



EDITORIAL

Guest Editorial Special Issue on Industrial Big Data and Artificial Intelligence-Driven Intelligent Perception, Maintenance, and Decision Optimization in Industrial Systems

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1 Introduction

In recent years, the rapid development of industrial big data and artificial intelligence (AI) technologies has revolutionized the industrial landscape. Industrial systems, such as manufacturing, energy, transportation, and logistics, have become increasingly complex, generating vast amounts of data [1–3]. These big data encompass a wide range of data sources, including sensor data, production logs, and maintenance records, which hold valuable insights [4–6]. Moreover, machine learning-based AI techniques can be applied to extract meaningful insights from this big data [7]. For example, deep learning allows machines to interpret and understand multisensory information, which can be utilized for quality control, defect detection, and object recognition in industrial systems. Transfer learning can improve predictive maintenance models, anomaly detection, and fault diagnosis by transferring knowledge learned from similar systems. Reinforcement learning empowers machines to learn from trial and error, making it suitable for optimization problems in industrial systems [8–10]. As such, the integration of industrial big data and AI enables intelligent perception, maintenance, and decision optimization, driving the intelligent upgrade of enterprises and enhancing productivity and quality. This special issue aims to bring together researchers and practitioners from academia and industry to explore the latest advancements in industrial big data and AI-driven intelligent perception, operation, and decision optimization in industrial systems. Submissions for this special issue in *Computers, Materials & Continua* are open from 13 November 2023 to 31 October 2024 and contain 11 outstanding papers in the above research fields.

2 Articles Included in the Special Issue

Pavement crack detection is of significant importance for road safety and infrastructure management. Alshawabkeh et al. [11] proposed the MaskerTransformer model, which combines the local segmentation precision of Mask R-CNN with the global contextual awareness of Vision Transformer (ViT), to enhance the accuracy and adaptability of pavement crack detection. The model was evaluated using two benchmark datasets, Crack500 and DeepCrack. The results showed that



MaskerTransformer significantly outperforms existing methods in terms of segmentation accuracy, recall, and Dice Similarity Coefficient (DSC). The proposed method demonstrates strong robustness and high reliability under diverse pavement conditions, enabling more efficient automated pavement crack detection. Meanwhile, Farooqui et al. [12] utilized Convolutional Neural Networks (CNN) along with two pre-trained models, YOLOv8 and EfficientNetB0, to enhance the accuracy of industrial corrosion detection. By comprehensively optimizing the dataset and training methods, the proposed approach achieved up to 100% accuracy, precision, recall, and F1-score. The experimental results demonstrate that, compared to current state-of-the-art methods, the new models exhibit stronger robustness and generalization across multiple industrial scenarios, providing valuable insights for future research in corrosion detection.

The fault diagnosis technology is crucial in the operation of industrial equipment as it can detect potential weak faults in advance, thereby effectively improving production efficiency and the safe operation capability of the equipment. Bai et al. [13] proposed a weak fault feature extraction method combining Flexible Analytic Wavelet Transform (FAWT) and Nonlinear Quantum Permutation Entropy (QPE) for fault diagnosis of rotating machinery. FAWT enhances the ability to capture weak fault features by adjusting frequency partitioning and oscillatory bases, while QPE improves the accuracy of vibration signal state representation through quantum theory. Experiments show that this method demonstrates excellent classification performance in rolling bearing and gearbox fault detection, with an improved recognition accuracy compared to traditional methods, validating its effectiveness and practicality. Chen et al. [14] proposed a multi-sensor fusion tensor machine based fault diagnosis scheme for railway switch machine, aiming to enhance the fault detection capabilities of switch machines in practical applications. By preprocessing one-dimensional signal data into two-dimensional images and generating fusion feature tensors using three-phase current data, the scheme utilizes tensor learning models for efficient diagnosis. Compared to existing methods, this approach significantly preserves the spatial structure information of time-series data and has demonstrated superior performance in terms of accuracy, recall, and F1-score through field data validation. The study provides effective technical support for the health monitoring and intelligent maintenance of railway switch machines. Liu et al. [15] proposed a complementary-label adversarial domain adaptation fault diagnosis network (CLADAN) to address the cross-domain fault diagnosis of machinery under time-varying rotational speed and weakly-supervised conditions. By introducing a low-cost complementary-label labeling method, combined with adversarial regularization and classification probability discretization strategies, the model significantly improves robustness and classification confidence. Additionally, virtual adversarial training enhances domain adaptation capabilities, enabling the model to perform accurate diagnosis even under the uncertainty conditions of the target domain. Experiments on rolling bearing and wind turbine gearbox datasets validated the effectiveness of the method, showing that the model outperforms existing techniques in terms of diagnostic accuracy and adaptability. Wang et al. [16] proposed a lightweight CNN-Transformer framework for rotating machinery fault diagnosis. By designing a separable multiscale depthwise convolution block (SMDC) and an efficient self-attention module (ESA), the model is able to extract and integrate local and global features while reducing computational complexity. Compared to existing CNN-Transformer models, SEFormer significantly reduces the model complexity while maintaining high diagnostic performance, making it more suitable for industrial applications.

