

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

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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.

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