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Identification of Inability States of Rotating Machinery Subsystems Using Industrial IoT and Convolutional Neural Network – Initial Research

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Abstract: Rotating parts can be found in almost all operational equipment in the industry and are of great importance for proper operation. However, reliability theory explains that every industrial system can change its state when failure happens. Predictive maintenance as one of the latest maintenance strategy emerged from the Maintenance 4.0 concept. Nowadays, this concept can include Industrial Internet of Things (IIoT) devices to connect industrial assets thus enable data collection and analysis that can help make better decisions about maintenance activity. Robust data acquisition system is a prerequisite for any modern predictive maintenance task as it provides necessary data for further analysis and health assessment of the industry asset. Fault diagnosis is an important task in the maintenance of industrial rotating subsystems, considering that early state change diagnosis and fault identification can prevent system failure. Vibration analysis in theory and practice is considered a correct technique for early detection of state changes and failure diagnostics of rotating subsystems. The identified technical state should be considered in a context of the ability and different inability states. Therefore, early different inability states identification is the next step in the rotary machinery diagnostics procedure. Most of the existing techniques for fault diagnosis of rotating subsystems that use vibrations involve the step of extracting features from the raw signal. Considering that the features that describe the behavior of the rotary subsystem can differ significantly depending on the type of equipment, such an approach usually requires an expert in the field of signal processing and rotary subsystems who can define the necessary features. Recently, the emergence of machine deep learning and its application in maintenance promises to provide highly efficient fault diagnostics while simultaneously reducing the need for expert knowledge and human labour. This paper presents authors aim to use self-developed IIoT system built as an IIoT accelerometer as the edge device, web API and database with convolutional neural network as deep learning-based data-driven fault diagnosis to detect and identify different inability states of rotating subsystems. Large dataset for two different rotational speed is collected using IIOT system and multiple convolutional neural network models are trained and tested to examine possibility of using IIOT for inability state prediction.

Keywords: accelerometer; automated data collection; CNN; fault diagnosis; Industrial Internet of Things

1 INTRODUCTION

Technology in today's world makes it possible to collect an ever-increasing amount of data. In such a situation, companies strive to optimize their processes by collecting and processing data and thus become better. According to the [1], companies that do not include data from the maintenance process in optimizing the efficiency of production processes are unable to fully utilize their resources and assets.

In order to do so, there are more and more examples in which predictive maintenance (PdM) shows clear potential and gain benefits when compared to other maintenance strategies. However, implementation of predictive maintenance usually includes additional costs in terms of hardware and software technology to support this strategy [2]. Nowadays, with the emergence of the Industry 4.0 concept, it can be said that one of the long-term technology an Industrial Internet of Things (IIoT) framework. Using of IIoT can help in ensuring robust and lightweight system for data collecting from the machinery and sending the data to the final destination. According to authors in [3], industrial internet of things seeks to connect various industry assets to identify, communicate, sense, process, operate and work together.

Assets characterized as a rotating system are often described as critical due to their working conditions and importance in the overall production process. Since rotary machines usually operate under severe operating conditions, this makes them more sensitive to various types of errors and increases the complexity of assessing their condition and identifying possible failures. Previous research and the author's experience lead to the conclusion that failures of such systems result not only in direct losses in the production process, but often have a long-term negative impact on the economic, environmental and security position of the company.

Vibration analysis is considered as powerful technique that can be used to assess rotary machinery health state since using vibration sensor can sense changes and enable fault diagnosis in early stage. Most commonly used sensors in vibration measurements are accelerometers. Using standard industrial IEPE accelerometers provides reliable yet expensive solution for data acquisition. The use of an IIoT system in combination with a MEMS accelerometer can be considered as an alternative due to the lower cost and the possibility of connecting to the Internet and transferring data over it. Due to this feature, data can be collected from different locations where internet connectivity is available.

With the ever-increasing amount of data collected, more and more resources are being invested in the development of techniques for assessing the condition of rotating equipment. Additionally, because of the continuous improvement of data acquisition ability [4], as well as the exponential growth of data volume [5], machine learning and artificial intelligence techniques for fault diagnosis have achieved great success and received widespread attention within PdM.

