or those coming from the stator current are often monitored. To extract useful features from these signals, methods such as time-frequency domain analysis, wavelet decomposition or statistical analysis are applied. These techniques allow highlighting specific features that indicate a fault.

In the case of a rotor fault, the most commonly used detection method is the analysis of the stator current, due to its simplicity of collection and processing. The Fourier transform and the Hilbert transform (very efficient methods in the frequency domain) are used to extract the characteristics of the stator current.

However, the traditional methods for diagnosing electric motor faults presented both at the beginning of this chapter and in the previous chapter are generally based on the manual selection and extraction of relevant signal characteristics, which brings uncertainty to the diagnostic process, being also accompanied by the complexity of the procedure and thus affecting the accuracy of the result.

A major advantage of using deep learning models in fault diagnosis is that they can extract relevant characteristics directly from the source signal in an automatic and adaptive way. This process eliminates the need for human intervention in the selection of features and, thus, reduces the negative impact that manual extraction can have on the accuracy and reliability of fault diagnosis.

Convolutional neural network (CNN) in the diagnosis process

Convolutional neural networks (CNNs) are known for their ability to handle large volumes of data, especially in areas such as image and visual data processing, where they can identify complex patterns. In the case of diagnosing faults in electric motors, CNNs are often used to analyze one-dimensional signals, such as electric current or vibrations. However, their performance becomes limited when they have to process multidimensional data, such as combinations of signals that come from multiple sources or that require deeper analysis on different dimensions (time, frequency, amplitude).

This limitation is due to the fact that the architecture of classical CNNs is optimized for images or data with a clear spatial structure, while electric motor signals may have subtle variations in several dimensions that are not efficiently captured by conventional CNNs. In addition, the detection of certain types of faults, such as rotor eccentricity or bearing faults, may require a combination of frequency and time domain information, which are not optimally handled by standard CNNs.

Although research progress has been made to extend the capabilities of CNNs to multidimensional data processing (such as by using 3D convolutional networks or hybrid techniques with other deep learning models), these approaches are still in the development phase. Thus, to effectively handle the complex types of faults encountered in electric motors, further research is needed to improve the ability of CNNs to process and understand this complex data.

The architecture of a convolutional neural network used for electric motor fault diagnosis consists of:

- **Step 1**: ***Signal collection***: An important issue is obtaining the operating signals of the equipment in both optimal and abnormal conditions. Here, various sensors (vibration, electric current or temperature) are used that will be optimally placed to capture these relevant signals in real time, while ensuring that the data reflects the operating conditions of the equipment as faithfully as possible. The signals thus extracted will be analyzed in the time domain (current variations over time) or in the frequency domain (frequency spectra that may indicate anomalies).

- **Step 2**: ***Signal pre-processing***: In order to be able to analyze them, these signals must first be processed. The steps involved in this process are noise filtering, data normalization, and signal segmentation into smaller portions. After these steps, the signals are divided into two sets: the training set and the testing set. This separation is meant to avoid overfitting and to ensure that the model can generalize well to new data.
- **Step 3**: ***Creating the CNN model***: After pre-processing the data, we move on to defining the structure of the convolutional neural network. In this stage, the input size is established, the number of filters (kernels) used, the scan (stride) that determines how far the kernels move on the signal, the number of hidden layers. The network's ability to obtain relevant features from the data sets is thus influenced by these aspects.
- **Step 4**: ***Training of the CNN***: Once the model is clearly defined, the training process of the model will be initiated. This process involves using the training set to adjust the network parameters using the error backpropagation method. The network parameters will be initialized and updated repeatedly based on the errors calculated between the model predictions and the actual values in the training set. The process continues until a maximum number of iterations is reached or until the model performance stabilizes. Regularization techniques can also be included in the model training process to avoid overfitting.
- **Step 5**: ***Diagnose of defect***: It is necessary to use the test dataset to evaluate the model's performance and identify faults. This process involves feeding the signals from the test dataset into the trained model and analyzing the results. The performance criteria of the model are precision, recall, and other relevant metrics to determine its ability to diagnose faults in real-world conditions.

