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EDITORIAL

Introduction to the Special Issue on Machine Learning-Guided Intelligent Modeling with Its Industrial Applications

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With the advancement of Artificial Intelligence (AI) technology, traditional industrial systems are undergoing an intelligent transformation, bringing together advanced computing, communication and control technologies, Machine Learning (ML)-based intelligent modelling has become a new paradigm for solving problems in the industrial domain [1–3]. With numerous applications and diverse data types in the industrial domain, algorithmic and data-driven ML techniques can intelligently learn potential correlations between complex data and make efficient decisions while reducing human intervention. However, in real-world application scenarios, existing algorithms may have a variety of limitations, such as small data volumes, small detection targets, low efficiency, and algorithmic gaps in specific application domains [4]. Therefore, many new algorithms and strategies have been proposed to address the challenges in industrial applications [5–8].

This special issue focuses on ML-guided intelligent modelling with its industrial applications and contains 1 review article and 14 research articles. The authors proposed their original improved algorithms to address the objective limitations that are difficult for computers to manage properly in the current industrial domain. These articles will contribute to the development of intelligence in industrial systems and provide effective references for future research.

The published papers in this special issue are herein briefly introduced as follows:

Load estimation is of great importance for reducing the cost of power generation. A deep learning-based load estimation algorithm using image fingerprint and attention mechanism was proposed in [9]. For image fingerprint construction, the measurement vector is first processed by cyclic shift and cubic spline interpolation. Then, the matrix is transformed into a color image by the proposed mapping function and grey-color transformation. To optimize the Convolutional Neural Network (CNN) structure, the Convolutional Block Attention Module (CBAM) is integrated to improve the quality of the feature representation.

Detecting small targets in optical remote-sensing images has always been a challenging task. To avoid subtle feature loss and noise interference during the deep learning process, the authors in [10] proposed Cross-Layer Fusion and Weighted Receptive Field-based YOLO (CAW-YOLO). Specifically, based on YOLOX-S, a novel variant of CBAM is used to preserve the information of small objects, and a weighted multi-receptive field atrous spatial pyramid pooling module is incorporated to dynamically adjust the weight of feature maps in different receptive fields. The proposed model can effectively filter the background noise and enhance the ability of the model to perceive small objects. In [11], the authors introduced a small target detection method for the classification of remote sensing images, which uses K-Nearest Neighbour (KNN) to extract local feature and fuses the local feature with the feature extracted by CNN. The combination of local feature and deep learning feature significantly improves the detection accuracy of the model for small objects.

Graph-based machine learning is a powerful tool, and its industrial applications have grown continuously in recent years. How to address the challenges of "distant node modelling deficiency" and "failure of the homophily assumption" that Graph Neural Networks (GNNs) face when dealing with heterophilic graphs is a topic that is currently being actively explored in the research community. In [12], the authors constructed the distant spatial embedding module and the proximal frequency embedding module to address the above issue. First, the concept of structural similarity is introduced for distant nodes during the structural encoding stage by high-order random walks originating from each node. Then, an adaptive filter is designed to effectively fuse the high and low-frequency signals from proximal nodes to reduce the noise interference caused by the failure of the homophily assumption. In [13], the authors proposed a graph model-based Transmission Line (TL) Parameter Identification (PI) method, which can consider the topological connection of multiple branches for simultaneous identification. The power grid data is transformed into a graph, and graph neural networks extract the topological constraint information. Since the topology constraint information is invariant under changing noise, the proposed method is robust to transient mixing and data contamination problems. Furthermore, a hard parameter-sharing multi-task strategy is adopted to reduce model redundancy.

Knowledge Graph (KG) is defined as a semantic network composed of nodes and directed edges, where the node represents an entity, and the edges interlink these nodes to construct the relationships between entities. With the rapid development of machine learning algorithms, KG construction techniques and application areas are becoming more diversified. In [14], the authors comprehensively reviewed the existing research and literature related to machine learning-based KG construction method. The challenges and open research issues are also critically discussed in the paper. The authors' work provided an effective reference for researchers in related fields. In [15], the authors constructed a software code Pull Request (PR) revision recommendation model based on KG. To develop a computer-aided automatic PR screening system to quickly help reviewers select valuable PRs and help contributors resolve simple errors, the authors first proposed a multi-dimensional feature-based PR review result prediction method, which uses a random forest classifier to analyze the filtered features and decide whether the PRs pass the review or not. For the unaccepted PRs, the authors constructed a PR review knowledge graph and recommended PR revisions to contributors through graph-based similarity calculation.