The main goal of this paper is to show the effort of the authors in both development of the IIOT data acquisition system and using sensor data in intelligent fault diagnosis performed by convolutional neural network model trained on data acquired from the developed system. The rest of the paper consists of the following: the related work in the field of intelligent fault diagnosis using IIoT is presented in Section 2, Section 3 describes developed IIoT while performed experiment as well as CNN architecture description is shown in Section 4. Results of experiment are presented in Section 5 and conclusion is drawn in Section 6.

2 RELATED WORK

As the field of application of IIOT for fault diagnosis in PdM is increasing, the number of papers related to this topic is increasing daily. In this section, the papers are briefly described. In their paper [6], Tiboni et al. provides extensive review of vibration-based condition monitoring of rotating machinery, concluding that is very likely that innovative diagnostic methods based on machine learning will be developed in the near future.

Paper [7] gives an overview of current state of predictive maintenance and intelligent sensors in smart factories. The results show four different types of maintenance used in smart factories—Industry 4.0 for predictive maintenance, smart manufacturing for condition-based maintenance, fault diagnosis for maintenance and prognostics, and remaining useful life analysis. The importance of predictive maintenance is also growing due to the growing number of robots, digitisation, and artificial intelligence introduced into production lines to automate routine activities. Paper [8] presents experiences in setting-up two different remote vibration monitoring systems using low-cost MEMS accelerometers available on the market in two different industrial settings. The installed vibration monitoring systems have successfully detected faults on two different critical assets.

The paper [9] presents developed experimental setup that used low-cost MEMS accelerometers and simple edge computing module to acquire and process sensor data. Further on, in a related paper [10] Raspberry Pi edge module is used in combination with a MEMS accelerometer to perform continuous monitoring of the machine tools. Server side Phyton program has been implemented in order to process data and calculate Fast Fourier transform. Frequency spectrum is used for further assessment. Node RED technology for hardware device wiring was used in [11] to collect temperature and humidity data using a Raspberry Pi. Node RED is an open-source rapid embedded environment design for easier integration of IoT devices and related software. In their previous work [12, 13], authors discussed possibilities of developing and using the IIOT system for condition monitoring yet they did not implement intelligent fault diagnosis using convolutional neural network.

Currently, in the field of predictive maintenance, many works can be found that deal with the application of convolutional neural networks for intelligent fault diagnosis. These works can be classified in different ways. If the structure of the convolutional neural network is observed, they can be divided into 1-dimensional (1D) fault diagnosis models and 2-dimensional (2D) fault diagnosis models. Historically, convolutional neural networks were originally developed to classify images that are 2-dimensional, so in such systems the input signal is expected to be in two dimensions. The signals collected from the vibration sensors differ. They are usually in one-dimensional form. Therefore, for the purposes of processing such a signal, the convolutional neural network was adapted to accept 1D signals as well. In recent years, multiple 1D CNN techniques for induction motors [14, 15], pumps and rolling element bearings [16] are presented in various papers. Author of this paper in [17] their previous work presented multi-channels 1D CNN (MC-DCNN) for human activity classification modified for 3 axis vibration data input with input size of 6400 × 1 × 3. This paper focuses on application of modified 1D CNN with input size of 1600 × 1 × 3 that is capable of dealing with accelerometer data acquired from developed IIOT system. Data is acquired for healthy baseline as well as 3 different inability states. Later on, different CNN based models for inability state detection are trained and evaluated on the acquired data to provide better understanding in system behaviour under different inputs.

3 IIOT SYSTEM DESIGN

Developed IIOT system architecture capable of data acquisition and storage is presented in Fig. 1.