Improving network resilience is crucial for ensuring reliable operation. Guo et al. [17] proposed an intelligent framework based on spatio-temporal aggregation and multi-head attention mechanisms to address the resilience recovery issues of Flying *Ad Hoc* Networks (FANETs) in dynamic topologies and disruptive environments. First, the framework constructs an optimization model by introducing a

task resilience metric, combining the network's connectivity and coverage status information. Then, a spatio-temporal node pooling method is proposed to update node location features after node damage. Finally, a recovery algorithm based on a multi-head attention graph network is designed to achieve rapid recovery. Experimental results show that this method outperforms existing studies in recovering connectivity and coverage performance, with improvements of 17.92% and 16.96%, respectively. The contributions of each improvement were quantified through ablation experiments, validating the model's potential for real-time task execution. To enhance the resilience of the Unmanned Weapon System-of-Systems (UWSOS) network, an Enhanced-Resilience Multi-Layer Attention Graph Convolutional Network (E-MAGCN) was proposed by Wang et al. [18]. The proposed method combines BERT to extract semantic information from nodes and edges, utilizing a regularization-based multi-layer attention mechanism and a semantic node fusion algorithm, significantly enhancing the resilience of UWSOS. Experimental results in various interference scenarios demonstrate that E-MAGCN outperforms existing methods in resilience, with an improvement range of 1.2% to 7%.

Fault diagnosis models often rely on large amounts of high-quality labeled data. Addressing the issue of data scarcity can significantly improve the model's performance. Song et al. [19] proposed an innovative method based on ETL (Extract-Transform-Load) technology to construct the ACXray dataset of customs contraband X-ray images, addressing the issues of insufficient existing datasets and difficulties in model transfer for practical applications. The study integrates X-ray image data from various sources through real-time data collection, cleaning, and fusion techniques, and improves the efficiency and accuracy of data annotation by combining neural networks with manual labeling. Additionally, the use of target and background fusion techniques expanded the number of positive samples, alleviating the dataset imbalance issue. Experimental results show that deep learning algorithms (such as Mask R-CNN) trained with the ACXray dataset significantly improve recognition accuracy in real customs scenarios, demonstrating strong generalization ability and potential for engineering applications. Chen et al. [20] proposed an interpolation method based on the GMDH (Group Method of Data Handling) network to address the issue of missing electricity consumption data in power systems. By incorporating prior knowledge to determine the upper and lower limits of missing data, and using random interpolation along with the optimal complexity model to predict missing values, they developed an efficient iterative interpolation algorithm. The method significantly improved the integrity of the electricity data, with experiments showing small errors at different noise levels (with a maximum error of no more than 0.605%). This study not only provides technical support for abnormal electricity consumption analysis and power metering fault diagnosis but also demonstrates potential applications in scenarios requiring high-quality data.

To address the issue of driver fatigue state detection being easily affected by external environmental factors and having poor reliability, Zhang et al. [21] proposed a multi-modal fatigue detection method based on information fusion. By integrating facial image features and physiological signals, a fatigue detection device and a simulated driving experiment platform were designed to collect multi-source data during driving. Feature layer fusion was performed using multi-kernel learning and canonical correlation analysis methods, significantly improving detection accuracy. Experimental results show that the fused model achieved a detection accuracy of up to 94%, outperforming single-mode detection methods, demonstrating the potential of multi-modal information fusion in driving fatigue detection.

3 Conclusion

In conclusion, the integration of industrial big data and artificial intelligence technologies is transforming industrial systems, enabling intelligent perception, enhanced maintenance, and optimized

decision-making. The rapid growth of industrial big data has provided new opportunities for extracting valuable insights through machine learning and AI techniques. Methods such as deep learning, transfer learning, and reinforcement learning offer powerful solutions for fault diagnosis, predictive maintenance, and optimization problems. As industries continue to evolve, we foresee that AI-driven technologies and the application of big data will play a crucial role in driving productivity, improving operational efficiency, and facilitating the intelligent upgrading of enterprises.

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