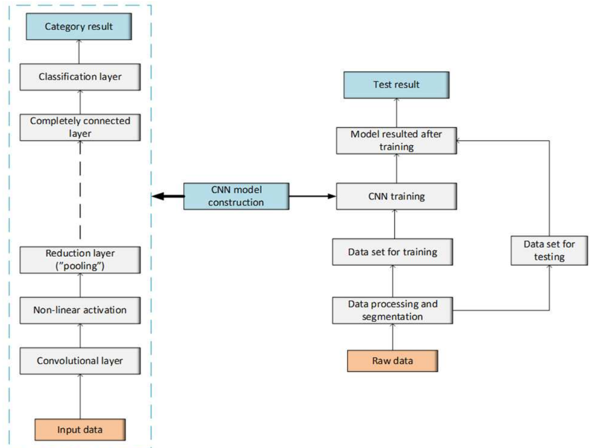

Fig. 7. CNN architecture used in the diagnosis process (Adapted from [27])

5. THE STUDY ON DEVELOPING AN AUTOMATIC PREDICTION MODEL THROUGH THE INTEGRATION OF RELATED "DEEP LEARNING" TECHNOLOGIES

To harmonize all the previously presented informational content, in this subsection, I will exemplify how we can model the asynchronous motor in a specialized application, introducing a series of faults (open circuit, short circuit, rotor bar fault/broken rotor bars). The data obtained is used as training material for the model based on the prediction algorithm.

Furthermore, I will reference a study extracted from specialized literature, which I used to identify the main ideas necessary for learning and mastering modern modeling/simulation techniques and predictive algorithm utilization.

The application used for modeling the three-phase asynchronous motor is presented in Fig.8. After simulating this model, we will obtain various waveforms, representing the behavior of the asynchronous motor during normal operation or when a short circuit occurs, or the existence of an open circuit, or the presence of a defect in the rotor bars, etc. It is necessary to identify this type of behavior and group it into a category according to severity.

