1-D Convolutional Neural Networks for Signal Processing Applications

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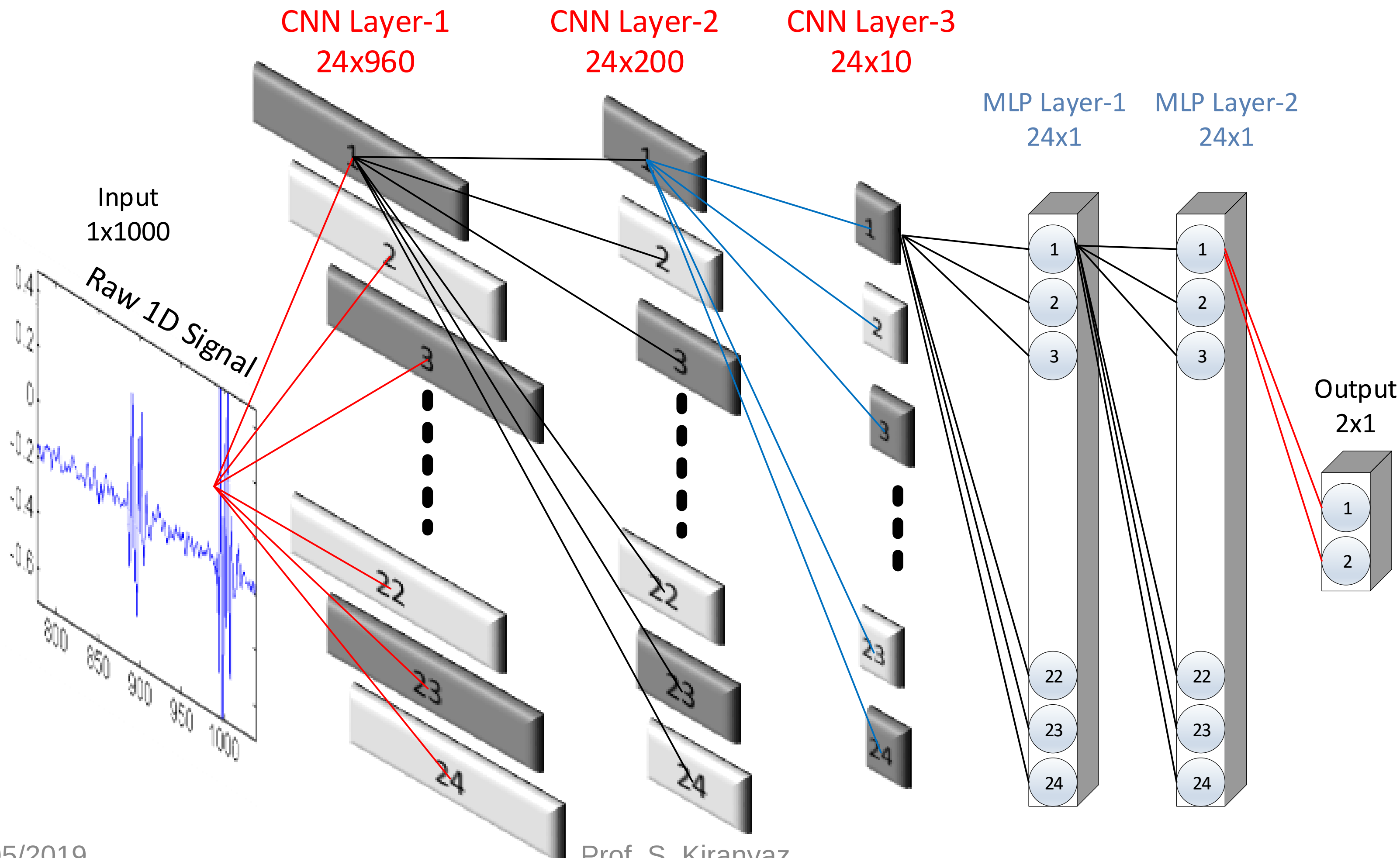
Presented by Nikolaos Passalis

Introduction

- 1D Convolutional Neural Networks (CNNs) have recently become the *state-of-the-art* technique for many key signal processing applications, e.g.
  - patient-specific ECG classification,
  - structural health monitoring,
  - anomaly detection in power electronics circuitry, and
  - motor-fault detection.
- The main difference between 1D and 2D CNNs is that 1D arrays replace 2D matrices for both kernels and feature maps.

A sample 1D CNN configuration with 3 (convolution) CNN and 2 (fully-connected) MLP layers



Advantages of 1D CNNs

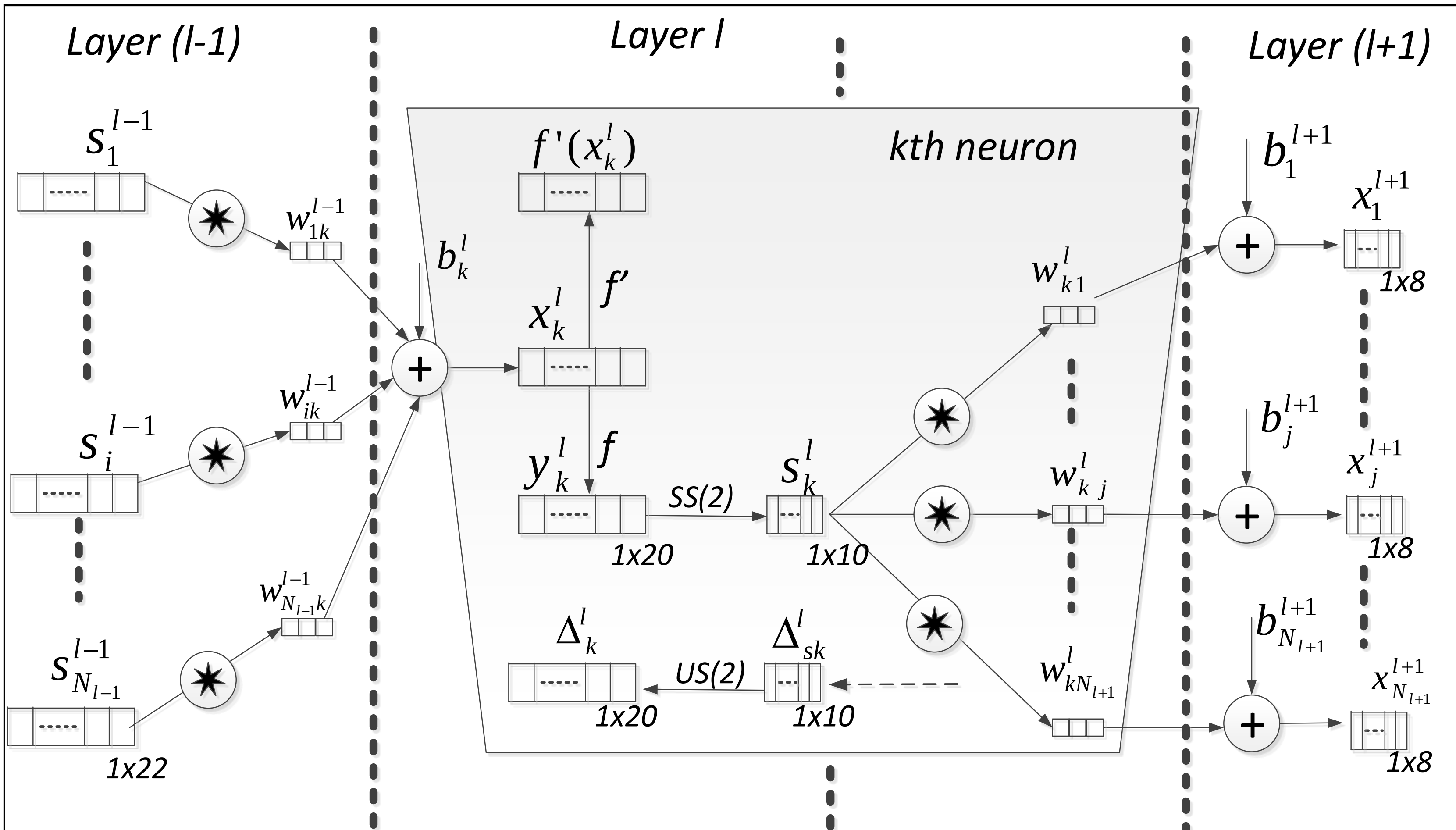
- Instead of matrix operations, simple array operations are needed for FP and BP
  - Lower computational complexity compared to 2D CNNs counterpart.

- Recent studies showed that 1D CNNs with relatively shallow architectures (i.e. small number of hidden layers and neurons) were able to learn challenging tasks involving 1D signals. On the other hand, 2D CNNs usually require deeper architectures to handle such tasks. Obviously, networks with shallow architectures are much easier to train and implement.

- Usually, training deep 2D CNNs requires special hardware setup (e.g. Cloud computing or GPU farms). On the other hand, any CPU implementation over a standard computer is feasible and relatively fast for training compact 1D CNNs with few hidden layers (e.g. 2 or less) and neurons (e.g. < 50).

- Due to their low computational requirements, compact 1D CNNs are well-suited for real-time and low-cost applications especially on mobile or hand-held devices.