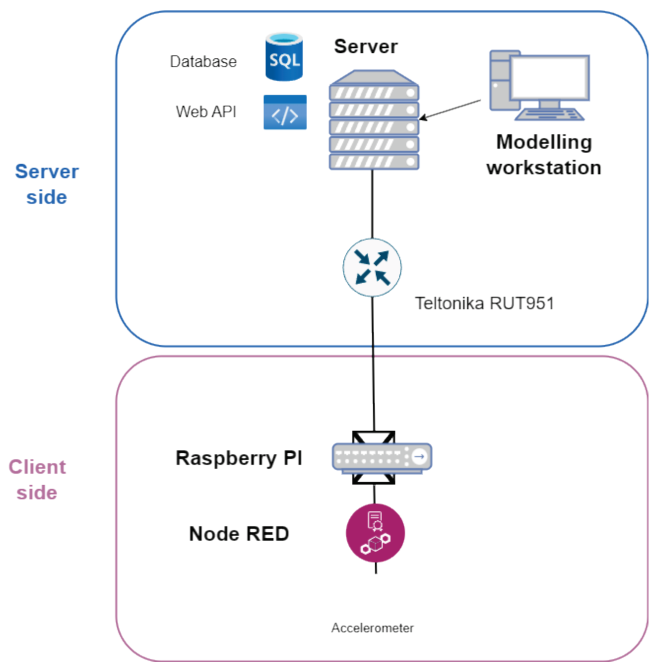

Figure 1 IIOT system scheme

It can be seen that the system consists of two separate subsystems named server and client side. The server side consists of the following components:

1) Teltonika RUT951 industrial IOT router – configured as access point for Raspberry PI and network holder.
2) Application/database server - hosts an IIS web server that runs the Web API. There is also an MSSQL server with a database on this server. The client side consists of the following components:
3) Raspberry PI 4 8GB – configured as edge module with Node-RED installed and HAT module used for sensor

connectivity. Installation-ready setup of the Raspberry Pi with HAT can be seen in Fig. 2. Raspberry PI is directly connected to local area network provided by Teltonika router.

4) IIOT sensor - for vibration data acquisition. Widely known KX122 MEMS sensor is used (Fig. 3).

The Raspberry Pi is configured as an edge node with an attached sensor. It runs the Node RED programming environment, which is designed for IoT environments. In the developed system, Node RED serves as a management tool which takes care of data collection and proper functioning of the client-side part of the IIoT system. Communication between the used sensors is performed with the help of the standards-based messaging MQTT protocol. MQTT is a fast and lightweight protocol that allows messaging between devices located on unstable networks and ensures secure, reliable and two-way messaging [18]. It is designed as a lightweight publish/subscribe messaging transport that is ideal for connecting remote devices with a small network bandwidth.

Figure 2 HAT module installed on the top of the Raspberry PI board

For this research, system is configured to acquire data from 1 accelerometer. Using described configuration, up to 8 sensors can be attached to one Raspberry PI edge node. This study use 3-axis MEMS accelerometer that can be configured to acquire data with sampling rate of up to 25,6 kHz. Accelerometer is shown in Fig. 4.

Figure 3 KX122 MEMS

Accelerometer specifications are listed in Tab. 1.

In this study, client-side is setup to acquire data with sampling rate of 1.6 kHz and ±8 g range with 16-bit resolution. It is possible to redefine sampling time for each sample that is initially set to 1 second.

Table 1 MEMS accelerometer properties

Property	Value
Output data rate	0.781 Hz - 25.6 kHz
Full-scale range	± 8 g
Sensitivity	4096 - 16384 counts/g
Offset	± 20 mg
Non-Linearity	0.6 %
Resolution	0.0001 g, 16-bit
Input voltage	1.71 – 3.6 V
Current consumption	145 mA
Output voltage	1.368 - 28.8 V

Data acquired is filtered using low-pass filter at 800 Hz to eliminate the possibility of aliasing. Using Node RED environment flows, each acquired sample containing 1600 samples is sent using the MQTT protocol to Web API and stored to SQL Server database. Authors previous research shown that, probably due to fact that MQTT protocol relies on publish/subscribe, it is not always possible to ensure data quality with higher sample rates (with sampling frequency <3 ms). To be able to collect with higher sampling rates, the system is developed in a way that it enable continuous call for streams of values that are sent from the accelerometer as series of values.