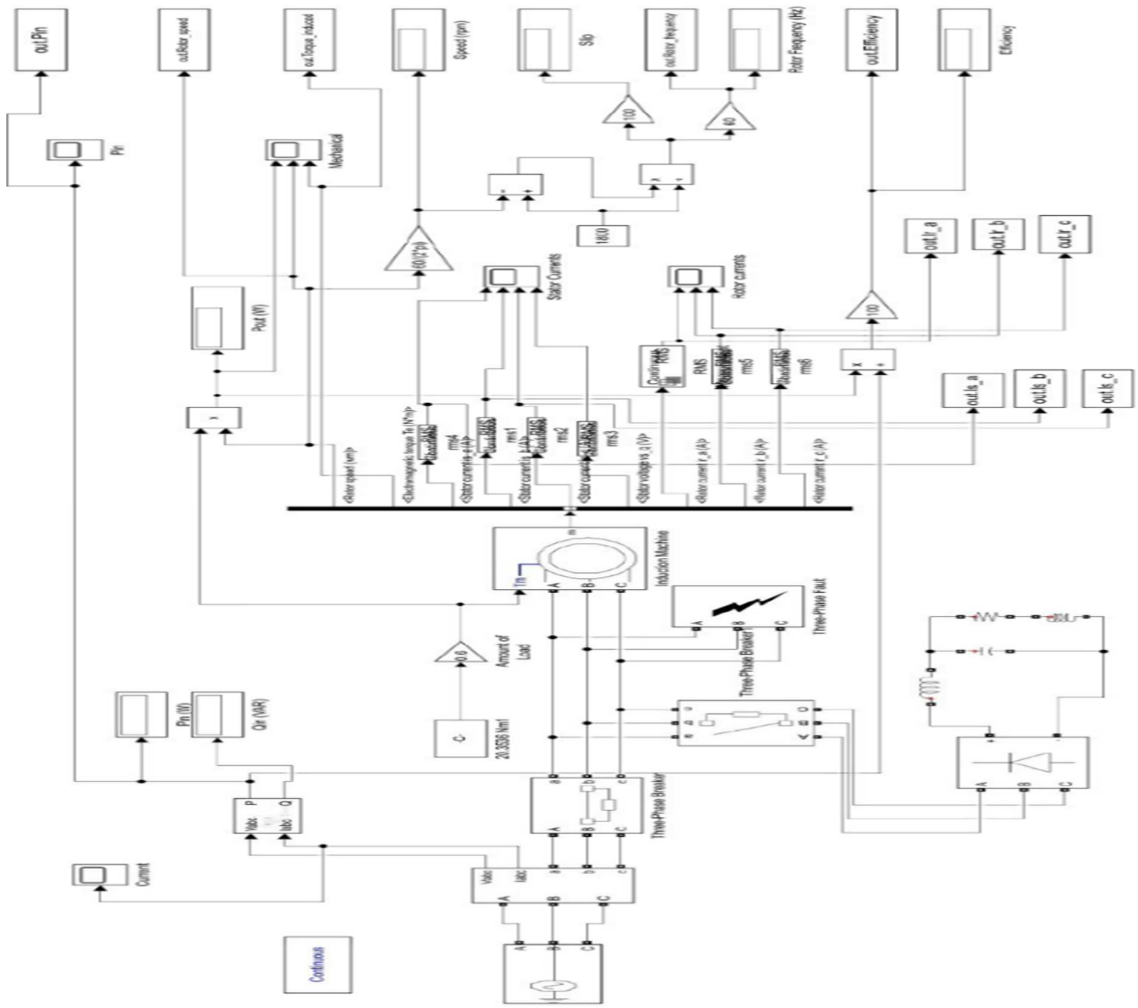

Fig. 8. Modeling the asynchronous machine in MATLAB Simulink [1]

Table 1

Asynchronous Machine parameters [1]

Parameter	**Value**
Mechanical power	5 hp
Nominal voltage	220 V
Nominal current	5.99 A
Nominal torque	22.2 Nm
Slip	5.06 %
Frequency	60 Hz
Nominal speed	1750 rpm

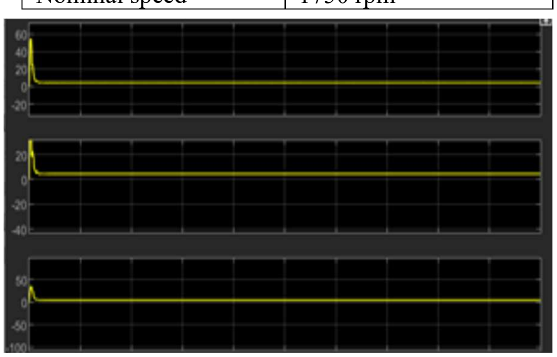

Fig. 9. Stator currents of a healthy induction motor [1]

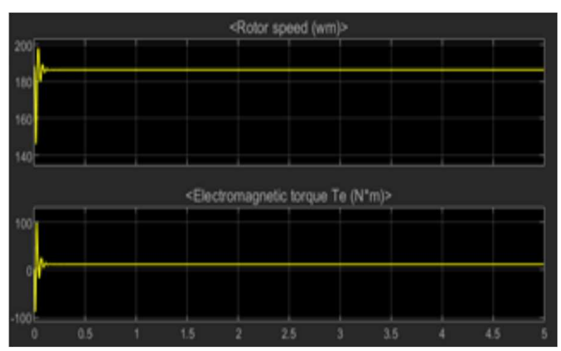

Fig. 10. Mechanical characteristics (speed/torque) of a healthy asynchronous motor [1]

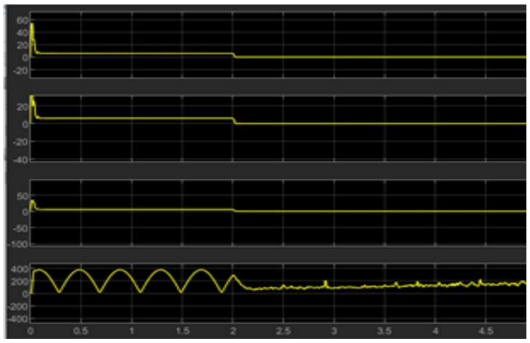

Fig. 11. Stator currents of an asynchronous motor with an open circuit fault [1]