Three consecutive CNN layers



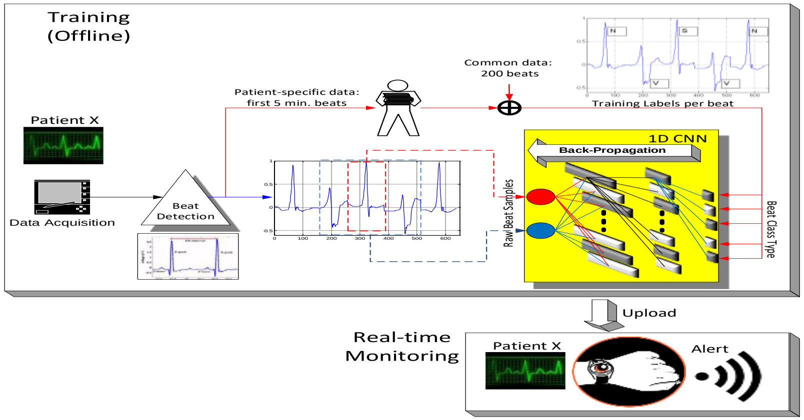
Back Propagation in 1D CNN

Initialize weights and biases (e.g., randomly, *~U(-0.1, 0.1)*)

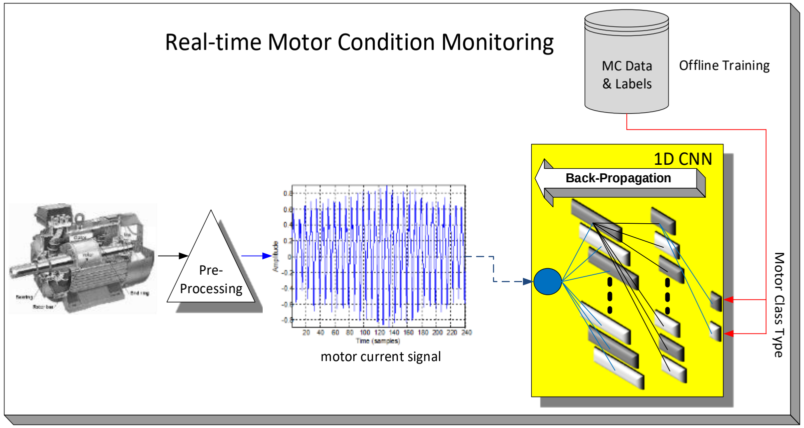
For each BP iteration **DO**:

- For each 1D raw signal in the dataset, **DO**:
  - ✓ **FP**: Forward propagate from the input layer to the output layer to find outputs of each neuron at each layer, s_i^l, $\forall i \in [1, N_l]$, and $\forall l \in [1, L]$.
  - ✓ **BP**: Compute delta error at the output layer and back-propagate it to the first hidden layer to compute the delta errors, Δ_k^l, $\forall k \in [1, N_l]$, and $\forall l \in [1, L]$.
  - ✓ **PP**: Post-process to compute the weight and bias sensitivities
  - ✓ **Update**: Update the weights and biases by (accumulating) sensitivities scaled with the learning factor, ε

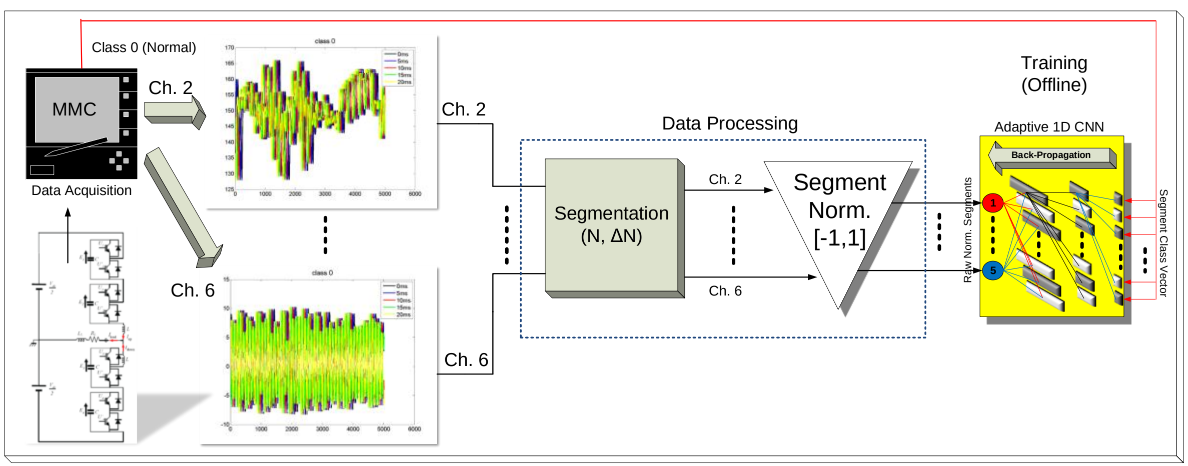
Some major applications of 1D CNNs



Real-time Electrocardiogram (ECG) monitoring for Arrhythmia detection



Real-time motor fault detection



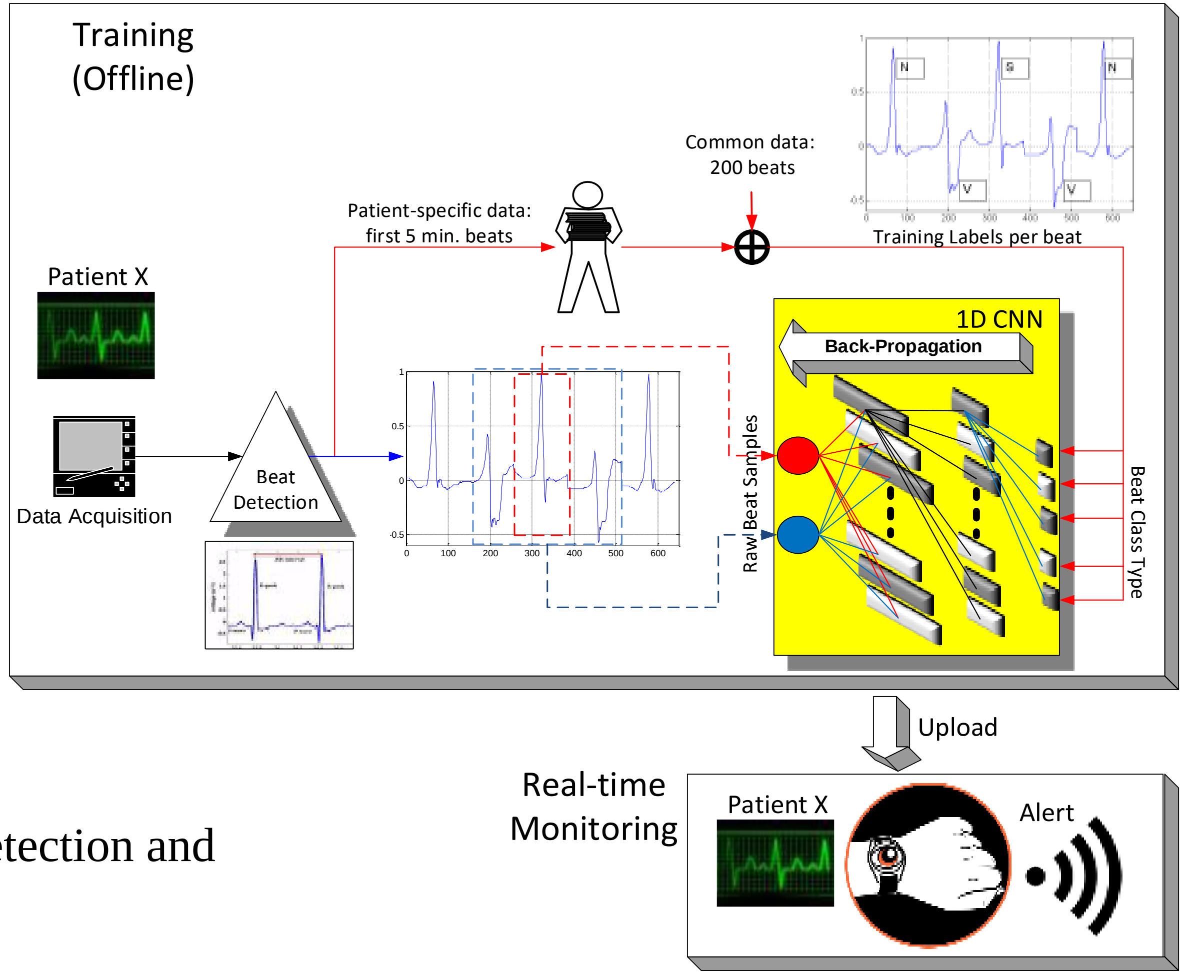
Fault detection in Modular Multilevel Converters (MMC)

Real-time Electrocardiogram (ECG) Monitoring

- Electrocardiogram (ECG) signals are extensively used by medical practitioners to monitor and evaluate the cardiac health.
- The first 1D CNN application was on ECG beat identification where a “patient-specific” solution was proposed, i.e., for each arrhythmia patient a dedicated compact 1D CNN was trained by using the patient-specific training data.

Real-time Electrocardiogram (ECG) Monitoring

S. Kiranyaz, T. Ince, and M. Gabbouj, “Real-Time Patient-Specific ECG Classification by 1D Convolutional Neural Networks”, *IEEE Trans. on Biomedical Engineering*, vol. 63, no. 3, pp. 664-675, Mar 2016.