4 EXPERIMENTAL SETUP
4.1 Test Bench

This study use machine fault simulator for generating signal for both healthy baseline and inability technical states of the rotary machinery. A SpectraQuest variable speed Machinery Fault Simulator (MFS) installed in Laboratory for Maintenance of University of Zagreb, Faculty of Mechanical Engineering and Naval Architecture is used. The simulation stand (Fig. 4) consists of main shaft loaded with main load and driven by 0.7 kW VFD powered motor. Main shaft is connected to motor with coupling. Additionally, there are two ER-12K rolling bearings that supports shaft assembly. Finally, simulator is equipped with a three-axis accelerometer and a tachometer that are connected to a developed IIOT system.

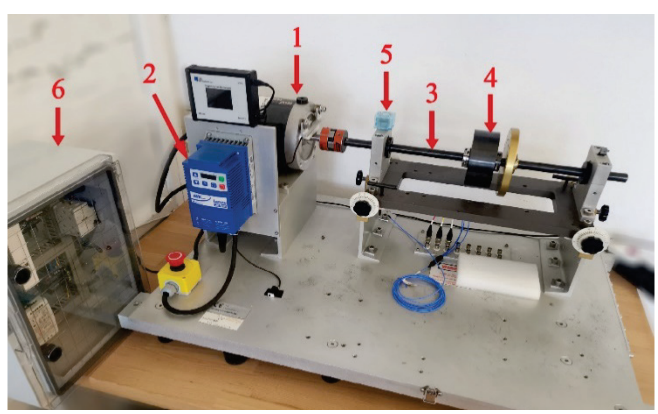

Figure 4 Experimental setup: 1 – Electric motor, 2 – VFD, 3 – main shaft, 4 – main load, 5 – three-axis accelerometer, 6 – Box with router and Raspberry PI edge node.

Table 2 Datasets collected for each rotating speed

Machine states	No. of samples	Training (80%)	Validation (5%)	Test (15%)
NS	1500	1200	75	225
ER	1500	1200	75	225
CR	1500	1200	75	225
DR	1500	1200	75	225
IRB	1500	1200	75	225
ORB	1500	1200	75	225
BB	1500	1200	75	225
CB	1500	1200	75	225
Total	12000	9600	600	1800

The triaxial vibration sensor is installed on the MFS left bearing housing as shown in Fig. 3. During the experiment, data was collected at a frequency of 1.6 kHz. The rotation speed was 150 revolutions per minute and 300 revolutions per minute, respectively. Accelerometer acquired data under both normal state (NS) and faulty conditions. There are three inability states related to rotor: due to eccentric rotor (ER), disbalanced rotor (DR), cocked rotor (CR). Additionally, four bearing related states were simulated as faulty conditions: outer ring damage (ORB), inner ring damage (IRB), ball bearing damage (BB) and combination of the ball bearing, inner ring and outer ring damage (CB), respectively. Bearings is intentionally damaged using electro erosion procedure. The operation in any of the inability state is considered as faulty condition, while running without any simulated faults is interpreted as healthy baseline, i.e. the operation of the rotary subsystem that remains in the healthy state (ability state). 1500 samples for each machine state for both 150 rpm and 300 rpm is collected. Composition of collected samples with quantities is presented in Tab. 2. All the samples are divided into training, test and validation sets required for modelling phase.

4.2 CNN Design

The artificial neural networks (ANN) used in this work as an algorithm for creating models are convolutional neural networks (CNN). It is a type of ANN that has also been used in other research to learn models based on inputs that are composed of multiple dimensions, and on the basis of which features can be learned. Although the initial application of the algorithm was envisioned in image processing, it was found that data from sensors in the maintenance area can also be interpreted using CNN-learned models [20-22].

