



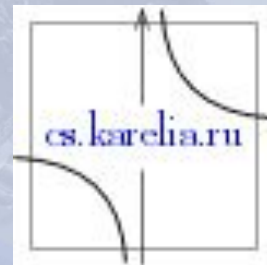
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Fault Diagnosis for Industrial Rotary Machinery based on Edge Computing and Neural Networking



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About

Presenter:

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PhD student, junior researcher at Petrozavodsk State University.

Field of interest: artificial intelligence and computer science.

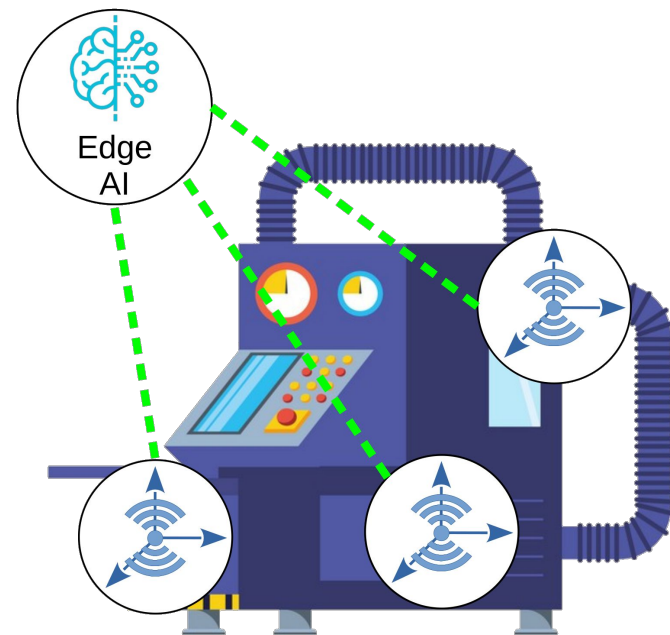
Project: development of the industrial monitoring system.

This research is implemented in Petrozavodsk State University (PetrSU) with financial support by the Ministry of Science and Higher Education of Russia within Agreement no. 075-11-2019-088 of 20.12.2019 on the topic “Creating the high-tech production of mobile microprocessor computing modules based on SiP and PoP technology for smart data collection, mining, and interaction with surrounding sources”.

Problem

Fault diagnosis for industrial rotary machinery:
bearing fault detection and classification

1. Convolutional Neural Network (CNN)
methods application to fault detection and
fault characteristics evaluation.
2. Usage of low-capacity edge IoT devices for
real-time data analysis.



Solution

1. CNN methods application to fault detection and fault characteristics evaluation.
CNN model:
 - a. architecture;
 - b. training;
 - c. testing.
2. Usage of low-capacity edge IoT devices for real-time data analysis.
 - a. concept of an industrial monitoring system based on an edge-centric NN computing device;
 - b. performance estimation in a prototype of a monitoring system.

The CNN model

1-D Convolutional Neural Network (CNN) for vibration signal based bearings fault detection.

Input: vibration signal frame (8192 samples at 64 kHz = 128 ms).

Output: bearing condition:

- healthy,
- outer ring damage,
- inner ring damage.

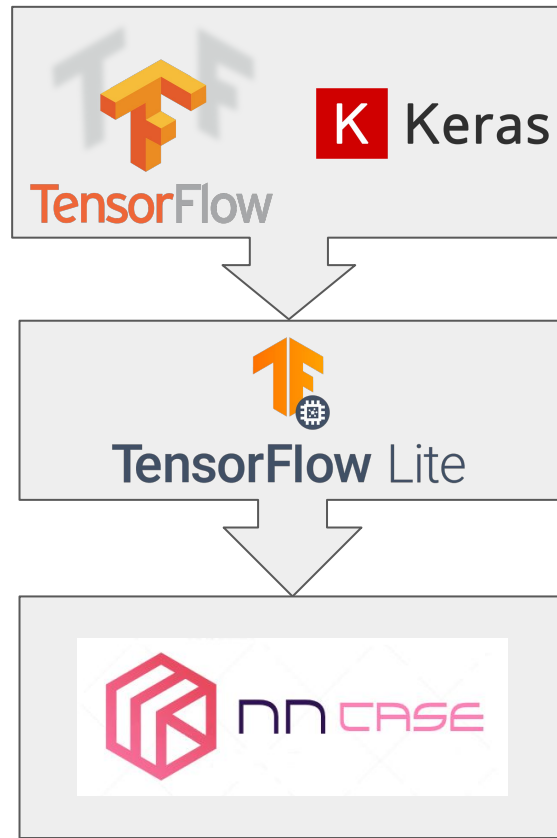
<i>Layer</i>	<i>Shape</i>	<i>Parameters</i>	
Input	(8192)		
1D Convolutional Layer	(8192, 2)	Activation	ReLU
		Filters	2
		Kernel Size	64
		Stride	1
		Padding	Same
1D Pooling Layer	(512, 2)	Pool size	16
1D Convolutional Layer	(512, 12)	Activation	ReLU
		Filters	12
		Kernel Size	32
		Stride	1
		Padding	Same
1D Pooling Layer	(32, 12)	Pool size	16
1D Convolutional Layer	(32, 32)	Activation	ReLU
		Filters	32
		Kernel Size	16
		Stride	1
		Padding	Same
1D Pooling Layer	(2, 32)	Pool size	16
Fully-connected layer	(150)	Activation	Sigmoid
		Units	150
Fully-connected layer	(3)	Activation	Softmax
		Units	3

Tools

Development and training

Deployment:

- platform-specific optimizations;
- enable hardware acceleration.