Overview of the arrhythmia detection and identification system

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Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks

Serkan Kiranyaz ; Turker Ince ; Moncef Gabbouj

Publication Year: 2016, Page(s):664 - 675

Cited by: Papers (144) | Patents (1)

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Dry-Contact Electrode Ear-EEG

Simon L. Kappel ; Mike L. Rank ; Hans Olaf Toft ; Mikael Andersen ; Preben Kidmose

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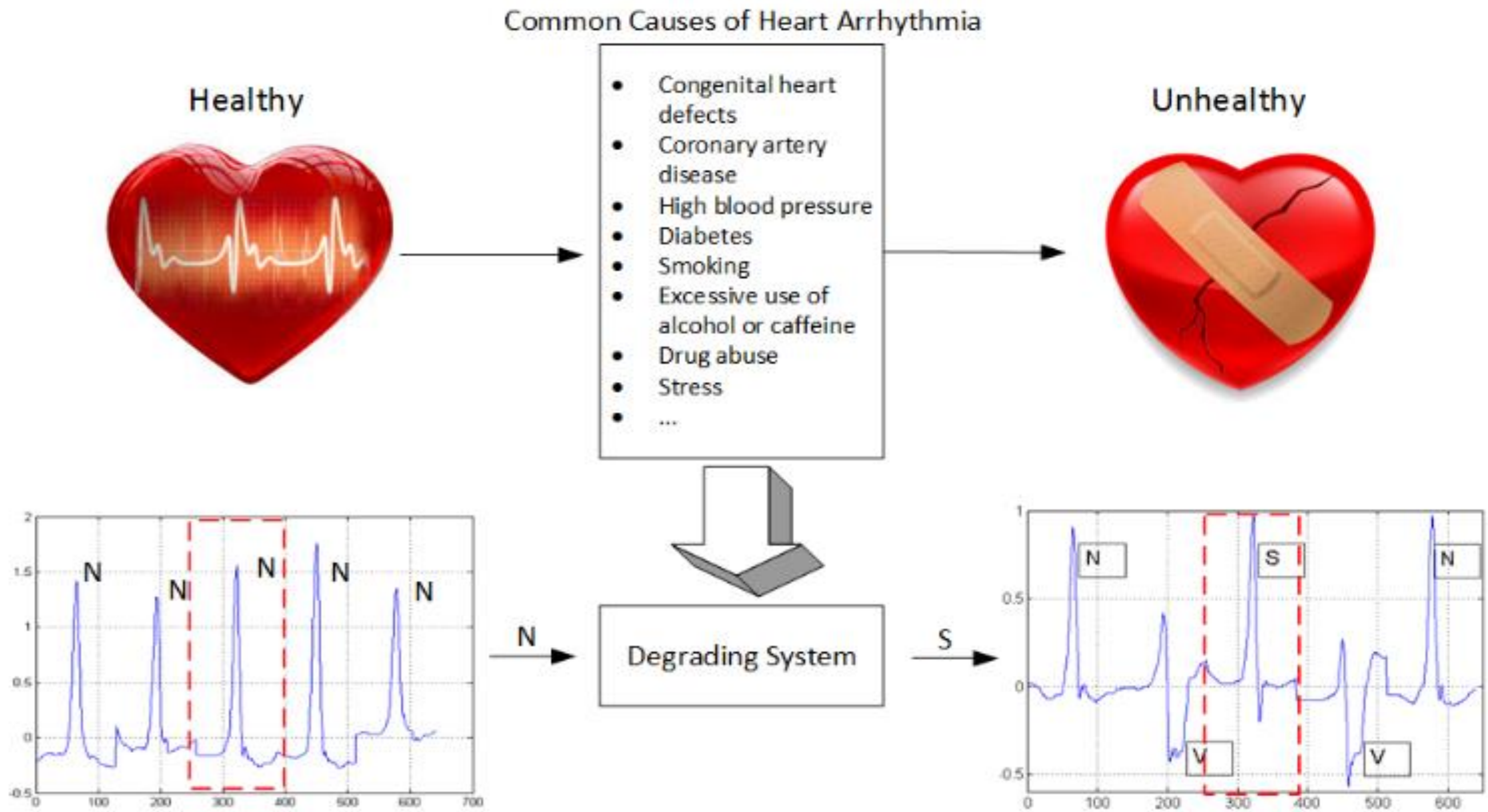
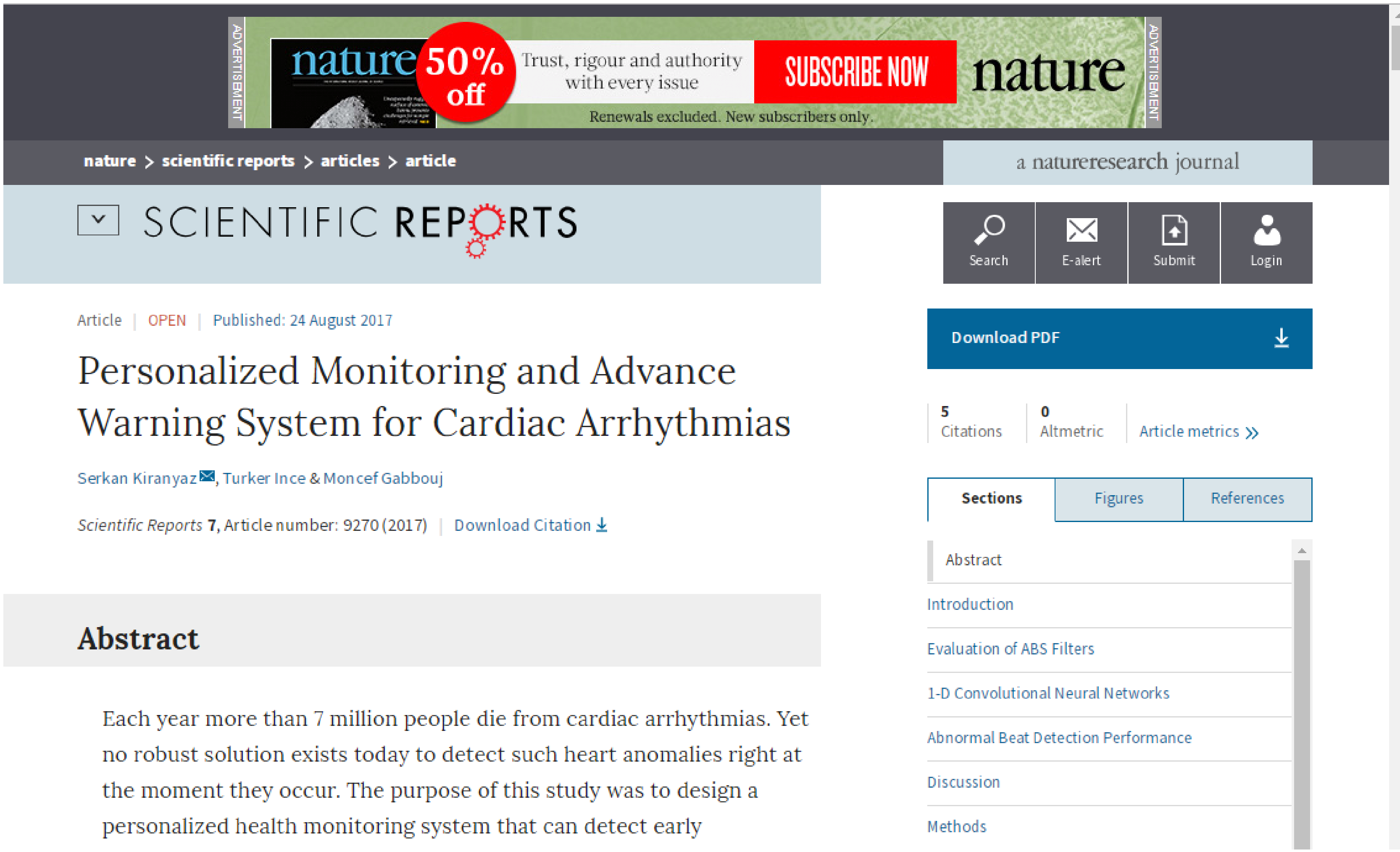
Medical Image Synthesis with Deep Convolutional Adversarial Networks

Advance Warning for Cardiac Arrhythmia



Kiranyaz, **Scientific Reports**, 2017. (Springer Nature)

Personalized Monitoring and Advance Warning System for Cardiac Arrhythmias



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Personalized Monitoring and Advance Warning System for Cardiac Arrhythmias

