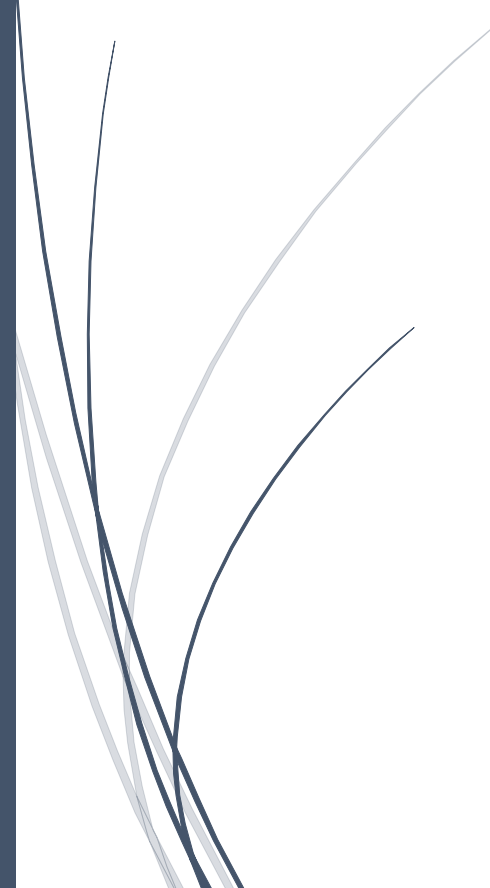


The logo for RADemics, featuring the text "RADemics" in white on a blue arrow-shaped background pointing to the right.

RADemics

Machine Learning- Based Fault Detection and Prognostics in Industrial Systems

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Machine Learning-Based Fault Detection and Prognostics in Industrial Systems

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Abstract

Machine learning (ML) has revolutionized fault detection and prognosis in industrial systems, offering unprecedented capabilities for predictive maintenance and real-time monitoring. The integration of advanced ML models, including supervised learning, deep learning, and data stream mining, has enabled industries to transition from reactive to proactive maintenance strategies. This chapter explores the applications of machine learning in fault detection and prognosis, highlighting the benefits of integrating these models within predictive maintenance frameworks. Emphasis is placed on the challenges associated with missing and incomplete data, as well as the role of uncertainty management in enhancing model reliability. By examining real-time fault monitoring through data stream mining, the chapter also underscores the importance of handling high-volume, high-velocity data streams for timely fault diagnosis and prognosis. Additionally, the chapter provides insights into hybrid machine learning models, which combine the strengths of various algorithms to improve fault diagnosis accuracy and decision-making. Through these discussions, this chapter contributes to the growing body of knowledge on leveraging machine learning for optimizing industrial system performance, reducing downtime, and ensuring the sustainability of operations.

Keywords: Machine Learning, Fault Detection, Prognostics, Predictive Maintenance, Data Stream Mining, Uncertainty Management.

Introduction

The rapid evolution of industrial systems, combined with advancements in data collection technologies, has led to a significant shift in the way maintenance is approached [1]. Traditional methods, which often rely on scheduled checks and reactive repairs, are increasingly being replaced by predictive maintenance strategies [2]. At the heart of this transformation lies machine learning (ML), a technology that enables the continuous analysis of vast amounts of sensor data to identify patterns, detect anomalies, and predict potential system failures before they occur [3]. By leveraging machine learning models [4], industries are able to optimize maintenance schedules, extend the lifespan of equipment, and reduce unplanned downtime, resulting in significant cost savings and improved operational efficiency [5].

Machine learning algorithms, such as supervised learning, unsupervised learning, and deep learning, have proven to be highly effective in identifying faults and predicting failures in complex

industrial systems [6]. These algorithms can process massive amounts of real-time data collected from sensors embedded in machinery, control systems, and production lines [7]. Through this data, machine learning models are capable of detecting minute deviations from normal operating conditions[8], allowing for the early detection of faults [9]. This proactive approach not only enhances the reliability of industrial systems but also facilitates the timely replacement or repair of parts, ensuring minimal disruption to operations [10].

The numerous advantages offered by machine learning in fault detection and prognosis [11], there are still significant challenges that must be addressed [12]. One of the primary obstacles is the quality of the data itself. Industrial systems often generate noisy [13], incomplete, or inconsistent data, which can hinder the effectiveness of machine learning models. Addressing these data quality issues requires advanced preprocessing techniques, such as noise filtering, imputation of missing values, and synchronization of data streams [14]. The ability to manage and preprocess data effectively is critical for the success of machine learning-based fault detection and prognosis systems [15].