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MOŻLIWOŚCI WYKORZYSTANIA GŁĘBOKICH SIECI NEURONOWYCH W KONSERWACJI PREDYKCYJNEJ

Streszczenie: W niniejszym opracowaniu dokonany zostanie przegląd powszechnie stosowanych technik uczenia maszynowego dla analityki predykcyjnej i technik utrzymania ruchu. Omówione zostaną niektóre popularne metody głębokiego uczenia oraz ich cechy i ograniczenia. Referat otworzy pole do możliwości dalszego szczegółowego rozwoju nowych technik predykcyjnego utrzymania ruchu z wykorzystaniem głębokich sieci neuronowych.

Słowa kluczowe: głębokie uczenie, LSTM, sieć neuronowa, konserwacja predykcyjna

POSSIBILITIES OF USING DEEP NEURAL NETWORKS IN PREDICTIVE MAINTENANCE

Summary: This study will review common-used machine learning techniques for predictive analytics and maintenance techniques. Some popular deep learning methods and their features and limitations will be discussed. The paper will open the scope for the possibility of further detailed development of new predictive maintenance techniques using deep neural networks.

Keywords: deep learning, LSTM, neural network, predictive maintenance

1. Introduction

Machine learning technology underpins many aspects of modern society. It is used to identify objects in images, convert speech to text, match news, messages, or products to user interests and select relevant search results. These applications use a class of techniques called deep learning.

At the same time, product technology and quality requirements are increasing in manufacturing and industry. New technological processes are causing the implementation of highly productive machining methods that also place higher

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demands on production machines and tools, their reliability, and the reliability of the production process itself.
There are many factors in production conditions that can negatively affect the production process. One of the most significant is the neglect of maintenance. Maintenance neglect is the main cause of failure and the associated costs and losses in the production process, since preventing failure is always cheaper in the end than eliminating its consequences. For this reason, one of the modern trends - the so-called predictive maintenance (PdM) - is gaining more and more popularity.
Predictive maintenance offers great scope for the deployment of artificial intelligence methods. Artificial intelligence in predictive maintenance can adapt routine maintenance activities to the needs of each facility. However, a large volume of data about the current and previous state of the system needs to be considered and processed. Therefore, predictive maintenance is also one of the directions for the application of deep learning in manufacturing.
In this paper, an overview of deep learning methods such as convolutional neural networks, LSTM, and autoencoders which are actively used in modern predictive analytics for anomaly detection and classification is presented.

2. Predictive maintenance in manufacturing

The term maintenance according to STN EN 13 306 is defined as the sum of all activities (management, technical and administrative) aimed at maintaining, preserving, or restoring the equipment to an operational state. Maintenance responds to production stimuli (checks the condition of machinery, eliminates faults, performs routine operations such as cleaning, lubrication, etc.), prevents breakdowns and reduces repair times of the equipment.
The main aim of maintenance is to maintain the operability of machinery, which means ensuring that the production process runs as smoothly as possible, minimizing production downtime, and eliminating the negative consequences of machine downtime. Also, maintenance objectives include achieving and prolonging the planned technical life of production machines and preventing occupational accidents and damage to the health of employees [1]. The main maintenance strategies are shown in Figure 1.

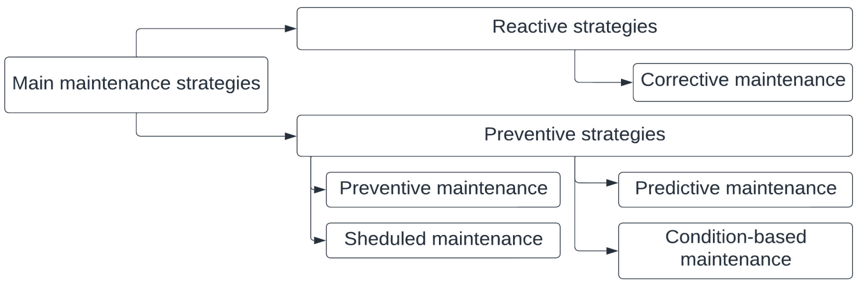

Figure 1. Main maintenance strategies

The length of the maintenance cycle is usually determined empirically by the equipment manufacturer based on certain parameters and experience and involves tolerances and risks. However, the maintenance interval set by the manufacturer is not always optimal.