The dataset description

Paderborn Bearing Dataset:

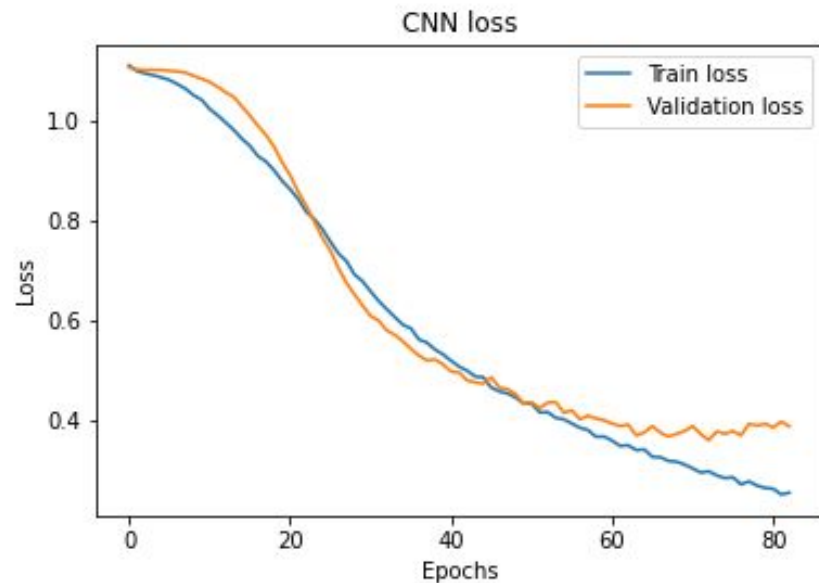
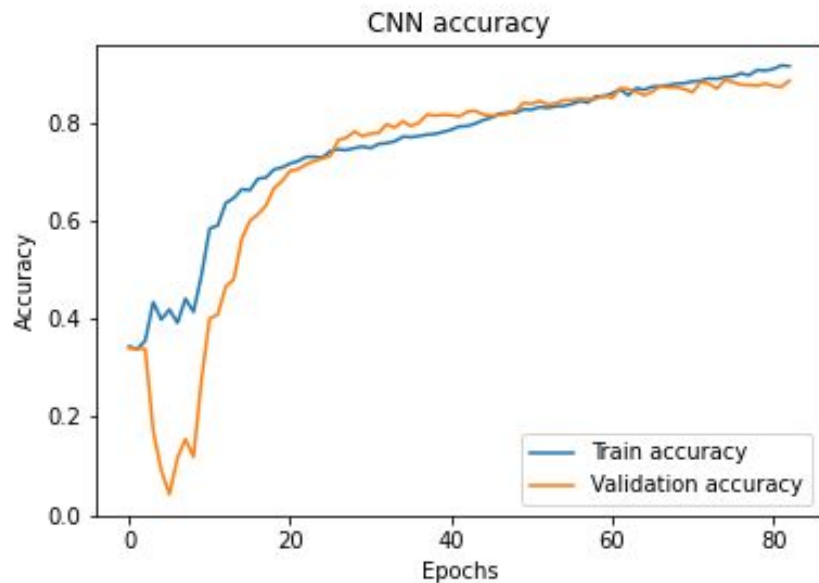
- 32 bearings, with real and artificial damages
- Vibration signal, 4 sec per operating condition, 20 conditions in total, 64kHz, 16-bit

Data selection and preparation:

- 5 bearings for each class (healthy, outer or inner ring damage)
- Validation split ratio 20%
- 8192 samples (128 ms) per frame
- Data normalization

