RADemics

Application of Convolutional Neural Networks in Real-Time Monitoring and Anomaly Detection

Sajitha M , J.Jasmine Hephzipah, C.Saravanakumar,
AJK COLLEGE OF ARTS AND SCIENCE, R.M.K. ENGINEERING COLLEGE, SRM VALLIAMMAI ENGINEERING COLLEGE.

4 Application of Convolutional Neural Networks in Real-Time Monitoring and Anomaly Detection

1Sajitha M, Asst professor & HoD, Department of Artificial Intelligence and Machine learning, AJK College of Arts and Science, Coimbatore. sajithas.mannadiar@gmail.com

2J.Jasmine Hephzipah, Department of Electronics and communication (Advanced Communication Technology), R.M.K. Engineering College, R.S.M.Nagar, Kavaraipettai, Thiruvallur Dt. jazzjoell@gmail.com

3C.Saravanakumar, Assistant Professor, Department of Electronics and Communication Engineering, SRM Valliammai Engineering College, Kattankulathur, India 603203. kanchi.saravana@gmail.com

Abstract

The application of Convolutional Neural Networks (CNNs) in real-time monitoring and anomaly detection has revolutionized industries by enabling automated, efficient, and accurate systems for identifying irregularities and patterns in complex datasets. This chapter explores the fundamental principles, architectural components, and advanced techniques that define CNNs, with a focus on their practical applications in real-time scenarios. Special attention was given to the integration of CNNs in monitoring systems, wherefacilitate continuous, high-performance analysis of sensor data, video feeds, and other real-time inputs, detecting anomalies thatotherwise go unnoticed. By examining various CNN architectures, including Inception Networks and Residual Networks, the chapter highlights how these models optimize computational resources while maintaining accuracy. Strategies such as transfer learning and fine-tuning are discussed as effective methods for adapting CNNs to diverse applications with limited data. The chapter also emphasizes the challenges in training CNNs, including the need for efficient learning rate scheduling and the prevention of overfitting. The findings presented in this chapter serve as a comprehensive guide to the evolving landscape of CNN-based real-time monitoring systems, showcasing their transformative potential across fields such as healthcare, manufacturing, and security.

Keywords: Convolutional Neural Networks, Real-Time Monitoring, Anomaly Detection, Inception Network, Residual Networks, Transfer Learning.

Introduction

Convolutional Neural Networks (CNNs) have revolutionized the landscape of real-time monitoring and anomaly detection, enabling systems to identify irregularities in complex datasets quickly and accurately [1]. With the growing volume and complexity of data generated in modern industries, traditional methods of detecting anomalies are becoming increasingly inefficient [2]. CNNs have demonstrated significant potential to address these challenges by offering automated solutions that can analyze high-dimensional data, such as images, sensor readings, and video streams, in real-time [3]. Their ability to learn hierarchical features from raw data makes them uniquely suited for tasks that require quick identification of outliers and anomalous patterns [4-5].

In real-time monitoring systems, the primary goal was to provide continuous, accurate analysis of incoming data streams [6]. CNNs achieve this by utilizing multiple layers that extract features at varying levels of abstraction, allowing the model to learn complex patterns within the data [7]. In industrial applications, CNNs can monitor sensor outputs for signs of malfunction or performance degradation [8]. In medical diagnostics, can analyze patient data for early signs of disease or abnormal behavior [9]. This capability to detect anomalies in real-time can significantly reduce response times and improve decision-making, ultimately enhancing operational efficiency and safety in various domains [10].

Applying CNNs to real-time anomaly detection introduces a set of challenges, particularly with regards to optimizing computational resources and ensuring model accuracy [11]. Real-time systems must operate under stringent time constraints, which means the models must be not only accurate but also efficient [12]. CNNs can be computationally expensive, especially when applied to large datasets [13]. This has led to innovations such as the Inception Network and Residual Networks, which allow for more efficient use of computational resources by incorporating techniques like dimensionality reduction and skip connections [14]. These architectures ensure that CNNs can operate in real-time without sacrificing performance, even in resource-limited environments [15].