Predictive maintenance deals with the problem of determining the correct length of maintenance cycles. It aims to schedule maintenance at the most appropriate and cost-effective time to optimize equipment lifetime.

The use of machine learning methods in predictive maintenance can adapt routine maintenance activities to the needs of each machine. It is necessary to consider the large amount of diverse data that includes [2]:

- Fault history. During the training of the model, the dataset needs to be compiled from patterns of correct system behavior, but also from examples of faulty states, which is necessary to make the model more accurate.
- Maintenance/repair history. The maintenance history contains information about what repairs have been made, what parts have been replaced, etc. It is needed to obtain additional data that could affect failure patterns.
- Machine operating conditions. This information can be obtained from various sensors. Continuous condition monitoring will help capture faulty patterns with anomalies that lead to degradation.

In the field of PdM, machine learning focuses on two major topics, i.e.: anomaly detection and fault/condition classification. Working with large amounts of data requires high demands on the ability of the proposed model to handle large volumes of information. With the increase in data volume and the high demand for finding information about the data, various deep machine-learning techniques are used for predictive maintenance purposes.

3. Deep learning methods in manufacturing

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. Each layer analyses represented data, and together the network learns a complex function as a chained sequence of sub-functions. While a neural network with one layer can still make approximate predictions, additional hidden layers can help optimize and refine accuracy.

In recent years, deep learning has been intensively studied and has extensive applications in manufacturing, especially in the field of computer vision. The advantage of deep learning over conventional machine learning methods is that conventional machine learning methods have a limited ability to process natural data in its raw form.

Building a pattern recognition requires decades of careful design and considerable domain expertise to develop a feature extractor that transforms the raw data (such as image pixel values) into a suitable internal representation or feature vector from which the learning subsystem will operate.

Traditional neural networks are less efficient at processing unlabelled data often encountered in real life. Deep learning techniques overcome these shortcomings. Deep architectures can learn feature representations from both labeled and unlabeled data. That is a reason why the benefits of deep learning are also gaining application in predictive maintenance. The following paragraph provides an overview of the most commonly used deep learning techniques for predictive maintenance purposes.

3.1 Convolutional neural networks

A convolutional neural network (CNN) is a deep learning algorithm that can take an input (image, sequence, signal), assign a value (trainable weights and biases) to different aspects/objects of the input, and distinguish one sample from another. The preprocessing required in CNN is much less compared to other classification algorithms. While in primitive methods, filters are created manually, with sufficient training, CNN can learn these filters/characteristics.
The architecture of the CNN is similar to the communication structure of neurons in the human brain and was inspired by the organization of the visual cortex. Principal architecture of the convolutional neural network is shown in Figure 2. Individual neurons respond to stimuli only in a limited region of the visual field, known as the receptive field. A set of such fields overlaps and covers the entire visual area.

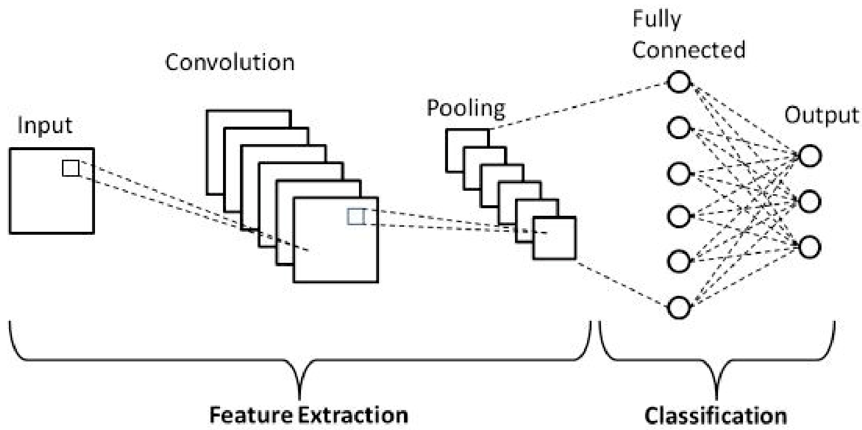

Figure 2. Principial architecture of CNN [3]