CNN training

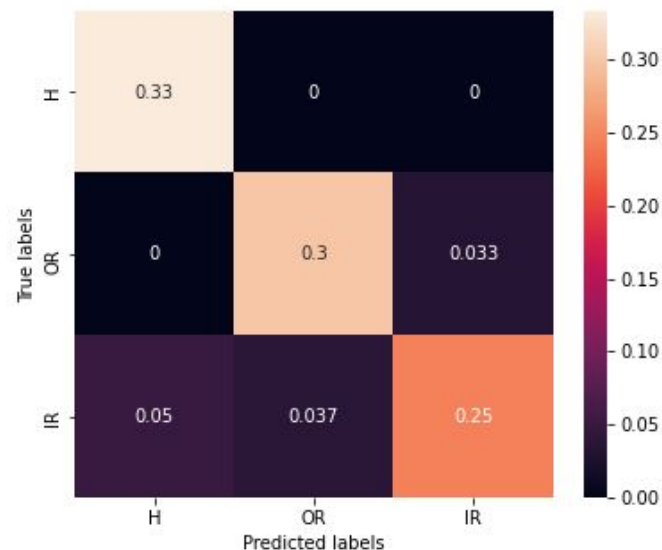
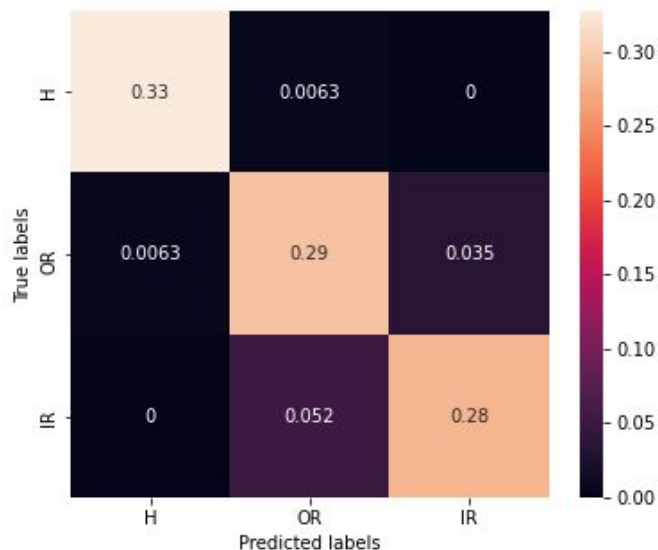
Training and validation accuracy (left) and loss (right) curves of CNN



The validation accuracy reach 88%

CNN testing

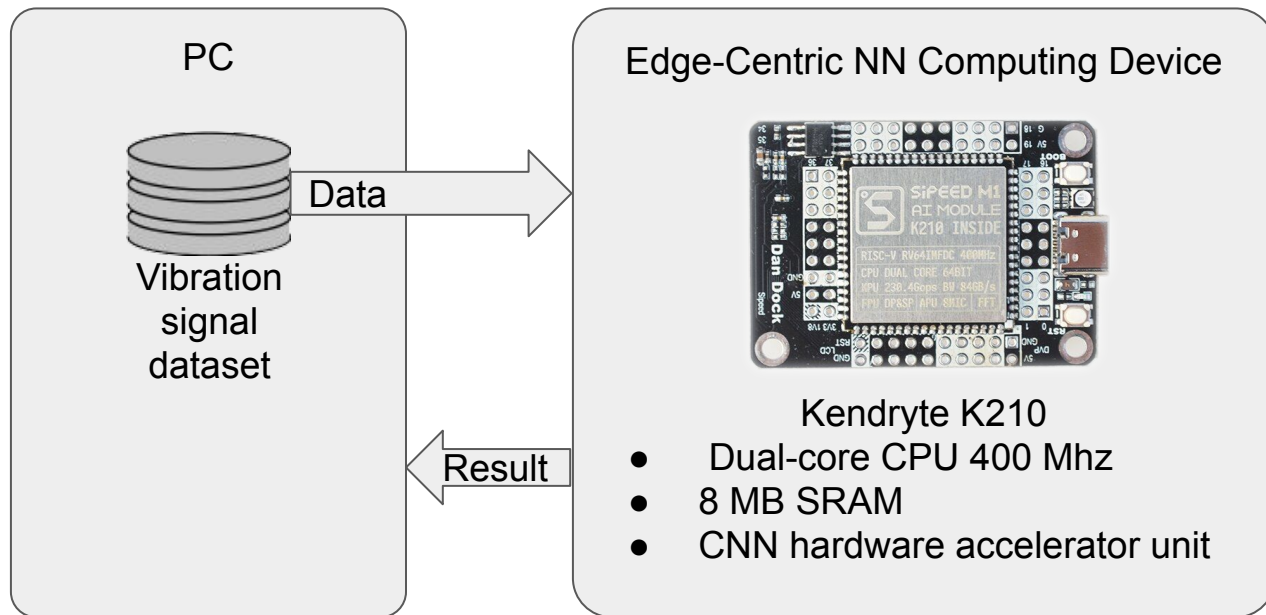
Confusion matrix of CNN on training (left) and validation (right) data normalized over all population.



Accuracy: 90% on training and 88% on test dataset.
Applicable both for fault detection and classification.

Edge-Centric Neural Network Computing Device

Monitoring system prototype



Acceleration could be obtained by leverage hardware acceleration of NN

CNN performance evaluation on the edge device

1. CNN model storage size 23 Kbytes. Runtime data size 81 Kbytes.



More than 200 CNNs like this could store simultaneously in SRAM to monitor and diagnose different units.

2. Neural network execution time 212 ms



Up to 5 units in real-time (check each unit every 1 seconds)

+ Further hardware-specific improvement available (usage of 1×1 or 3×3 convolutions instead of 1×64 , 1×32 , and 1×16 convolutions)

Conclusion

1. CNN methods application to fault detection and classification.
 - a. lightweight CNN architecture;
 - b. high accuracy both for fault detection and classification.
2. Usage of low-capacity edge IoT devices for real-time data analysis.
 - a. concept of an industrial monitoring system based on an edge-centric NN computing device;
 - b. real-time fault detection and classification possible.