In [16], the authors introduced a Deep Adaptive Evolutionary Ensemble model applied to user purchase intention prediction, which effectively mitigates the limitations of deep neural networks in terms of data volume and hyperparameters. The model consists of a model selection layer and a cascading layer. The Binary Differential Evolution algorithm is used for model selection in the model selection layer. A feature importance weighting strategy and meta-classifiers are introduced in the cascading layer to optimize the network structure. The experimental results show that the authors' deep ensemble learning strategy improves the model's robustness, accuracy and operational efficiency.

In order to prevent failures and abnormal processes, industrial plants often need to monitor the working status of platforms during operation. The inertial system platform is an important precision equipment applied in many industrial fields, and it is characterized by the difficulty of state data collection and small data set size. In [17], the authors focused on system health monitoring and fault prediction and proposed a fast small-sample one-class SVM modelling method with non-support vectors pre-elimination. Experimental results of the model proposed in the paper for inertial devices demonstrate good fault prediction capability for small sample data and improved prediction efficiency. In [18], the authors presented a novel method for constructing a health degree model and a condenser cleaning time prediction model. Exposure of condensers to seawater can cause scaling and corrosion issues, and determining the appropriate condenser cleaning time is important for improving the condensing system's operational reliability and the turbine unit's economic efficiency. The authors proposed an improved high-dimensional Mahalanobis distance function to monitor the health state. Based on the health degree model, a combined prediction model based on Generalised Correntropy-Informer-Markov Error Correction (GC-Informer-MEC) is established to predict the condition trend of deterioration. The calculated condition of the condenser using the proposed approach is congruent with its actual condition based on the examination of field time series data, which provides a more accurate prediction of the equipment cleaning time.

Degraded images tend to affect the performance of deep neural networks in image classification. In [19], the authors discussed the performance of three currently commonly used CNN networks in classifying degraded images and proposed a Degradation Type Adaptive Image Classification Model (DTA-ICM) for degraded image classification. Considering six common types of degradation, the proposed model first predicts the type of degradation and then activates the corresponding classifier to obtain the final classification result.

Robots and humans may take turns as leaders and followers in performing human-robot cooperation tasks and giving robots specific initiatives can lead to more efficient and smoother task completion. In [20], the authors proposed a real-time adaptive role allocation method based on reinforcement learning for human-robot cooperation, which dynamically adjusts the role weight of the robot during work in response to different tasks. The authors established a human-robot cooperation model for installing glass curtain wall units and designed a reward and action mechanism for the reinforcement learning module. The proposed model achieved timely adjustment of the robot's role during the installation process, improved work efficiency, and fully exploited the advantages of both human and robot.

To improve the ability of electric vehicles to accurately identify charging ports and avoid obstacles in complex real-world environments, in [21], the authors proposed an improved rapidly exploring random trees (RRT) algorithm to plan a smooth and continuous curvature-optimized path for vehicles, which effectively saves path search time and distance. Specifically, the proposed path planning algorithm obtains an asymptotically optimal and collision-free path through continuous iterative search and optimizes the final result based on the B-sample curve.

In [22], an application of machine learning in numerical computation was investigated. The Boundary Element Method (BEM) is a numerical method for solving partial differential equations (PDEs) that can be transformed into Boundary Integral Equations (BIEs). The authors developed a robust, accurate and efficient numerical integration scheme for BEM based on an Artificial Neural Network (ANN) that can quickly find mapping relationships between complex data. Specifically, the authors used a neural network classification algorithm to predict the minimum number of Gaussian quadrature points for a given accuracy, and the model achieved 90% prediction accuracy for the two-dimensional potential problem of a circular structure.

Various industrial infrastructures are part of our modern way of working and living, and the threat of malware to industrial systems is a pressing issue. In [23], the authors incorporated a transfer learning strategy and proposed a novel network architecture for malware sequence classification using one-dimensional convolution. Malware Application Programming Interface (API) sequences are transformed into vectors during data preprocessing and fed into a convolutional network for feature extraction. The authors experimentally selected the appropriate transfer strategy: transfer the weights of the top two convolutional layers of the pre-trained model. Experimental results on six tasks show that the 1-D convolutional architecture effectively learns transferable features.

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