Serkan Kiranyaz, Turker Ince & Moncef Gabbouj

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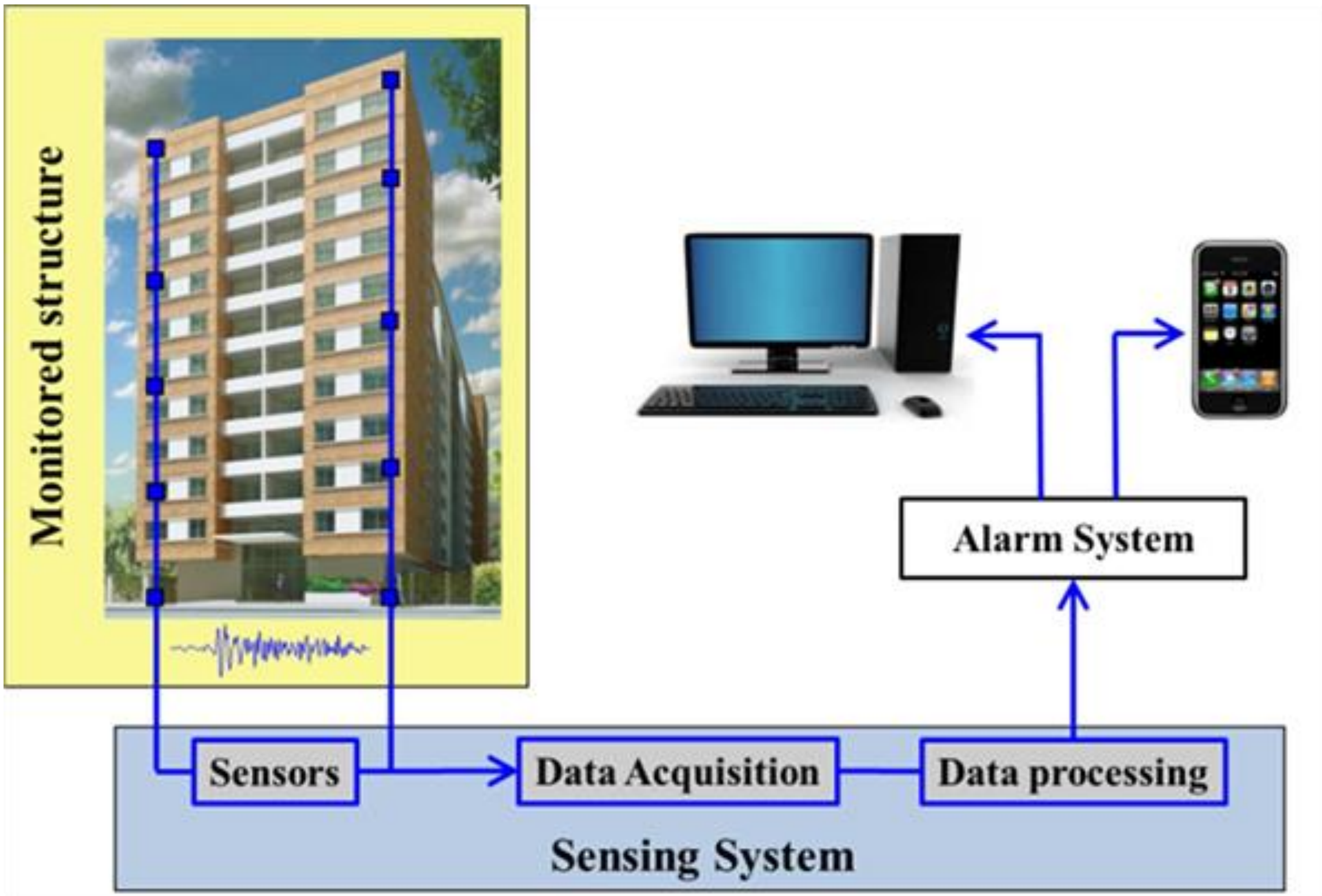
Abstract
Introduction
Evaluation of ABS Filters
1-D Convolutional Neural Networks
Abnormal Beat Detection Performance
Discussion
Methods

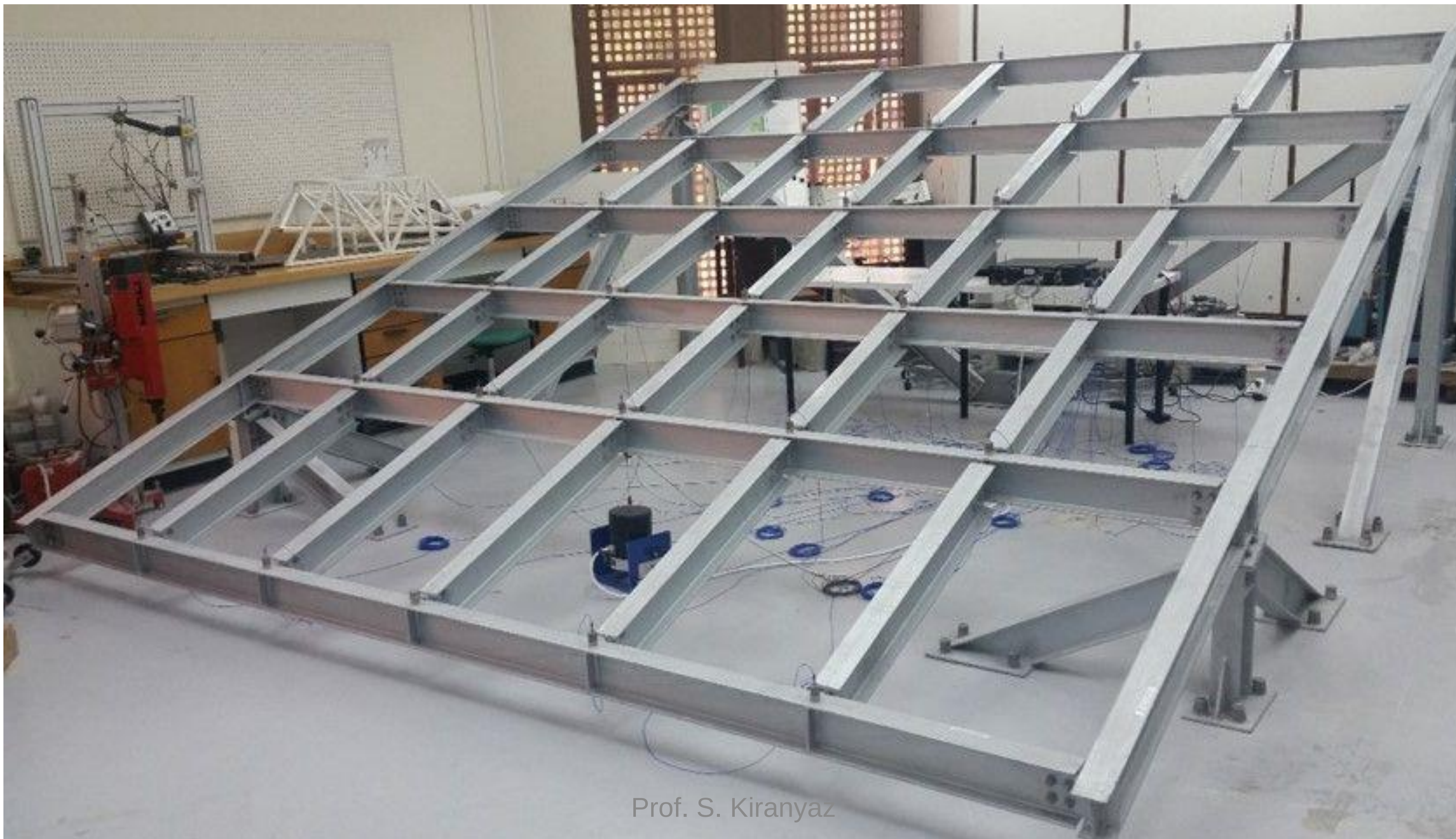
Abstract

Each year more than 7 million people die from cardiac arrhythmias. Yet no robust solution exists today to detect such heart anomalies right at the moment they occur. The purpose of this study was to design a personalized health monitoring system that can detect early

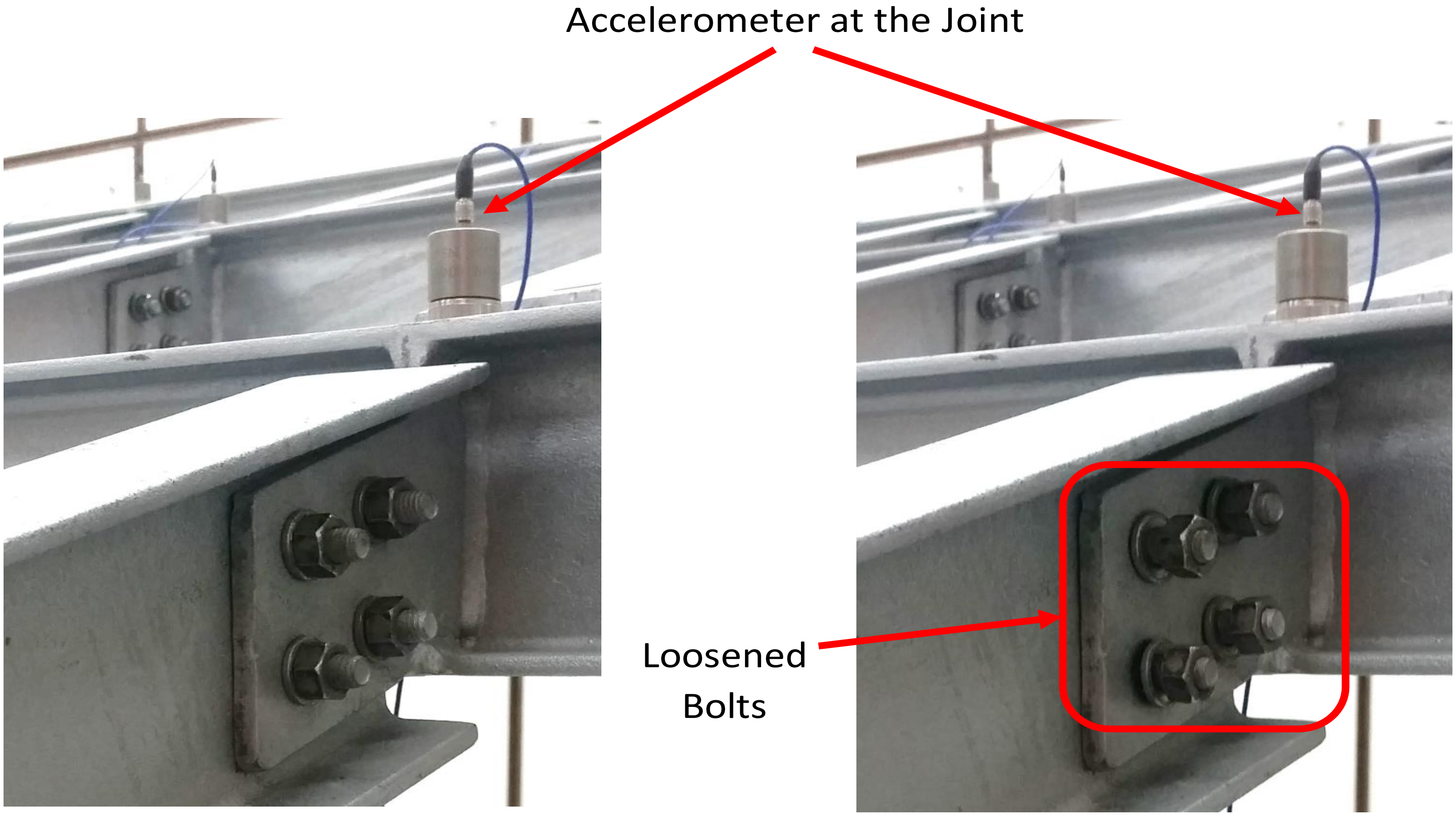
Vibration-Based Structural Damage Detection in Civil Infrastructure