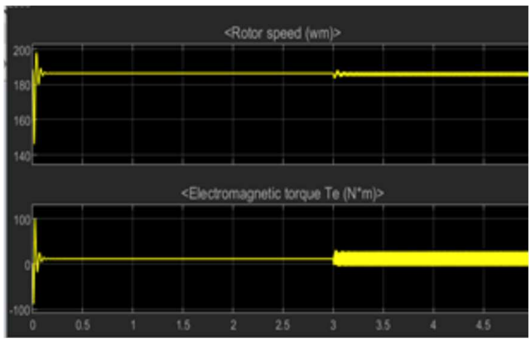

Fig. 12. Mechanical characteristic (speed/torque) of an asynchronous motor presenting as a fault: open circuit [1]

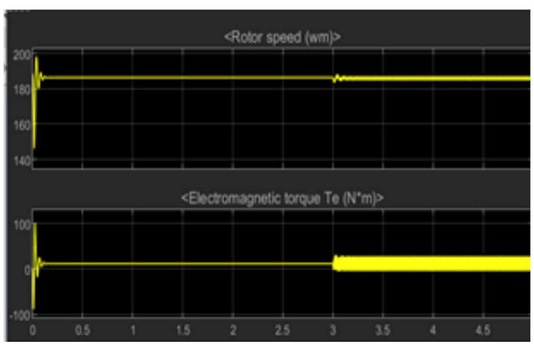

Fig. 13. Stator currents of an asynchronous motor with a short-circuit fault [1]

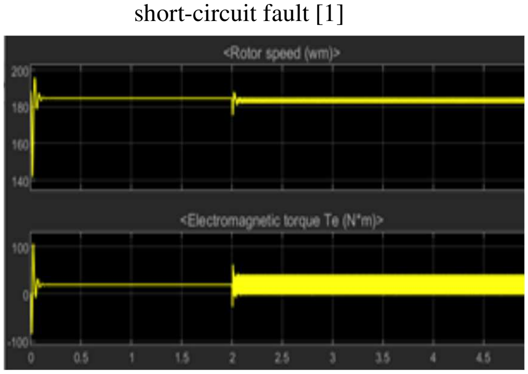

Fig. 14. Mechanical characteristic (speed/torque) of an asynchronous motor presenting as a defect: short circuit [1]

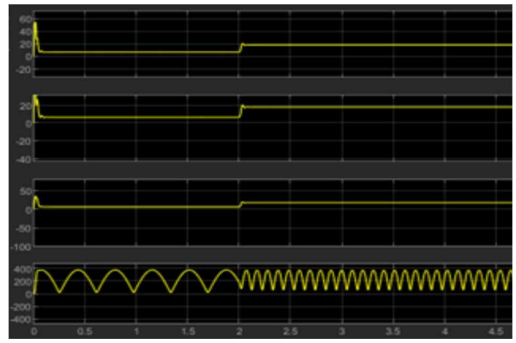

Fig. 15. Stator currents of an asynchronous motor with the following fault: overload [1]

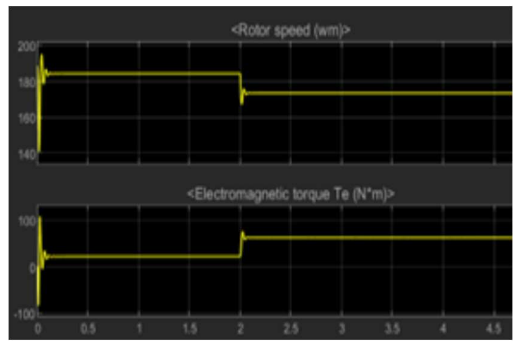

Fig. 16. Mechanical characteristic (speed/torque) of an asynchronous motor presenting as a defect: overload [1]

To perform a spectral analysis of waveforms and implicitly signal processing, it is necessary to transform the information from amplitude-time terms into amplitude-frequency terms, but more compactly, as can be seen in Fig. 17.

