Innovative Application of Intelligent Mechanical Manufacturing Based on Self-Supervised Learning and Graph Neural Network Fusion Optimization

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Keywords: self-supervised learning, graph neural networks, pre-training, intelligent manufacturing, optimization models

Received: November 14, 2024

In the current context of industrial automation, with the rapid development of the Internet, artificial intelligence and other technologies, intelligent mechanical manufacturing technology has received widespread attention. The study builds an intelligent manufacturing optimization model using methods based on self-supervised learning and graph neural networks to address the issue of insufficient efficiency and accuracy in mechanical manufacturing. Based on the traditional manufacturing method, the comparison self-supervised learning model is utilized to mine the available data and monitor the quality of mechanical equipment by constructing pre-training tasks to improve the efficiency of equipment production. Then it is fused with graph neural networks to design intelligent manufacturing optimization model based on self-supervised learning and graph neural networks intelligent manufacturing. The experimental results indicated that the comprehensive performance and practical application of the research model were good on both. Compared to the three performance types of multi-behavior models on different datasets, the model improved by 10.8%, 8.5%, and 6.3%, respectively. The noise robustness of the research model improved by 5.36% and 6.27% compared to the NGCF and EHCF models, respectively. The performance of the research model reached its optimal state when the selected parameters were β=0.01, K=30, and L=2. The results demonstrate that the designed optimization model based on self-supervised learning and graph neural networks intelligent manufacturing has advantages in terms of operational efficiency and index performance. The research results are of great significance for intelligent mechanical manufacturing.

Povzetek: V članku je opisan inovativen optimizacijski model inteligentne mehanske proizvodnje na osnovi samonadzorovanega učenja in grafovskih nevronskih mrež (GNN), ki izboljša učinkovitost in robustnost proizvodnje (do 10,8 %).

1 Introduction

Today, with the continuous development of information network and artificial intelligence (AI), automation technology is silently penetrating and changing people's way of life at an unprecedented speed. Intelligent mechanical manufacturing, as a necessary path for industrial automation, has been increasing in market demand, and the traditional manufacturing methods are no longer able to meet the demand [1-2]. This phenomenon not only originates from the surge of market demand for product personalization and customization, but also because of the increasingly fierce competition in the global market, which requires enterprises to be able to respond to market changes more quickly and realize product iteration and upgrade [3]. With its strong automatic recognition capability, machine learning (ML) approaches have drawn the attention of several researchers in recent years who are attempting to predict possible equipment failures of machinery. However, the existing ML techniques are still insufficient in terms of recognition efficiency and accuracy, and the wide range of applications cannot meet the basic requirements of intelligent mechanical manufacturing [4]. The primary concerns have centered on the utilization of self-supervised learning (SSL) and graph neural networks (GNNs) technologies to enhance the accuracy and efficiency of intelligent recommendation systems in mechanical manufacturing processes, with a focus on improving anomaly detection and fault prediction. SSL is one of the most classical techniques in ML technology. By analyzing the data generated during the operation of mechanical equipment to identify abnormal patterns, the effect of quality detection can be achieved. Moreover, GNN, as a tool for information aggregation (IA) and transfer, can capture the complex relationship between users and equipment for the recommendation of relevant mechanical parts [5]. In this context, to improve the efficiency and accuracy of mechanical manufacturing, the study attempts to innovatively design an optimization model based on SSL and GNN intelligent manufacturing. The novelty of the research lies in the introduction of heterogeneous graphs and meta-paths to combine SSL with GNN to innovatively improve anomaly detection and failure prediction capabilities in intelligent mechanical manufacturing. This integration not only improves the model performance, but also enhances the adaptability and generalizability to complex industrial scenarios. It aims to provide a technical foundation for intelligent mechanical manufacturing that can improve production efficiency and quality.

