Universidade de Pernambuco
Programa de Pós-Graduação em Engenharia da Computação (PPGEC)

Proposta de Dissertação de Mestrado

Área: Computação Inteligente

Título: Improving Multivariate Time Series Anomaly Detection with Novel Datasets and Representation Learning

Orientador(a): Diego Marconi Pinheiro Ferreira Silva (dmpfs@ecomp.poli.br)
Coorientador: Carmelo José Albanez Bastos Filho (carmelofilho@ecomp.poli.br)

Descrição:

Machine failure in the industrial sector can lead to social, economic, and environmental issues, jeopardizing worker safety, economic stability, and the availability of products to society [1-2]. To address these challenges, the industry is experiencing increased demand for predictive maintenance, which aims to detect early signs of imminent failure [3-4]. In this maintenance strategy, anomaly detection using machine learning models has been widely explored for Multivariate Time Series (MTS) derived from sensor data to identify unexpected behaviors [5-6]. Recent works have shown that complex, high-dimensional data, such as acoustic signals and vibrations, enable early-stage detection in the machine's failure path trajectory [7]. Despite this, from shallow to deep machine learning approaches struggle to handle multimodal, high-dimensional data, often disregarding powerful handcrafted feature extraction techniques and multiple representations (e.g., temporal, relational, frequency) of MTS [8]. In real-world applications, the industry has a wide variety of machines and environments. However, proposed machine learning approaches often lack in-distribution (ID) and out-of-distribution (OoD) analysis, providing limited evidence of robustness to changes in application scenarios [9-10]. In addition, datasets used for machine learning training and testing often lack detailed information on the data acquisition process and machinery conditions, motivating the development of new datasets to support anomaly detection and robustness analysis [11]. This proposal's main goal is to enhance and develop simpler to complex machine learning pipelines for handling complex MTS across ID and OOD scenarios by leveraging handcrafted feature extraction techniques, multiple MTS representations, and developing fine-grained multimodal datasets.

Referências Bibliográficas:

[1] Y. Chinniah, “Analysis and prevention of serious and fatal accidents related to moving parts of machinery,” Safety Science, vol. 75, pp. 163–173, June 2015, doi: 10.1016/j.ssci.2015.02.004.

[2] R. De Paula Monteiro, M. C. Lozada, D. R. C. Mendieta, R. V. S. Loja, and C. J. A. B. Filho, “A hybrid prototype selection-based deep learning approach for anomaly detection in industrial machines,” Expert Systems with Applications, vol. 204, p. 117528, Oct. 2022, doi: 10.1016/j.eswa.2022.117528.

[3] L. F. M. Filho, R. D. P. Monteiro, D. Pinheiro, P. T. Endo, and A. M. N. C. Ribeiro, “Forecasting Imminent Failures in Electrical Industrial Centrifuge using Machine Learning,” in 2023 IEEE Latin American Conference on Computational Intelligence (LA-CCI), Recife-Pe, Brazil: IEEE, Oct. 2023, pp. 1–6. doi: 10.1109/LA-CCI58595.2023.10409489.

[4] M. Cerrada et al., “A review on data-driven fault severity assessment in rolling bearings,” Mechanical Systems and Signal Processing, vol. 99, pp. 169–196, Jan. 2018, doi: 10.1016/j.ymssp.2017.06.012.

[5] H. Purohit et al., “MIMII Dataset: Sound Dataset for Malfunctioning Industrial Machine Investigation and Inspection,” Sept. 20, 2019, arXiv: arXiv:1909.09347. doi: 10.5281/zenodo.3384388.

[6] H. Zhou, K. Yu, X. Zhang, G. Wu, and A. Yazidi, “Contrastive autoencoder for anomaly detection in multivariate time series,” Information Sciences, vol. 610, pp. 266–280, Sept. 2022, doi: 10.1016/j.ins.2022.07.179.

[7] S. R. Saufi, Z. A. B. Ahmad, M. S. Leong, and M. H. Lim, “Challenges and Opportunities of Deep Learning Models for Machinery Fault Detection and Diagnosis: A Review,” IEEE Access, vol. 7, pp. 122644–122662, 2019, doi: 10.1109/ACCESS.2019.2938227.

[8] G. Pang, C. Shen, L. Cao, and A. van den Hengel, “Deep Learning for Anomaly Detection: A Review,” ACM Comput. Surv., vol. 54, no. 2, pp. 1–38, Mar. 2022, doi: 10.1145/3439950.

[9] J. Xu, M. Kovatsch and S. Lucia, "Open Set Recognition for Machinery Fault Diagnosis," 2021 IEEE 19th International Conference on Industrial Informatics (INDIN), Palma de Mallorca, Spain, 2021, pp. 1-7, doi: 10.1109/INDIN45523.2021.9557572. keywords: {Fault diagnosis;Deep learning;Training;Neural networks;Training data;Process control;Convolutional neural networks;fault diagnosis;open set recognition;deep learning},

[10] H. He, Q. Zhang, K. Yi, K. Shi, Z. Niu, and L. Cao, “Distributional Drift Adaptation with Temporal Conditional Variational Autoencoder for Multivariate Time Series Forecasting,” Apr. 02, 2024, arXiv: arXiv:2209.00654. doi: 10.48550/arXiv.2209.00654.

[11] Y. Koizumi, S. Saito, H. Uematsu, N. Harada, and K. Imoto, “ToyADMOS: A Dataset of Miniature-Machine Operating Sounds for Anomalous Sound Detection,” Aug. 09, 2019, arXiv: arXiv:1908.03299. doi: 10.48550/arXiv.1908.03299.