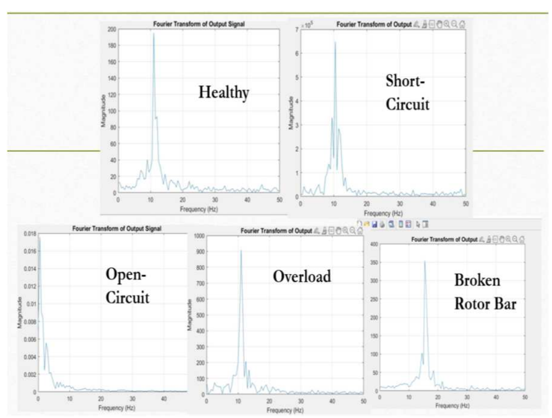

Fig. 17. Fourier transform of stator currents [1]

In case of a short circuit there are components in the frequency domain that have a fairly high magnitude, while in the case of an open circuit there are components that have a reduced magnitude.

The next necessary step involved collecting data and creating a database that is used as input for training the model. A small part of the data set obtained from the simulations is presented below:

Table 2

Data set generated from the simulation [1]

Stator current [A]	**Rotor current [A]**	**Electrical power [W]**	**Rotor frequency [Hz]**	**Rotor speed [rpm]**	**Induced torque [Nm]**	**Efficiency [%]**	**Defect category**
5.53	1.31	8,489	1.11	185.01	17.35	35.49	4
5.53	1.30	8,956	1.11	185.01	17.35	33.64	4
5.53	1.30	8,448	1.11	185.01	17.35	35.66	4
5.53	1.29	7,417	1.11	185.01	17.35	40.61	4
5.53	1.29	6,683	1.11	185.01	17.35	45.08	4
5.53	1.28	6,763	1.11	185.01	17.35	44.54	4
5.53	1.28	6,781	1.11	185.01	17.35	44.43	4
5.53	1.28	6,781	1.11	185.01	17.35	44.43	4
5.53	1.28	7,133	1.11	185.01	17.35	42.23	4
5.53	1.28	7,830	1.11	185.01	17.35	38.47	4
5.53	1.28	8,246	1.11	185.01	17.35	36.53	4
5.53	1.27	8,056	1.11	185.01	17.35	37.39	4
5.53	1.27	7,382	1.11	185.01	17.35	40.80	4
5.53	1.26	6,673	1.11	185.01	17.35	45.14	4
5.53	1.26	6,356	1.11	185.01	17.35	47.40	4

After this step, the application of machine learning algorithms follows. The MATLAB "Classification Learner" application is used on the obtained data set. In Fig. 18 we can visualize the resulting matrix based on the simulation data.

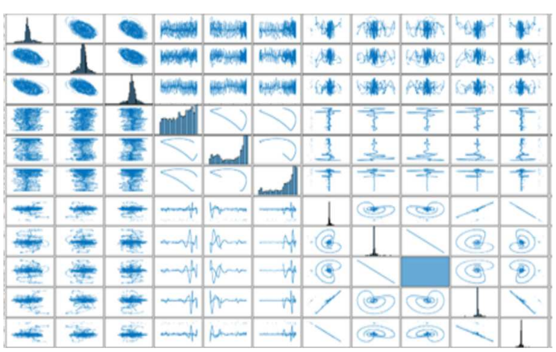

Fig. 18. The data matrix obtained in the simulation [1]

In this study used as a reference, it should be noted that artificial neural networks (ANN) were not used to train the model, but algorithms corresponding to the Machine Learning branch: Decision Trees, Naive Bayers, Support Vector Machines, etc. Although these algorithms used as automatic learning and prediction methods were not exemplified in this paper, this does not constitute an impediment to observing the working method, the results obtained and the possibilities for improvement. Both the Artificial neural network and the Decision Trees are effective machine learning methods, used to solve problems such as data classification or estimating values. Both use mathematical formulas to learn from data, but their performance depends on the quality of the information provided. Although they differ significantly in implementation and complexity, both models can present errors such as overfitting, requiring measures to correctly record data in the learning process. Essentially, these methods share the same objective: building a high-performance model that creates the best possible connection between the relationships between input and output variables, thus adapting to various types of problems.

Their use also depends very much on the specifics of the problem: if interpretability is crucial, trees are preferable; for high performance and large data sets, neural networks are the optimal choice.