Structural Health Monitoring & Damage Detection

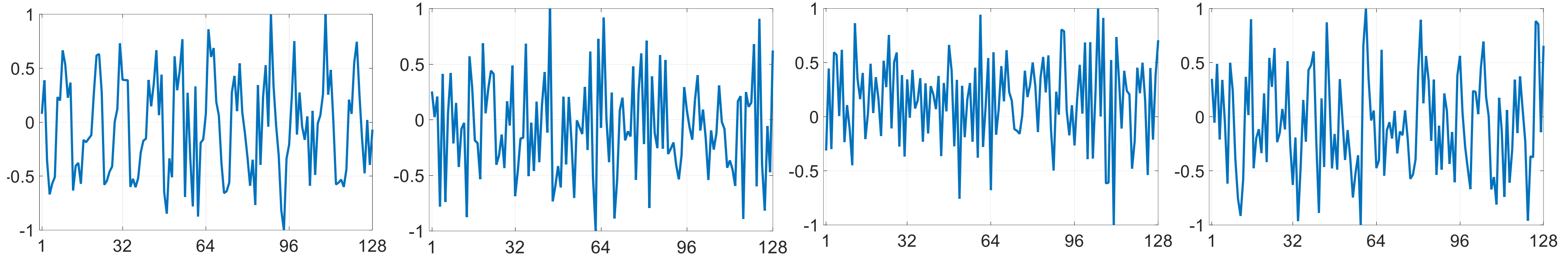


Healthy vs. damaged joints

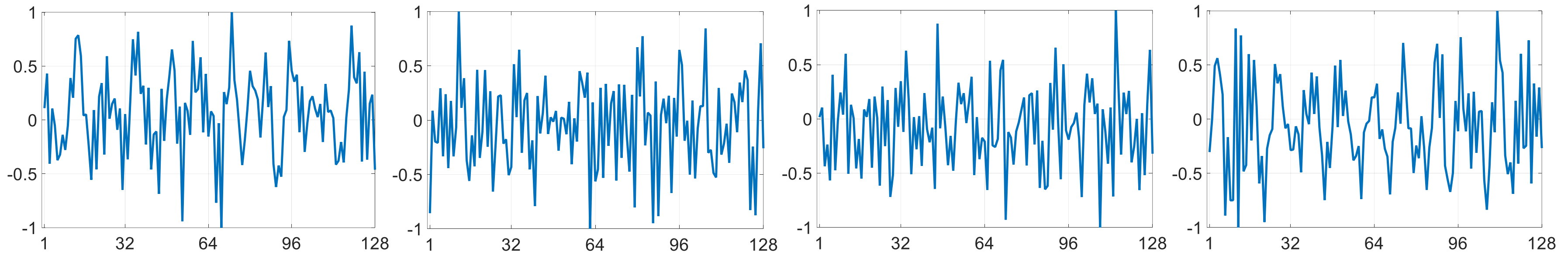


(a) (b)

Vibration Signals: healthy vs. damaged
Can you see the difference?



(Examples of undamaged acceleration signals)



(Examples of damaged acceleration signals)

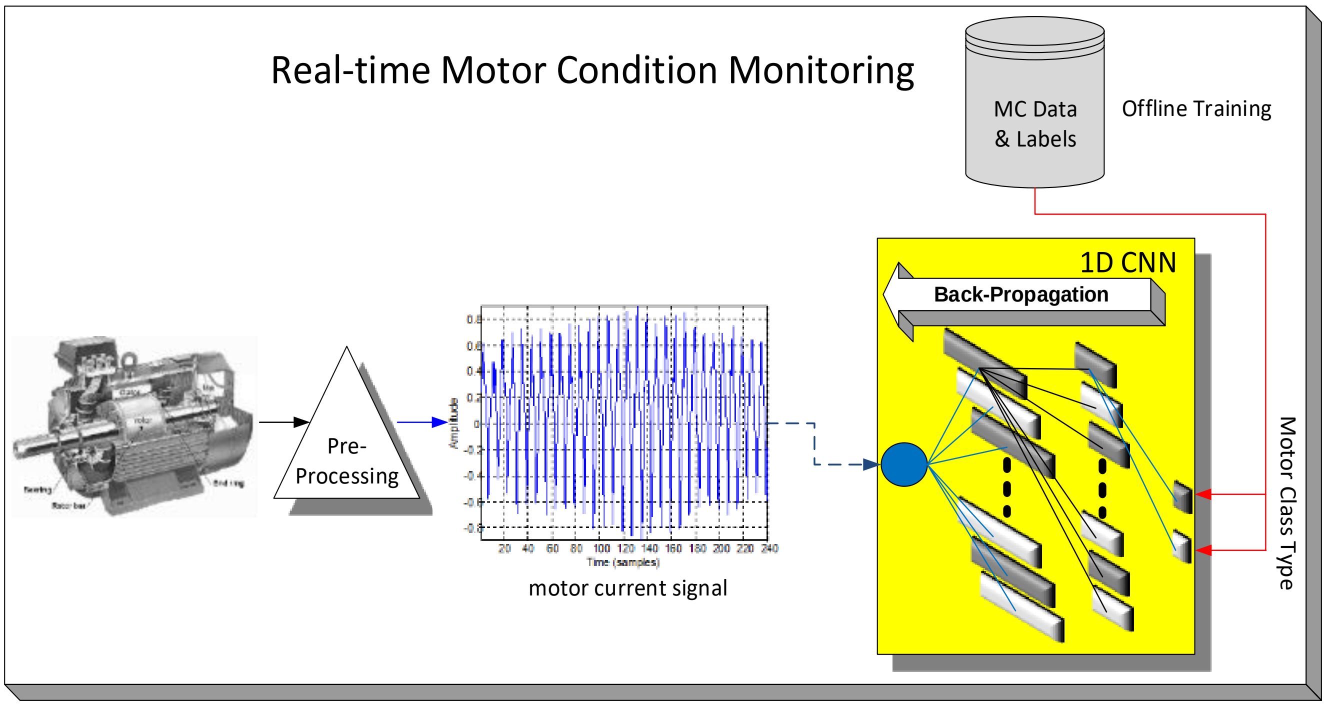
Recent Publications

- O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, D. J. Inman, “Wireless and real-time structural damage detection: A novel decentralized method for wireless sensor networks” in ***Journal of Sound and Vibration (Elsevier),*** vol. 424, pp. 158-172, June 2018. https://doi.org/10.1016/j.jsv.2018.03.008.