For mechanical devices, it is important to automatically extract fault signs from the signals obtained from the device using condition monitoring. Convolutional neural networks (CNN), which were specifically designed for use with variable and complex signals, have been shown to outperform all other techniques [4].
As a deep architecture, CNN can automatically extract features without prior information at a high level compared to shallow architectures that mainly rely on prior information. Convolutional neural networks typical application field is image processing and computer vision. Besides that, many researchers have successfully implemented CNNs in PdM. The one-dimensional convolutional neural network model by [5] has higher fault diagnosis accuracy for fixed shaft gearbox and planetary gearbox than traditional diagnosis methods. Another successful example is the use of CNN for bearing fault diagnosis and faults classification in the work [4] in which 97,3% accuracy of fault predicting was achieved.
According to [6] CNN has the potential in monitoring the operation and predictive maintenance of photovoltaic panels. Janessens et al. [7] successfully used a feature extraction CNN-based model on raw data for rotating machinery fault diagnosis and classification.
The major advantage of CNNs is that less domain expertise is required to achieve very good results, as has been shown for computer vision research in the past. However,

a lot of training data is required for CNN to be effective. Also, the training process could take a particularly long time if the computer does not have a good GPU.

3.2 LSTM neural networks

So-called LSTM neural networks ("Long-Short Term Memories") are a special kind of recurrent neural network that is designed to work with long-time dependencies.
Classical recurrent neural networks (RNNs) have a big disadvantage when working with long-time series, because of the vanishing error problem. Since the magnitude of the error signal propagated backward in time depends exponentially on the magnitude of the weights, the backward propagated error quickly either disappears or increases sharply in the extreme. Thus, standard RNNs are incapable of effectively learning to learn in the presence of time delays greater than 5-10 discrete time steps between relevant input events and target signals. To avoid the vanishing gradient problem, LSTM is constructed by replacing each hidden neuron with a memory cell.
LSTM memory cells consist of different neural networks called gates. The gates control the interaction between the memory blocks and decide which data should be stored or forgotten during training. The input gate is responsible for deciding whether the state of a memory cell can be changed by the input signal, and the output gate determines whether the state of other memory cells can be changed by the input signal. Finally, the forget gate is responsible for deciding whether to forget or recall the previous state of the signal [8], [9]. The structure of LSTM memory cell is shown in Figure 3.

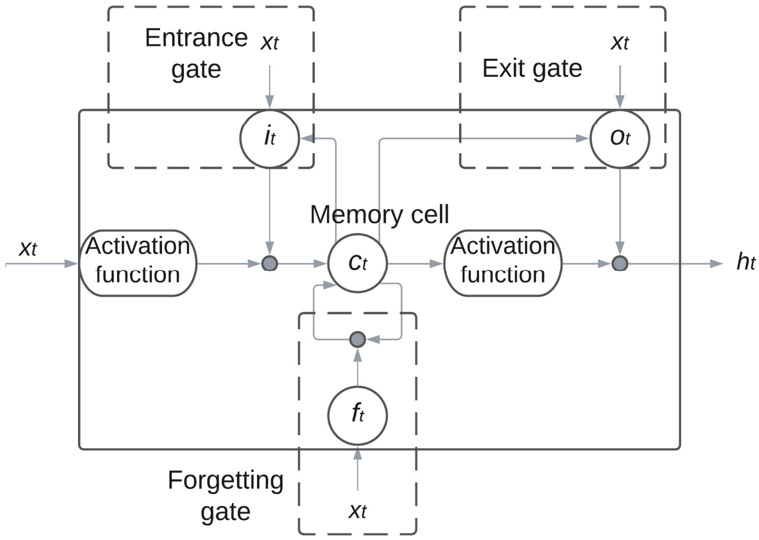

Figure 3. The LSTM cell structure

Using the LSTM network allows tracking the dependencies of new observations with past (even very distant) ones. Wu et al. [10] applied an LSTM-based model for predicting critical states of the running bearing, while Bruneo and De Vita [11] presented a predictive maintenance LSTM approach on a set of engines through the