In this paper, modified 1D MC-DCNN visualized in Fig. 5 is used to for model inability states modelling. Data from triaxial accelerometer is used as an input thus input layer of the 1D MC-DCNN is prepared to process exactly one sample of acquired data. As each sample consist of 1600 samples in each layer, input layer use 1600 × 1 × 3 structure. Convolutional layers of the CNN calculate the output of the neurons. Max pooling function is used to pass over sections (pools) of accelerometer data and extract maximum values of each section. Finally, fully connected layer is used as sample classifier using SoftMax activation function and classification output layer. The structure of the CNN used in this paper is drawn in Fig. 5. Although different CNN structures have been investigated in authors' previous research, it is concluded that usage of described structure is appropriate for learning of the model.

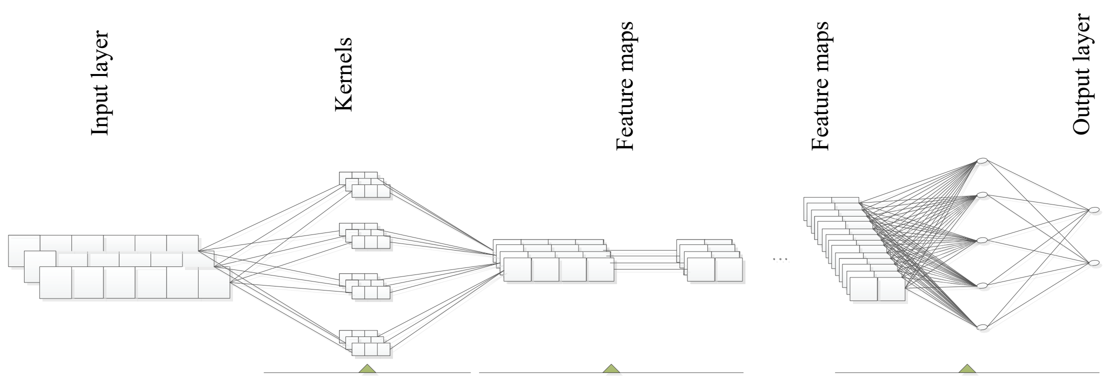

Figure 5 Structure of MC-DCNN

To ensure better results, authors tested grid of hyperparameters values by using variable k that connects multiple hyperparameters. For this research, grid of k = [2 4 8 16] is used. The CNN learning algorithm can be adjusted using a number of hyperparameters, and in this paper, the change in the number of kernels as well as the size of the kernels was tested. Hyperparameters that will be grid searched are number of convolutional layers, number of kernels, and kernel size, respectively. Details about each convolutional layer are given in Tab. 3. From the table, it can be concluded that every convolutional layer use k variable for the calculation of the number of kernels. In this paper, Matlab 2022b is used to design, train and test modified 1D MC-DCNN and all training is done on GPU (GeForce RTX 3080 graphics card).

The Tab. 3 shows that as k increases, so does the number of kernels in each convolutional layer, but also their size in the first two layers. The size of the cores does not change in the last 4 layers, which is marked italic. The paper examined neural networks with one to six convolutional layers. The procedure proceeded so that first a CNN with all 6 layers is learned, then the 6th layer is removed in order to learn a network with 5 layers. After that, the 5th layer is removed to train a 4-layer network. The last network that is learned is a network with only one convolutional layer. Each of those 6 neural networks is trained with 4 values of k (2, 4, 8, 16), leading to a total of 24 neural networks for one rotation speed. The number of 3 learning repetitions of each network is chosen, in order to obtain as few deviations as possible. Then the average accuracy of those 3 networks is calculated, which means that 72 convolutional neural networks were learned for one rotation speed. As the aim of the paper is to examine the results at two rotation speeds (150 rpm and 300 rpm), this leads to a final number of 144 learned convolutional neural networks. Other hyperparameters remain constant during the entire training period.