- M.S.O. Abdeljaber, O. Avci, S. Kiranyaz, M. Gabbouj and D. J. Inman, “Real-Time Vibration-Based Structural Damage Detection Using One-Dimensional Convolutional Neural Networks”, ***Journal of Sound and Vibration (Elsevier)***, vol. 388, pp. 154-170, Feb. 2017. http://dx.doi.org/10.1016/j.jsv.2016.10.043

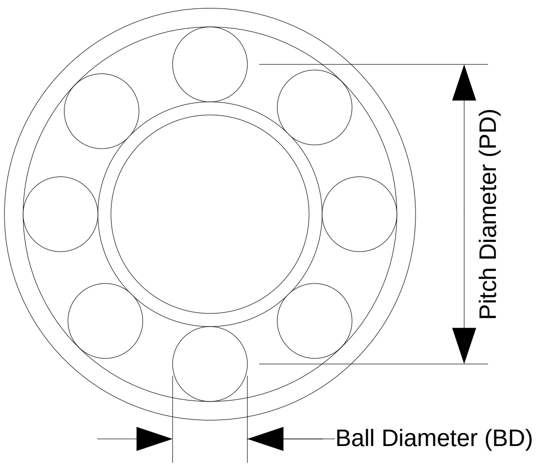
- M.S.O. Abdeljaber, O. Avci, S. Kiranyaz, H. Sodano and D. J. Inman, “1-D CNNs for Structural Damage Detection: Verification on a Structural Health Monitoring Benchmark Data”, ***Neurocomputing (Elsevier)***, Vol. 275, pp. 1308 - 1317 Jan. 2018. https://doi.org/10.1016/j.neucom.2017.09.069

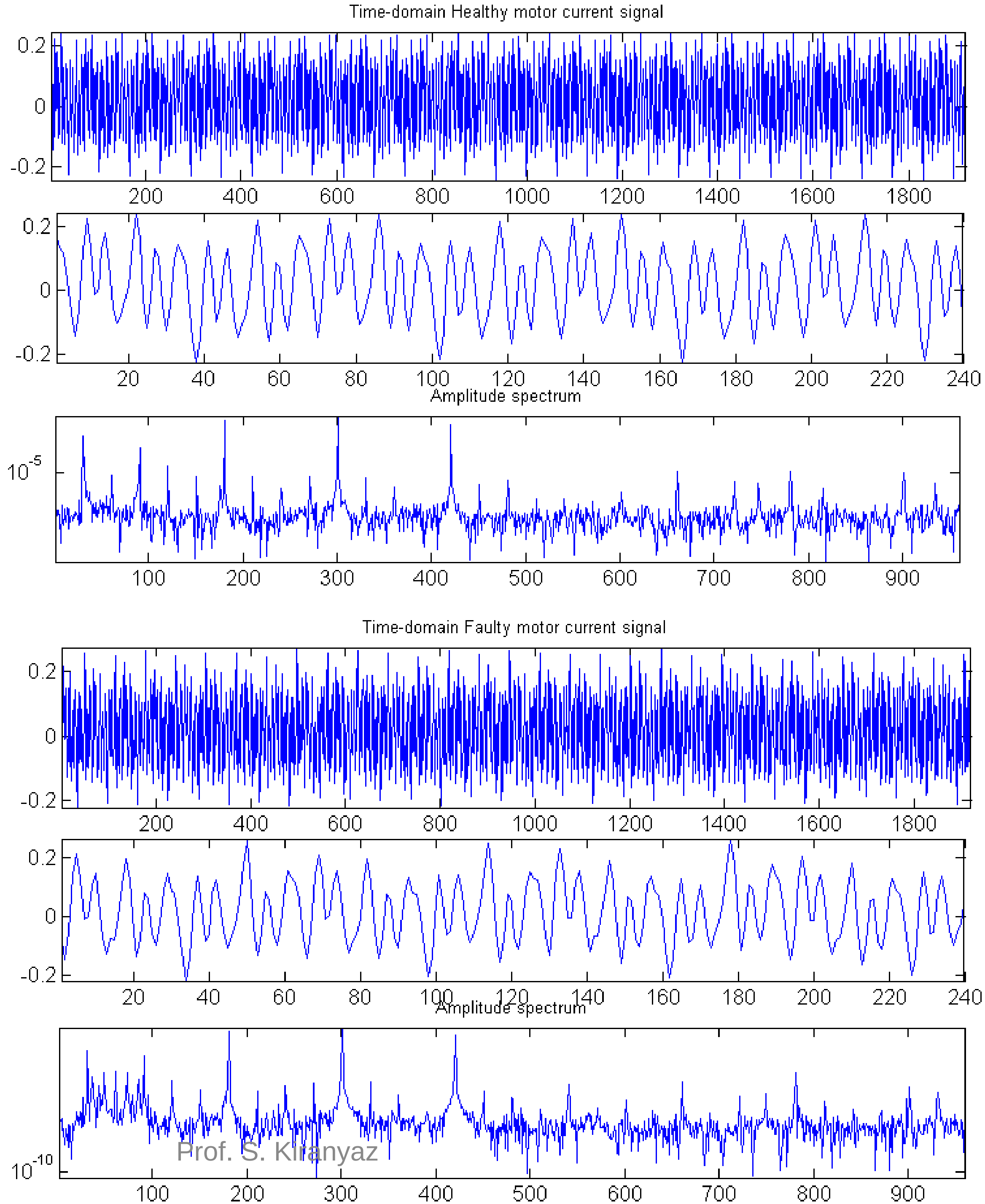
Condition Monitoring in Rotating Mechanical/Aerospace Machine Parts



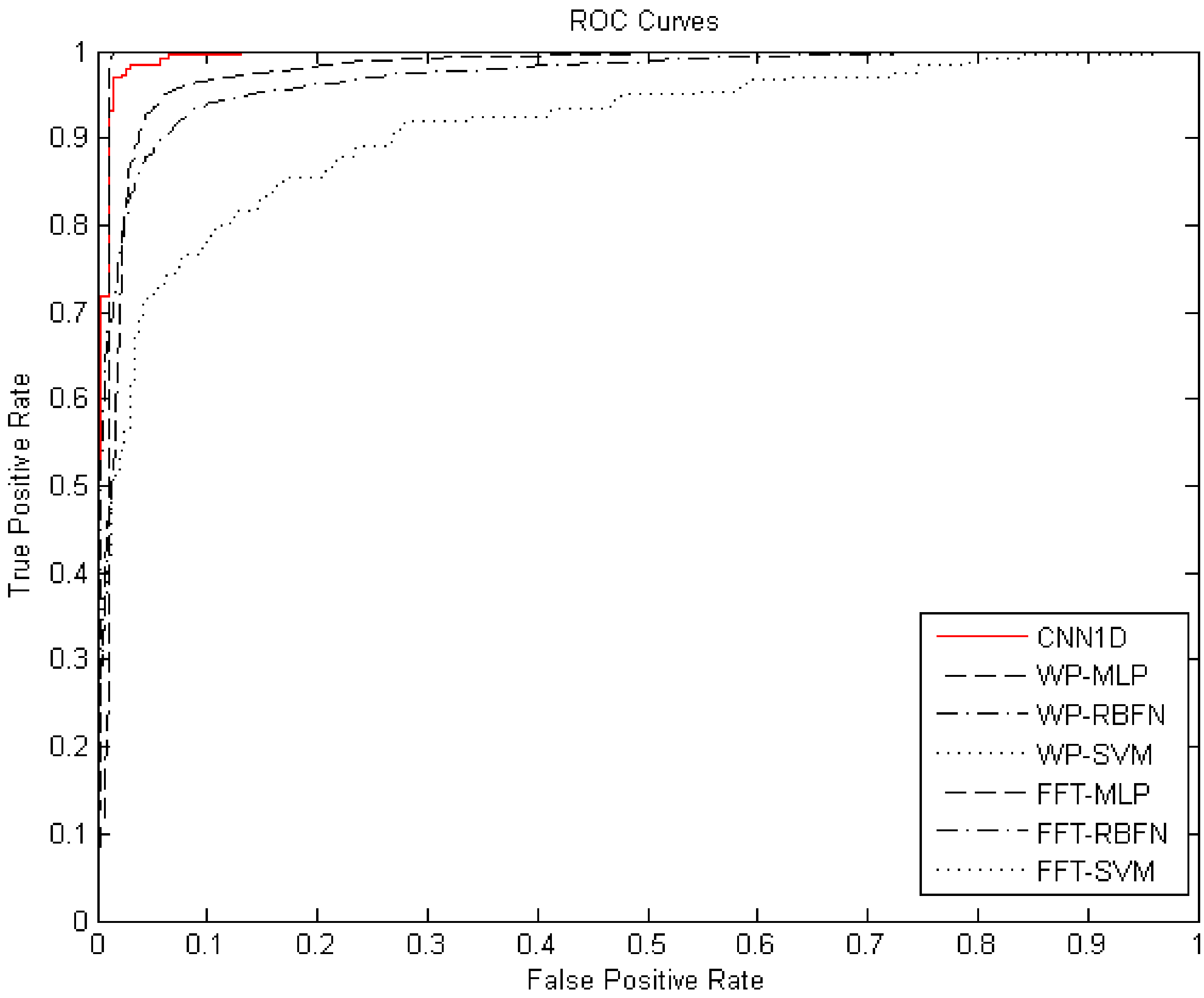
T. Ince, S. Kiranyaz , L. Eren , M. Askar and M. Gabbouj, “Real-Time Motor Fault Detection by 1D Convolutional Neural Networks”, ***IEEE Trans. of Industrial Electronics***, vol. 63, Issue 11, pp. 7067 – 7075, Nov. 2016.

Healthy (top) vs. Faulty (bottom) motor current signals





ROC plots of 1D CNN and 6 different methods. The x- and y-axis represent the false positive rate and true positive rate, respectively.