Remaining Useful Life (RUL) estimation. In research by Rahhal and Abualnadi is shown LSTM neural network's better prediction ability for a classical RNN approach [12].

3.3 Autoencoders

Autoencoders (AEs) are a special type of direct transfer neural networks in which the input is the same as the output. They compress the input into a lower dimensional code, and then reconstruct the output from this representation. The code is a compact "summary" or "compression" of the input signal, also called a latent space representation.

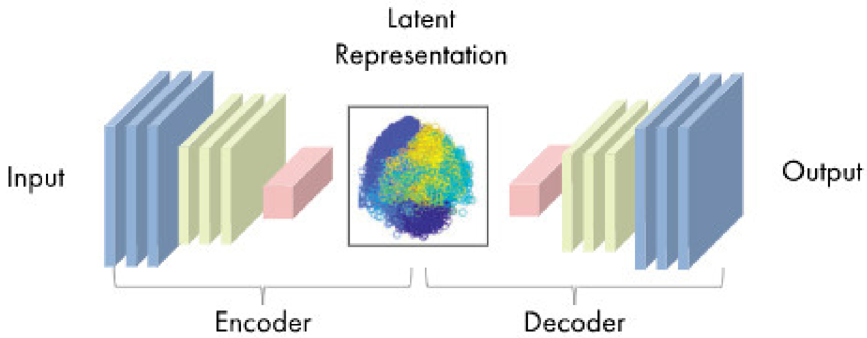

Figure 4. An autoencoder's structure [13]

As shown in Figure 4, an autoencoder consists of three components: an encoder, a hidden representation, and a decoder. The encoder compresses the input data and produces a code, the decoder must then reconstruct the input data using only this code.

To build an autoencoder it is necessary to define: an encoding method, a decoding method, and a loss function to compare the output with the target. Autoencoders have some specific properties such as:

- Data specificity. Autoencoders are only capable of compressing data similar to that on which they have been trained.
- Losses. The output of the autoencoder will not be the same as the input, it will be a close but degraded representation.
- Unsupervised. Autoencoders are considered unsupervised because they do not need explicit labels to learn.

Since in the learning process the autoencoder tries to replicate at the output the data obtained at the step, the application of predictive models based on autoencoders finds application in situations where there is no data on previous system failures, which makes it impossible to use classical classifier neural network. AEs do not require any labels specifying, and can capture the underlying error-free distribution of the signal sequence. Moreover, data shifts from the learned distributions can easily be obtained from the reconstruction error at the AE output. However, because of their inability to work with datatypes which were not a part of training data, autoencoders are mainly used in hybrid PdM systems.

According to Fathi et al. [14] research, a hybrid deep network structure with an autoencoder was provided for anomaly detection in signal sequences from sensors of the 3DOF delta robot. An integrated strategy for dynamic predictive maintenance scheduling based on a deep auto-encoder and deep forest-assisted failure prognosis method was produced by Yu et al. [15].

4. Conclusion

As mentioned, maintenance of machinery and equipment is one of the key tools for maintaining system uptime and reducing costs and losses in production. In this paper, an overview of the use of selected deep machine learning techniques for predictive maintenance and predictive analytics tasks, such as convolutional neural networks, long short-term memory networks, and autoencoders have been presented. It was shown that various deep learning techniques are capable of reliably handling large volumes of data collected by condition monitoring. The study will open up the possibility of further detailed development of new predictive maintenance techniques using deep neural networks.

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