To have high performance in identifying the type of defect, several machine learning algorithms have been identified and used, and the results obtained on their accuracy are as follows:

Table 3

Performance of machine learning algorithms [1]

Model	**Accuracy**	**Recall rate**	**F1 score**
Decision Trees	*92.1 %*	*0.95*	*1.13*
Logistic Regression	*61.3 %*	*0.43*	*0.87*
Naive Bayes	*42.8 %*	*0.78*	*1.07*
K-Nearest Neighbors (KNN)	*52 %*	*0.63*	*0.8*
Support Vector Machines (SVM)	*63 %*	*0.74*	*0.6*

The machine learning algorithm "Decision Trees" performed the best, with an accuracy of 92.1%. The "Confusion Matrix" is a tabular matrix that compares the predictions with the actual data. This kind of matrix is also generated for the algorithm.

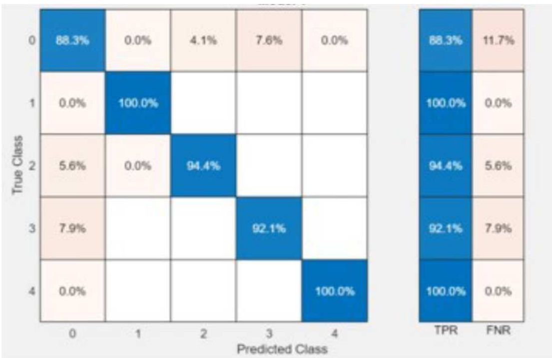

Fig. 19. Confusion Matrix of the Decision Trees algorithm [1]

This study [1] on the creation of an automatic prediction model by integrating related technologies of "Machine Learning" represented a way to learn about the existing possibilities in this field and with the help of which we can improve this branch of predictive maintenance and the efficiency of electricity quality using the most current, easy and reliable technology.

6. CONCLUSIONS AND FUTURE WORK

Following the analysis conducted in this study case, several significant observations can be drawn.

First, each model has distinct advantages. For instance, the Deep Belief Network (DBN) has the ability to learn data features without requiring a predefined mathematical model, making it efficient in avoiding dimensionality issues. Moreover, the semi-supervised training method resolves the limitations of traditional methods.

The deep autoencoder network (AE) reduces computational complexity and generates more concise features, thereby improving issues related to noise in datasets.

CNN stands out for its ability to handle large volumes of data, benefiting from local perception and weight sharing, which helps prevent network overfitting.

Lastly, the Recurrent Neural Network (RNN) proves highly applicable for time-series analysis and has a strong capacity to express dynamic systems.

On the other hand, these models also exhibit shortcomings. DBN may have a slower training process and an inadequate selection of parameters can lead to convergence to a local optimum. The standard AE is prone to overfitting, and its dimensions can limit the features it can represent. Implementing CNNs is complex and requires large amounts of data, which may affect training speed and efficiency in industrial applications. Additionally, standard RNNs face issues with vanishing gradients, although Long Short-Term Memory networks can mitigate these problems and are often used as classifiers.

An essential aspect to be addressed in future work is performing a comparative analysis between artificial neural networks and decision trees to precisely determine which type of algorithm is more suitable for use in the predictive maintenance process of asynchronous motors, based on factual results obtained from simulations.

Regarding research perspectives, it is evident that deep learning methods are still in an early stage of research for diagnosing faults in the electric motors. There is a lack of robust mathematical theories to support deep learning models, and training speed remains a major concern, requiring further optimization. Combining deep learning methods with classical fault diagnosis techniques holds significant potential, but more research is needed to achieve effective compatibility between them.

In conclusion, CNNs and RNNs prove to be the most promising for fault diagnosis due to their ability to handle large data volumes, provide improved accuracy, and dynamically respond to fault detection. These observations underscore the importance of continuing research to overcome current limitations and integrate these models into industrial practices.