2 Related works

With the intelligent and automated development of the manufacturing industry, the traditional manufacturing methods have been unable to meet the production needs, while intelligent mechanical manufacturing has become an important trend in the development of the manufacturing industry. As a result, numerous academics have studied intelligent mechanical manufacturing techniques in related fields. He H combines deep reinforcement learning with graph neural networks (GNN) to propose an intelligent network traffic scheduling algorithm to solve traffic scheduling problems in large-scale dynamic network environments. This algorithm leverages the decision-making capabilities of deep reinforcement learning and the advantages of GNNs in processing graph structured data to achieve an efficient decision-making process from macro strategy formulation to micro-operation execution through a hierarchical reinforcement learning framework. The experimental results show that the algorithm exhibits excellent robustness and generalization ability [6]. Sharma T et al. constructed fuzzy ensemble technology based on mathematical analysis of trust scores and deep neural networks to promote the research of automatic ALSC. The proposed method can correct the misclassification of basic deep learners through reward and punishment strategies. The experimental results conducted on five benchmark datasets show that this method has advantages over component-based deep neural networks and other important benchmarks [7]. Yao X et al. proposed a blockchain-based value-added industrial meta-universe solution for intelligent manufacturing based on cyber-physical systems. The study used intelligent manufacturing social technology, enhanced intelligent manufacturing architecture and framework to achieve high resource utilization. The results indicated that the proposed scheme was intelligently resilient and sustainable [8]. Aldrini J et al. proposed intelligent fault diagnosis and self-healing conceptual model architecture for intelligent manufacturing system to overcome the performance and safety issues of intelligent manufacturing. The approach improved the performance of intelligent manufacturing systems through fault detection as well as self-healing fault-tolerant strategies. Experimental results indicated that the proposed structure had a good robustness [9]. To facilitate intelligent decision-making in dynamic scheduling and reconfiguration, Yang S. suggested a mathematical model of intelligent scheduling based on deep reinforcement learning. According to test results, the suggested model has good scheduling efficiency [10].

Intelligent mechanical manufacturing often introduces artificial networks and ML methods for research, and several scholars have conducted research on SSL and GNN. Krishnan R proposed self-supervised methods and models for medicine and healthcare in response to the problem of medical AI development. The study investigated SSL's benefits and drawbacks while creating models with multimodal datasets. The suggested approach could hasten the development of medical AI, according to the findings [11]. Rani V et al. proposed SSL detection for image processing problems. The study used unstructured and unlabeled data to develop an AI system to perform downstream computer vision tasks. The findings indicated that this method had good applicability [12]. Kumar P incorporated contrast learning into SSL to investigate the conditions of application in different domains. The findings indicated that this method has positive significance for complementary contrast learning [13]. To address the issue of information overload, Wu S. et al. presented a recommendation model based on GNN. The method provided information categorization based on the type of information used and the recommendation task, and extracted content from the interaction information. Numerous experiments indicated that the proposed method had a good stability [14]. Zhou Y proposed a new classification method to overcome the limitations of GNN. The study categorized the GNN into the corresponding categories after showing the full picture of the GNN. The test results indicated the superiority of the proposed approach in categorization [15]. The summary and analysis of existing research methods are shown in Table 1.

Table 1: Summary and analysis of currently available research methods

Methodologies	Performance indicators	Gaps	Limitations	Unique requirement
He H [6]	Network traffic scheduling efficiency	Traffic scheduling problem in large-scale dynamic network environment	The efficiency and robustness of traditional algorithms in handling large-scale dynamic networks	Improve scheduling efficiency and robustness
Sharma T et al. [7]	Automatic ALSC	Integrated	Error classification	Improve the

	performance	technology of mathematical analysis based on trust scores and deep neural networks	of basic deep learners	accuracy and robustness of automatic ALSC
Yao X et al [8]	Speed of redeployment of resources	Slow to respond to market changes	Lack of real time	Real-time resource allocation
Aldrini J et al [9]	Self-healing time	Slow response of self-healing systems	Limited ability to self-heal	Rapid self-healing ability
Yang S. [10]	Movement control accuracy	Poor adaptation of highly dynamic scheduling	Inadequate adaptation	Dynamic Scheduling Adaptation
Krishnan R [11]	generalization capability	Inadequate ability to generalize medical data	Limitations of multimodal data processing	Multimodal data processing
Rani V et al [12]	Outlier detection rate	Poor handling of image processing outliers	lack of robustness	Enhanced robustness
Kumar P [13]	Cross-domain accuracy	Insufficient flexibility in cross-cutting applications	Poor cross-cutting adaptation	Cross-cutting adaptability
Wu S. et al. [14]	processing speed	Poor stability of massive data processing	information overload	Information processing efficiency
Zhou Y [15]	Classification accuracy	Poor classification of complex network structures	Insufficient classification accuracy	Improvement of classification accuracy

To summarize, although many experts and scholars have carried out related research on intelligent mechanical manufacturing, there has not been an approach that combines with SSL and GNN. In view of this, the study proposes an intelligent mechanical manufacturing model based on SSL and GNN. The study combines the data characteristics and technological advantages of real-world application scenarios to construct a supervised networked intelligent manufacturing innovation approach. This can improve production efficiency and quality and contribute to expanding the innovative applications of intelligent mechanical manufacturing.