Table 3 Convolutional neural network layers information regarding *n*-factor

$k = 2$						
Convolutional layer	1st	2nd	3rd	4th	5th	6th
No. of kernels	k	$4k$	$4k$	$4k$	$4k$	$4k$
Kernel size	[2n 1 3]	[n/2 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]
$k = 4$						
Convolutional layer	1st	2nd	3rd	4th	5th	6th
No. of kernels	k	$4k$	$4k$	$4k$	$4k$	$4k$
Kernel size	[4 1 3]	[1 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]
$k = 8$						
Convolutional layer	1st	2nd	3rd	4th	5th	6th
No. of kernels	k	$4k$	$4k$	$4k$	$4k$	$4k$
Kernel size	[8 1 3]	[2 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]
$k = 8$						
Convolutional layer	1st	2nd	3rd	4th	5th	6th
No. of kernels	k	$4k$	$4k$	$4k$	$4k$	$4k$
Kernel size	[16 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]
$k = 16$						
Convolutional layer	1st	2nd	3rd	4th	5th	6th
No. of kernels	k	$4k$	$4k$	$4k$	$4k$	$4k$
Kernel size	[32 1 3]	[8 1 3]	[4 1 3]	[4 1 3]	[4 1 3]	[4 1 3]

5 RESULTS AND DISCUSSION

The learning process of a neural network can be described as a procedure with the aim of determining the weights and biases of neurons that is calculated in iterations. CNN adjusts learnable parameters by minimizing previously defined loss function:

$$E = -\sum_t \sum_k y_k^*(t) \log(y_k(t)) \tag{1}$$

where $y_k^*(t)$ and $y_k(t)$ are the target and predicted values of the t^{th} training example of the k^{th} class, respectively. To ensure learning capability, this work apply backpropagation algorithm that compute stochastic gradient descent in order to minimize error, consequently allowing network to update learnable parameters during training. In this research, learning rate of 0.009 with drop factor of 0.1 for each 10 iteration and momentum of 0.8 were used.

As previously stated, total of 24 neural network were trained. The results of models tested on test set using accuracy as metrics are shown in Tab. 4, Fig. 6 and Fig. 7, respectively.

Table 4 Convolutional neural networks models accuracy

150 rpm		k-factor / accuracy				300 rpm		k-factor / accuracy			
		2	4	8	16			2	4	8	16
Number of layers	1	0,537	0,755	0,696	0,689	Number of layers	1	0,606	0,784	0,805	0,677
	2	0,845	0,862	0,934	0,986		2	0,732	0,847	0,822	0,892
	3	0,907	0,975	0,987	0,991		3	0,928	0,944	0,959	0,986
	4	0,988	0,995	0,999	0,999		4	0,991	0,991	0,995	1,000
	5	0,998	0,999	0,999	0,999		5	1,000	1,000	1,000	1,000
	6	0,999	1,000	0,999	1,000		6	1,000	1,000	1,000	1,000

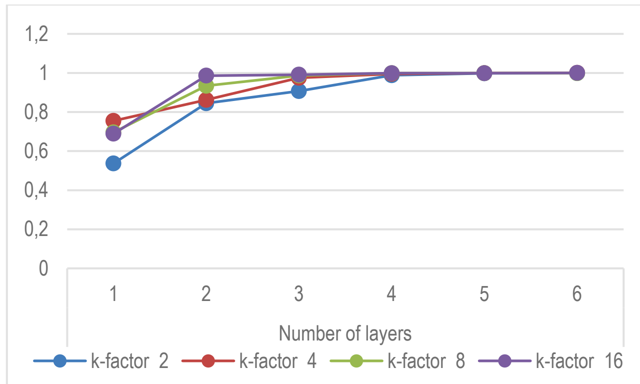

Figure 6 Neural network accuracy related to the number of convolutional layers and k-factor for 150 rpm

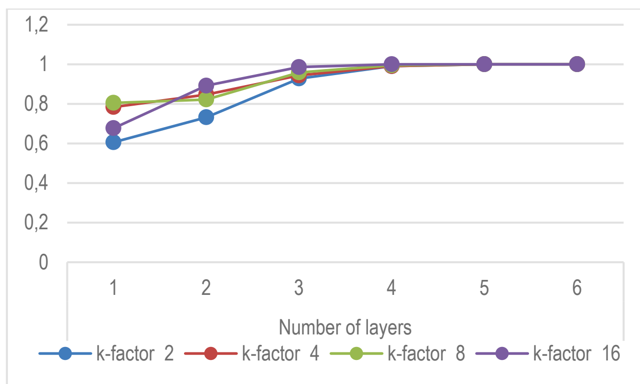

Figure 7 Neural network accuracy related to the number of convolutional layers and k-factor for 300 rpm