7. REFERENCES

[1] MUHAMMAD Samiullah, HASAN Ali, SHEHRYAR Zahoor, ANAS Ali, *"Fault Diagnosis on Induction Motor using Machine Learning and Signal Processing"*, School of Electrical Engineering and Computer Science, National University of Sciences and Technology Islamabad,

Pakistan, 2024, doi:10.48550/arXiv.2401.154

[2] S.Nikolic, C.Rados., *„Motor Current Signature Analysis in Predictive Maintenance”*, Journal of Energy – Energija, vol. 67, no.4, pp. 3-6, 2018, doi:10.37798/201867462.

[3] C.Martis, *„Mentenanța sistemelor industriale”*, Materiale de curs – Universitatea Tehnică Cluj, https://memm.utcluj.ro/mentenanta.htm

[4] A. da Silva, *„Induction motor fault diagnostic and monitoring methods”*, A Thesis submitted to the Faculty Of the Graduate School, Marquette University, Milwaukee – Wisconsin, May 2006, https://www.researchgate.net/publication/243055807

[5] M. Samiullah, H. Ali, S. Zahoor, A. Ali *„Fault Diagnosis on Induction Motor using Machine Learning and Signal Processing”*, School of Electrical Engineering and Computer Science, (SEECS) National University of Sciences and Technology, Islamabad, Pakistan, January 2024, doi:10.48550/arXiv.2401.15417

[6] O.V.Thorsen,M. Dalva, *“Failure identification and analysis for high voltage induction motors in petrochemical industry”*, Conference Record of 1998 IEEE Industry Applications Conference. Thirty-Third IAS Annual Meeting (Cat. No.98CH36242), pp. 291-298, 1998, doi:10.1109/28.777188

[7] D. Miljković, *„Brief Review of Motor Current Signature Analysis”,* CrSNDT Journal, vol. 5, https://www.researchgate.net/publication/304094187_Brief_Review_of_Motor_Current_Signature_Analysis/stats

[8] W. Jung, S-H. Kim, S-H. Yun, J. Bae, Y-H. Park, *„Vibration, acoustic, temperature, and motor current dataset of rotating machine under varying operating conditions for fault diagnosis”,* Data in Brief, vol. 48, 2023, doi:10.1016/j.dib.2023.109049

[9] Z. A. Bukhsh, A. Saeed, I. Stipanovic, A. G. Doree, *„Predictive maintenance using tree-based classification techniques: A case of railway switches”,* Transportation Research Part C: Emerging Technologies, vol. 101, pp. 35-54, 2019, doi:10.1016/j.trc.2019.02.001

[10] I. Buciuman, *„Sisteme Inteligete – cu mare răspundere funcțională- în transportul feroviar”,* Club Feroviar, București, 2021

[11] H. Meriem, H. Nora, O. Samir, *“Predictive Maintenance for Smart Industrial Systems: A Roadmap”,* Procedia Computer Science, vol. 220, pp. 645-650, 2023, doi:10.1016/j.procs.2023.03.082

[12] C. Hegedus & P. Ciancarini, F. Attila, A. Kancilija, I. Moldován, G. Papa, S. Poklukar, M. Riccardi, A. Sillitti, P. Varga, *“Proactive Maintenance of Railway Switches”,* Conference: 5th International Conference on Control, Decision and Information Technologies, Thessaloniki, Greece, 2018, doi:10.1109/CoDIT.2018.8394832

[13] M-H. Le Nguyen, F. Turgis, P-E. Fayemi, A. Bifet, *“Real-time learning for real-time data: online machine learning for predictive maintenance of railway systems”,* Transportation Research Procedia, vol.72, pp. 171-178, 2023, doi:10.1016/j.trpro.2023.11.391

[14] P. Mallioris, E. Aivazidou, D. Bechtsis, *“Predictive maintenance in Industry 4.0: A systematic multi-sector mapping”,* CIRP Journal of Manufacturing Science and Technology, vol. 50, pp.80-103, 2024, doi:10.1016/j.cirpj.2024.02.003

[15] H. Henao, C. Martis and G. . -A. Capolino, *"An equivalent internal circuit of the induction machine for advanced spectral analysis,"* in IEEE Transactions on Industry Applications, vol. 40, no. 3, pp. 726-734, May-June 2004, doi:10.1109/TIA.2004.827480