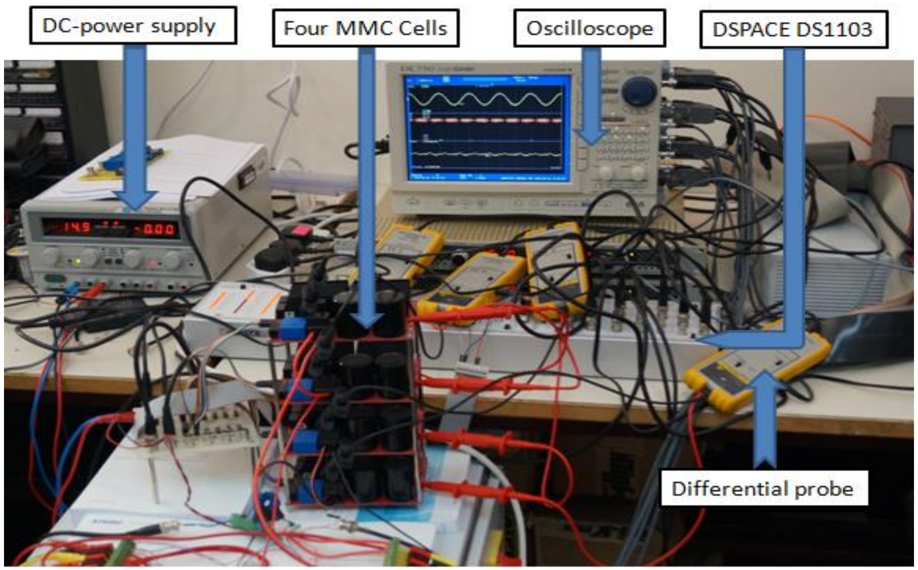
Recent Publications

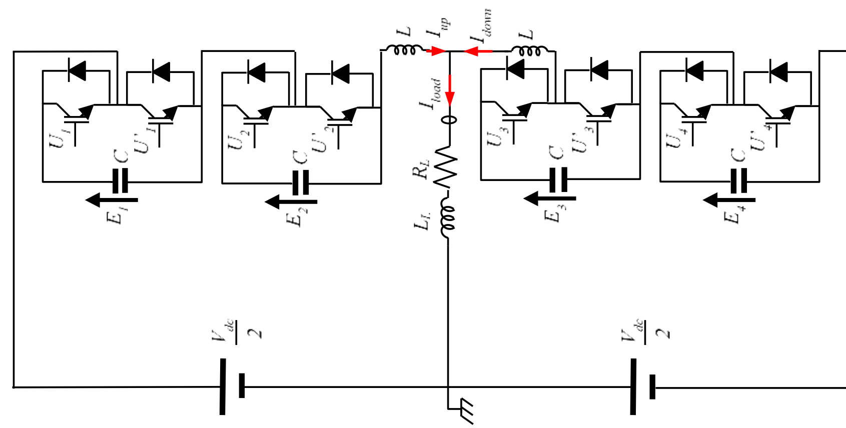
- O. Abdeljaber, S. Sassi, Onur Avci, S. Kiranyaz, A. Ibrahim and M. Gabbouj, “Fault Detection and Severity Identification of Ball Bearings by Online Condition Monitoring”, ***IEEE Transactions on Industrial Electronics*,** Dec. 2018. DOI: 10.1109/TIE.2018.2886789
- L. Eren, T. Ince, S. Kiranyaz, "A Generic Intelligent Bearing Fault Diagnosis System Using Compact Adaptive 1D CNN Classifier", in ***Journal of Signal Processing Systems***, vol. 91, issue 2, pp. 179-189, Feb. 2019.
- L. Eren, “Bearing fault detection by one-dimensional convolutional neural networks,” ***Math. Probl. Eng***. (2017). doi:10.1155/2017/8617315.
- W. Zhang, C. Li, G. Peng, Y. Chen, Z. Zhang, “A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load,” ***Mech. Syst. Signal Process***. (2018).

Fault Detection in Modular Multilevel Converters (MMC)

- High-power multilevel converters have been utilized extensively for efficient power conversion. The modular multilevel converters (MMC) are arguably the most efficient and feasible multilevel converter topology for medium power to high power applications.
- Each cell may have one or more switches and a switch failure may occur in anyone of these cells. The steady-state normal and fault behavior of a cell voltage vary significantly based on the changes in the load current and the fault timing, which makes it difficult to detect and identify such faults in a fast manner.

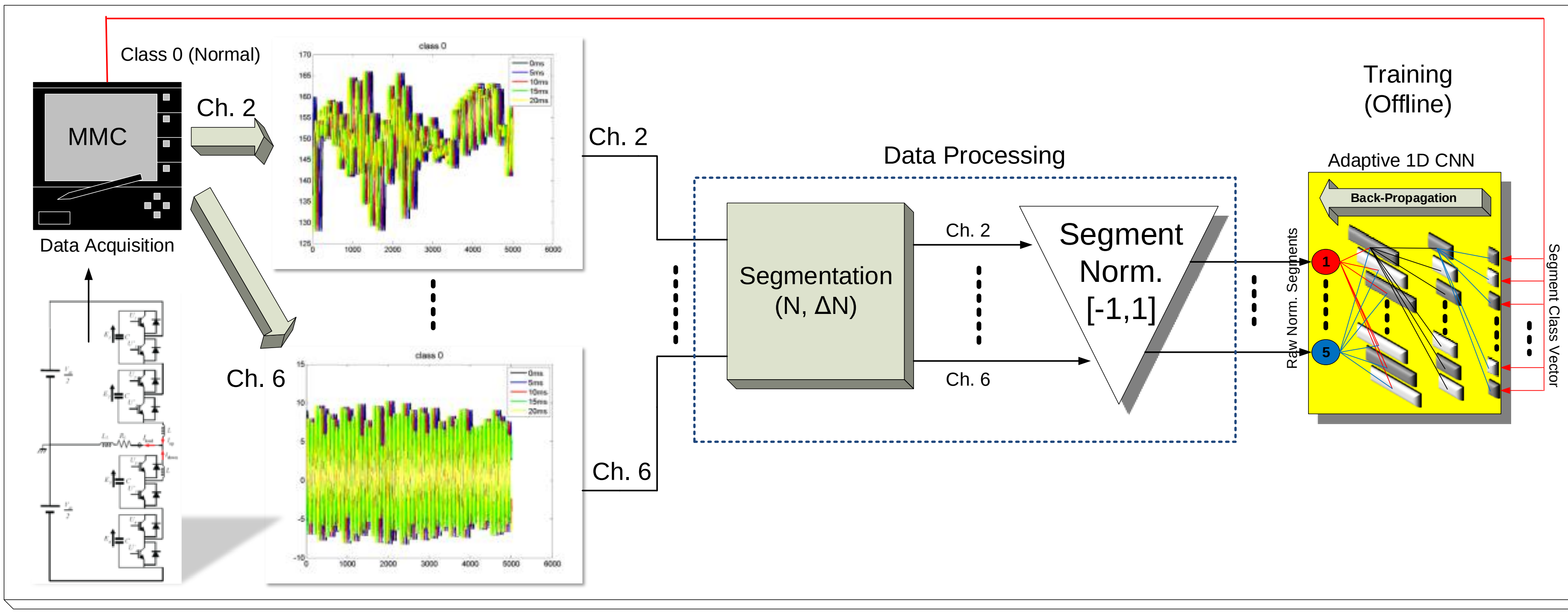
Implementation (left) and configuration (right) of the 4-cell MMC circuit