It can be seen that most networks with 3 or more convolutional layers would give extremely good results, while absolute accuracy on the test data set can be achieved with CNN with 5 or 6 layers, depending on the rotation speed. From the presented results, it can be concluded that CNN with smaller number of layers would not perform not as good as the network trained with higher number of layers. Other than that, factor k used as kernel size multiplicator plays important role during training of the network with less than 4 convolutional layers. This can be related to the fact that in the experiment this factor is used only in first two layers to confirm that in the shallow architecture higher values of kernel size and number of kernels produces models with better results. As kernels represents features learned during the training period, it becomes clear that more features learned means better performance during the scoring phase.

As data are collected for two different rotational speed, in the last phase of the research, the applicability of the network model learned at a lower rotation speed was tested on test data collected at a higher rotation speed. Namely, due to the large amount of rotary equipment that rotates at different speeds in the industry, the good performance of networks learned at one rotation speed on test data collected at another rotation speed would give reason to believe that one learned model can be applied for intelligent inability stete prediction of the same type of equipment, and which rotates at different speeds. Factor k = 4 is chosen for comparison and all networks regarding CNN number of layers factor is tested. Firstly, network learned on 150 rpm with best results for the k = 4 (named k4_150) for each CNN number of layers is tested on 300 rpm test data. Later on, network learned on 300 rpm with best results for the k = 4 (named k4_300) for each CNN number of layers is tested on 150 rpm test data. Results of such testing is shown in Tab. 5.

Table 5 Convolutional neural networks models accuracy

CNN layers	k4_150 on 150 rpm	k4_150 on 300 rpm	k4_300 on 300 rpm	k4_300 on 150 rpm
1	76,9 %	23,5 %	81,7 %	17,3 %
2	87,4 %	24,9 %	83,5 %	12,5 %
3	97,5%	20,3 %	98,1 %	15,8 %
4	99,5 %	23,5 %	99,8 %	12,5 %
5	100 %	17,7 %	100 %	12,5 %
6	100 %	12,5 %	100 %	12,5 %

According to Tab. 5, models learned for one rotational speed underperforms when tested on different rotational speed. Consequently, experiment show that using models trained on one set of data for prediction of machine state on different set of data is not recommended, although only rotational speed is changed as experiment input. Two another interesting rules are readable from Tab. 5. Model trained on lower speed performance are better on higher speed test then performance of the model trained on higher performance when tested on lower speed test data. Also, in this experiment models with fewer layers generally perform better which means they can learn more general features of the data they are learning on.

6 CONCLUSION AND FUTURE WORK

Finally, results of the paper can be summarized as follows: It is possible to acquire datasets containing raw accelerometer signal using the low-cost self-developed IIOT platform. It is shown that developed solution can acquire data in a laboratory environment.

Additionally, it is proven that IIOT system vibration data acquired during the experiment are useful for learning intelligent models for fault detection and diagnostics. That is shown using 1D-MDCNN, models with high accuracy on the test data can be trained. Multiple CNN-s are trained using the data acquired from the IIOT. The influence of different amounts of certain hyperparameters (number of kernels, kernel size, and number of layers) on the accuracy of the network was examined. Based on these results, it was concluded that increasing the number and size of kernels and the number of layers in the network contributes to increasing the accuracy of the model in the scoring phase.

Finally, application of CNN model learned at one rotation speed to predict classes of data collected at another rotation speed was also tested. The results obtained lead to the conclusion that such an application is not possible. Therefore, the question arises of the applicability of this technique of predicting results in production conditions in case of the variable rotational speeds.

In future research, authors plan to integrate different sensor fusion to enable more data, as well as develop specific purpose edge node with integrated prescriptive maintenance decision making model. In this way, it will be possible to process data directly on the edge, reducing the need of sending raw signal data to the server for further processing and prediction logic.

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