[16] S. Ciceo, M. R. Raia, J. Gyselinck and C. Martis, *"On the use of parametric stator models for electrical machine vibration computation,"* 2023 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific), Chiang Mai, Thailand, 2023, pp. 1-7, doi:10.1109/ITECAsia-Pacific59272.2023.10372275

[17] C. Adăscăliţei, C. S. Marţiş and A. Ferreira, *"Thermal Analysis of a Permanent Magnet Synchronous Machine at Different Supply Voltage Levels,"* 2023 10th International Conference on Modern Power Systems (MPS), Cluj-Napoca, Romania, 2023, pp. 01-06, doi:10.1109/MPS58874.2023.10187559

[18] S. H. Kia, H. Henao, G. -A. Capolino and C. Martis, *"Induction Machine Broken Bars Fault Detection Using Stray Flux after Supply Disconnection,"* IECON 2006 - 32nd Annual Conference on IEEE Industrial Electronics, Paris, France, 2006, pp. 1498-1503, doi:10.1109/IECON.2006.347595

[19] I. Mustakerov and D. Borissova, *"An intelligent approach to optimal predictive maintenance strategy defining,"* 2013 IEEE INISTA, Albena, Bulgaria, 2013, pp. 1-5, doi:10.1109/INISTA.2013.6577666

[20] S. Kocbek and B. Gabrys, *"Automated Machine Learning Techniques in Prognostics of Railway Track Defects,"* 2019 International Conference on Data Mining Workshops (ICDMW), Beijing, China, 2019, pp. 777-784, doi:10.1109/ICDMW.2019.00115

[21] C. Jung, A. K. A. Toguyeni and B. O. Bouamama, *"Supervised machine learning from digital twin data for railway switch fault diagnosis,"* 2023 European Control Conference (ECC), Bucharest, Romania, 2023, pp. 1-7, doi:10.23919/ECC57647.2023.10178257

[22] C. Jung, A. K. A. Toguyeni and B. O. Bouamama, *"Supervised machine learning from digital twin data for railway switch fault diagnosis,"* 2023 European Control Conference (ECC), Bucharest, Romania, 2023, pp. 1-7, doi:10.23919/ECC57647.2023.10178257

[23] G. E. Hinton, R. R. Salakhutdinov, *"Reducing the Dimensionality of Data with Neural Networks",* Science 313, 504-507, 2006, doi:10.1126/science.1127647

[24] Bengio Y., Lamblin P., Popovici D., Larochelle H.," Greedy *layer-wise training of deep networks",* Advances in Neural Information Processing Systems, Universite de Montreal, Montreal, QC, Canada, 2007; pp. 153–160

[25] Bengio Y.,*" Learning deep architectures for AI",* now, 2009, doi:10.1561/2200000006

[26] Yang Y., Haque M.M.M., Bai D., Tang W.,*" Fault Diagnosis of Electric Motors Using Deep Learning Algorithms and Its Application: A Review"*, Energies 2021, 14, 7017, doi:10.3390/en14217017

[27] VREJOIU Mihnea*," Reţele neuronale convoluţionale, Big Data şi Deep Learning în analiza automată de imagini",* Revista Română de Informatică şi Automatică, 2019, pp. 91-114, doi:10.33436/v29i1y201909

Învățarea automată și algoritmii predictivi pentru diagnosticarea anomaliilor în mașinile electrice

Rezumat: Inteligența Artificială (AI), Învățarea Automată (ML) și Învățarea Profundă (DL) au o importanță deosebită în domeniul mașinilor electrice. „Inteligența Artificială" se referă la capacitatea unei mașini de a îndeplini anumite sarcini în mod autonom (fără implicarea umană), cum ar fi: recunoașterea anumitor tipare, întreținerea predictivă, optimizarea performanței motorului electric. Prin utilizarea AI, mașinile electrice pot fi monitorizate și controlate în timp real, devenind astfel mai eficiente și mai sigure.

Scopul principal al acestui studiu este de a ne aduce în atenție cele mai importante metode bazate pe Rețele Neuronale Artificiale pentru detectarea problemelor care apar în funcționarea motoarelor electrice.

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