3 Intelligent mechanical manufacturing method based on SSL and GNN

3.1 Intelligent mechanical manufacturing design based on SSL

With the increasing demand for intelligent mechanical manufacturing, the traditional manufacturing methods are more and more incompetent in terms of efficiency, precision and flexibility [16]. Therefore, it is necessary to propose an innovative manufacturing program that can improve the production efficiency and product quality of mechanical manufacturing. The SSL technique has gained a lot of traction in ML in recent years. From a vast amount of unlabeled data, it automatically learns usable feature representations by using the properties of the data itself as supervised information. When compared to conventional supervised learning techniques, SSL shows a more potent and adaptable approach to data use. Its core advantage lies in getting rid of the reliance on external labels and utilizing the internal structure and properties of the data to automatically generate supervised signals [17]. This feature enables SSL to generate the potential to effectively mine large-scale data. Fig. 1 depicts the SSL model.

In Fig. 1, the SSL model learns advanced representations or features of data by designing pre-training tasks. The pre-training task of SSL is designed as contrastive learning, which involves data encoding, positive and negative sample pair generation, and similarity comparison operations in sequence. These pre-training tasks help the model extract useful information from data without external labels, improving the model's ability to detect abnormal patterns in mechanical manufacturing processes. Therefore, it can be migrated to other related supervised learning tasks for efficient and accurate model training. The SSL algorithmic models can be categorized into three types: adversarial, generative, and comparative models. Since intelligent mechanical manufacturing requires comparative damage determination, the study mainly uses comparative SSL models for learning. Fig. 2 depicts the contrastive model's structure.

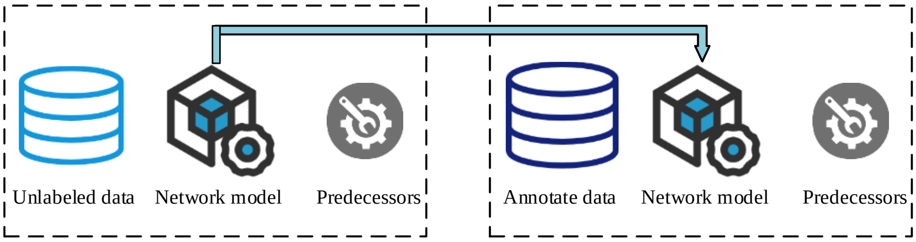


Fig. 1 SSL model architecture

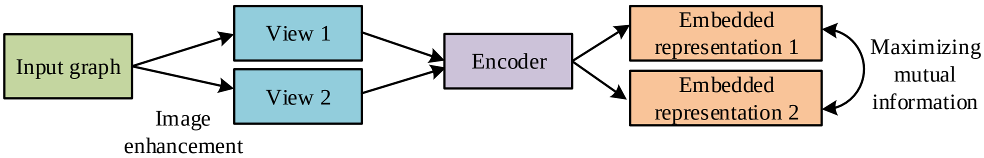


Figure 2: Comparing the structure of self-supervised learning models

In Fig. 2, the comparative model works by first encoding the input data efficiently by training the encoder. The encoded data are fed into the discriminator, and subsequently these encoded data are used to perform similarity comparison operations, contrasting losses to maximize mutual information. By analyzing the massive amount of data generated during operation, the SSL algorithm can automatically identify anomalous patterns and predict potential equipment failures. The original identification formula is shown in Equation (1).

$$\tilde{G}_r = (N_r, M_r \square E_r) \qquad (1)$$

In Equation (1), G is the graph. N for the set of nodes. r is the type of relationship. $\tilde{G}_r$ is the original data (OD) sample. N_r is the set of nodes in the data sample. M_r represents the original mask vector, which is used to randomly discard the edges of the OD. E_r represents the set of edges in the OD sample. Next, the loss identification is performed as shown in Equation (2).

$$\tilde{G}_S = (N_S, M_S \square E_S) \qquad (2)$$

In Equation (2), S is the loss generation. $\tilde{G}_S$ is the processed loss samples. N_S represents the node set of loss samples. M_S represents the loss mask vector. E_S represents the set of edges in the loss sample. Then, determine the positive probability of unlabeled data features by first calculating the cosine similarity of each data point, then calculating the sum of the similarities of all data points. Finally, the ratio of these two sums is the probability of positive samples, as shown in Equation (3).

$$y_{i+}^r = Soft\max(\cos(\tilde{e}, e_i^s)) \qquad (3)$$

In Equation (3), y_{i+}^r is the probability that the data i in the unlabeled sample set is positive for a given data feature. $\tilde{e}$ is the embedding representation of the data in the unlabeled sample set. e_i^s is the feature embedding representation of the data. $\cos(\square)$ is the cosine similarity. Then, it is necessary to obtain the data self-supervised signal (SsS) and define a set of SsSs that includes all cosine similarity values exceeding the threshold. As shown in Equation (4).

