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T.Pandiselvi ,C. Nagavani ,J.Vijaya Barathy
KAMARAJ COLLEGE OF ENGINEERING AND TECHNOLOGY,
KAMARAJ COLLEGE OF ENGINEERING AND TECHNOLOGY,
PERUNTHALAIVAR KAMARAJAR ARTS COLLEGE.

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1T. Pandiselvi, Associate Professor, Department of Electronics and Communication Engineering, Kamaraj College of Engineering and Technology, Vellakulam, Tamil Nadu, India. pandskt@gmail.com

2C. Nagavani, Assistant professor, ECE Department, Kamaraj College of Engineering and Technology, K.VellaKulam.(near Virudhunagar), nagavaniece@kamarajengg.edu.in

3J. Vijaya Barathy, Assistant Professor, Department of Computer Applications, Perunthalaivar Kamarajar Arts College, Pondicherry. barathyviji01@gmail.com

Abstract

The rapid expansion of critical infrastructure systems has led to an exponential increase in multi-modal sensor data, which demands advanced methods for anomaly detection to ensure operational reliability and safety. Autoencoders, a class of unsupervised deep learning models, have emerged as a powerful tool for analyzing complex and heterogeneous data streams. This chapter explores the application of autoencoders for anomaly detection in multi-modal sensor networks, emphasizing challenges such as data imbalance, missing modalities, and cross-domain adaptation. Advanced strategies, including transfer learning, fusion techniques, and domain adaptation, are discussed to enhance detection accuracy in new and evolving systems. Comprehensive evaluations of preprocessing methods, feature alignment, and model optimization are provided to address the nuances of multi-modal data handling. Metrics and evaluation frameworks tailored to multi-modal anomaly detection are outlined, offering critical insights into model performance and system robustness. The chapter highlights the significance of leveraging autoencoders to bridge the gap between diverse data modalities and optimize anomaly detection in critical infrastructure, laying a foundation for scalable, efficient, and resilient monitoring systems.

Keywords: Autoencoders, Multi-modal sensor data, Anomaly detection, Transfer learning, Data imbalance, Critical infrastructure systems.

Introduction

The proliferation of critical infrastructure systems, encompassing sectors such as energy, transportation, healthcare, and water management, has significantly increased reliance on multi-modal sensor networks [1-3]. These networks generate vast amounts of heterogeneous data in real-time, facilitating proactive monitoring and predictive maintenance [4]. Detecting anomalies within this data remains a substantial challenge due to its volume, complexity, and the diverse nature of the modalities involved [5]. Anomalies, which often signal critical system faults or security breaches, be subtle, rare, and distributed across multiple sensor types, making their detection imperative for maintaining operational efficiency and preventing catastrophic failures [6-7]. This necessitates the adoption of advanced analytical approaches capable of addressing the intricate demands of multi-modal anomaly detection [8-10].

Autoencoders, a specialized class of neural networks, have gained prominence for their ability to model high-dimensional and complex data patterns without requiring labeled datasets [11]. These models operate by learning compressed representations of input data through dimensionality reduction and reconstruction, allowing them to identify deviations from expected patterns [12]. In the context of multi-modal sensor networks, autoencoders are particularly well-suited for anomaly detection ascan simultaneously analyze data streams from different sensors while capturing correlations across modalities [13-14]. The integration of multi-modal data presents unique challenges, including the need for effective data fusion, synchronization, and handling missing or imbalanced data [15].

A critical aspect of applying autoencoders in multi-modal systems was ensuring robust data preprocessing and fusion. Multi-modal data often involves varying sampling rates, units, and scales across sensors, requiring normalization and alignment techniques to achieve consistency [16]. Designing fusion strategies that preserve inter-modality relationships was essential for enhancing detection accuracy [17]. Strategies such as early, late, and hybrid fusion are explored to optimize the integration of sensor data for effective anomaly detection [18]. The choice of fusion strategy directly impacts the model's ability to capture meaningful patterns and relationships within the data, influencing its performance in identifying anomalies [19-20].