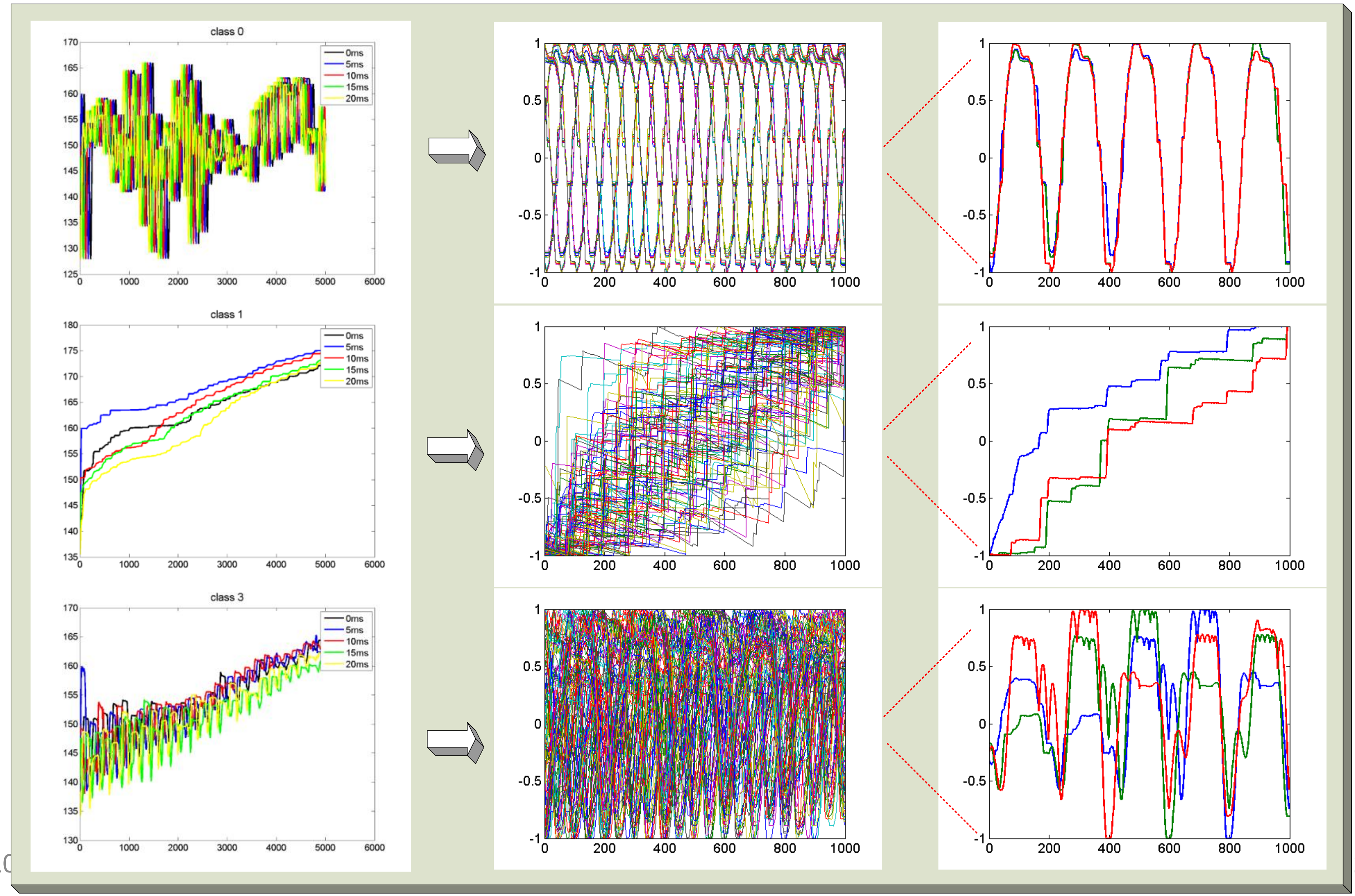


S. Kiranyaz, A. Gastli, L. Ben-Brahim, N. Al-Emadi, M. Gabbouj, Real-Time Fault Detection and Identification for MMC using 1D Convolutional Neural Networks, ***IEEE Transactions on Industrial Electronics*** (2018). doi:10.1109/TIE.2018.2833045.

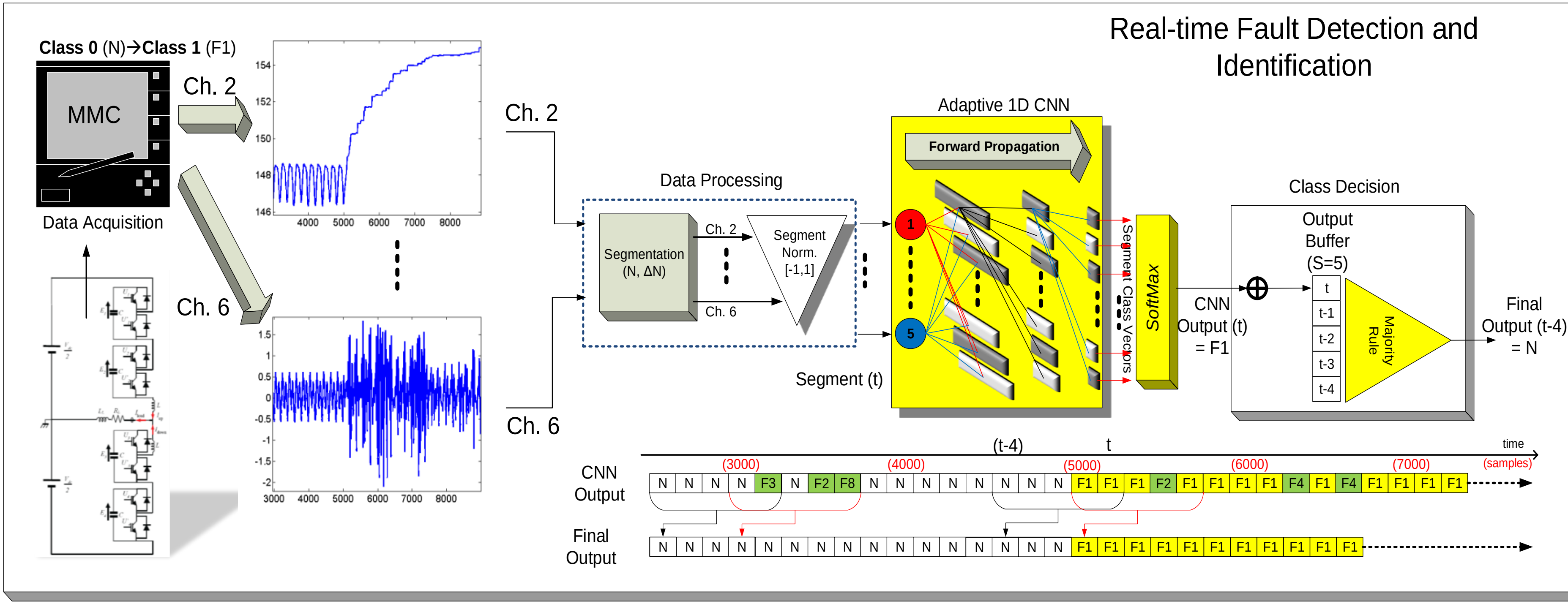
The main blocks of the proposed system and the offline training of the compact 1D CNN



The output of the data processing block over the cell1 capacitor voltage (channel 2) of the normal and 2 fault classes (classes 1 and 3) for I_{load}=1A.



The proposed system architecture for real-time fault detection and identification after the (offline) training of the 1D CNN..



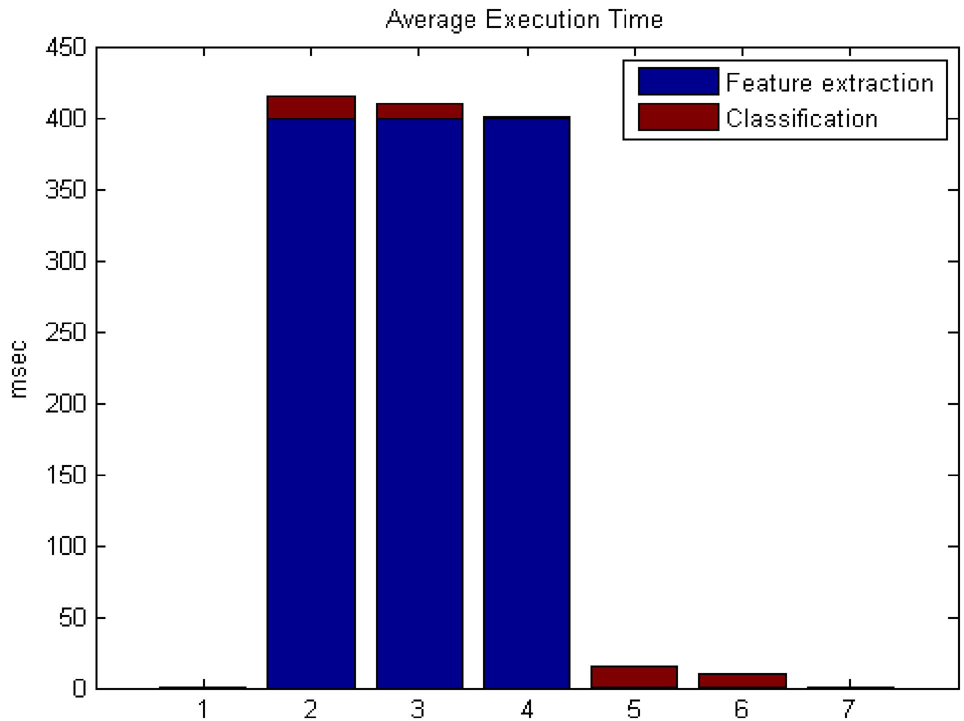
In the sample data acquisition above, the switch 1 in cell1 of the MMC circuitry failed at the sample 5000.

Computational Complexity

- In many applications covered in this study, it has been shown that 1D CNNs are relatively easier to train and offer the minimal computational complexity while achieving state-of-the-art performance levels.
- They are especially suitable for mobile or hand-held devices with limited computation power and battery life.
- For instance, specifically for the single-CPU implementation of ECG arrhythmia detection and identification method, the total time for a FP of a single beat to obtain the class vector is about 0.58msec and 0.74msec for 64 and 128 samples beat resolutions, respectively.
- Note that this speed is more than 1000x faster than the real-time requirement.

For the motor fault detection, the average execution times (in msec) of:

Leftmost bar plot 1: the 1D CNN method, bar plots and competing algorithms [1-4]



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[4] G.F. Bin, J.J. Gao, X.J. Li, B.S. Dhillon, Early fault diagnosis of rotating machinery based on wavelet packets - Empirical mode decomposition feature extraction and neural network, Mech. Syst. Signal Process. 27 (2012) 696–711. doi:10.1016/j.ymssp.2011.08.002.

Conclusions

- With a proper systematic approach, compact 1D CNNs can surpass conventional approaches.
- Compact 1D CNNs provide an advantage for those applications where labeled data is scarce, and where a low-cost and real-time implementation is desired.
- In many applications covered in this study, it has been shown that 1D CNNs are easier to train and offer the minimal computational complexity whilst achieving state-of-the-art performance.
- 1D CNNs papers are increasingly attracting attention; for instance, two recent 1D CNN publications cited earlier have immediately become *the most-popular* and *most-cited* articles in their journals.

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