$$P_{i+}^r = \left\{ \tilde{e}_k \middle| k \in Top - K(y_{i+}^r), \tilde{E} \sim \tilde{G}_r \right\} \qquad (4)$$

In Equation (4), P_{i+}^r is the set of SsSs for information i under data information interaction. $\tilde{e}_k$ is the K data with the highest value after passing the confidence test. k represents all data of the confidence test. E is the set of edges. $\tilde{E}$ represents the set of edges in the data. These signals are used to train the model to learn useful feature representations from the structure of the data itself. Similarly, the feature-based SsS for data under data information interaction can be obtained as in Equation (5).

$$P_{i+}^s = \left\{ \tilde{e}_k \middle| k \in Top - K(y_{i+}^s), \tilde{E} \sim \tilde{G}_s \right\} \qquad (5)$$

In Equation (5), P_{i+}^s represents the set of SsSs for information i under data information interaction. y_{i+}^s represents the probability that the data in the labeled sample set is positive for a given data feature. To accurately express the structural relationships, path lengths and other factors in the intelligent network, the study introduces heterogeneous graphs and meta-paths shown in Fig. 3.

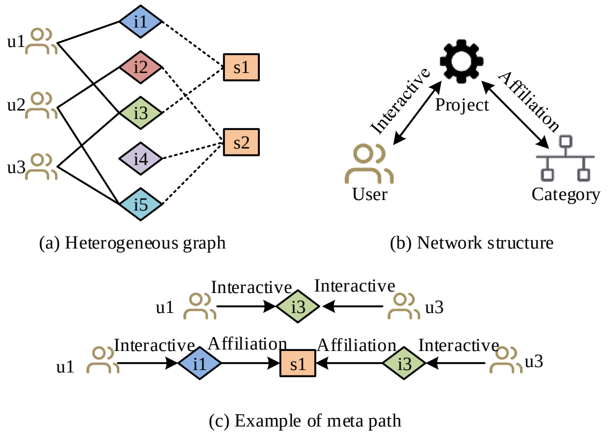


Figure 3: Schematic diagram of heterogeneous graph and meta path

In Fig. 3(a), the heterogeneous graph is a complex data structure that can accommodate multiple types of nodes and relationships. At the same time, nodes can exhibit diverse performance characteristics. To explore the higher-order relationships between nodes in depth, the introduction of meta-paths can effectively portray these complex, non-direct inter-node connections. In Fig. 3(b), the mechanical network structure constructs a hidden relationship between users, items and categories through a meta-path. This path not only shows the possible connections between the three, but also provides a new perspective for understanding the underlying workings of the network in great detail. In Fig. 3(c), after completing the detailed portrayal of different types of node association patterns, the node associations in the whole network become clearly visible. This visualization provides a solid foundation for the subsequent analysis and mining work of intelligent mechanical manufacturing.

3.2 Optimization strategies for intelligent mechanical manufacturing incorporating GNN

A significant amount of unlabeled data can be automatically learned by the model to create valuable feature representations through SSL, which are essential for ensuring prediction, classification, or optimization tasks. GNN can create more precise and thorough models of mechanical systems by taking use of the intricate interactions that exist between mechanical components. GNNs are a subset of neural networks that are specifically trained on graph-structured data (GSD). By capturing the intricate interrelationships between nodes, GNNs are able to learn the properties of the data more precisely [18]. Therefore, the research will incorporate GNN for the optimization of intelligent mechanical manufacturing. Equation (6) illustrates the formalization process of the graph learning-based recommendation system.

$$T = \arg Maxf\,(S(\Theta)|G) \quad (6)$$

In Equation (6), T represents the optimal recommendation result. $S(\Theta)$ represents the recommendation model based on graph learning. G represents the data structure information of the interaction graph. Θ represents the parameters in the interaction graph. Then the complex relationship between users or devices is captured by GNN based on the demand degree of related parts. The demand degree formalization process is shown in Equation (7).

$$nor\_Pop_i = \frac{Pop_i - \min\_Pop}{\max\_Pop - \min\_Pop} \quad (7)$$

In Equation (7), nor_Pop_i represents the demand degree after normalization of the part data. $\min\_Pop$ and $\min\_Pop$ represents the maximum and minimum value of the part demand degree. Then the difference value of demand degree between two parts can be obtained, and the formula is as in (8).

$$Pop\_Bias_{i,j} = |nor\_Pop_i - nor\_Pop_j| \quad (8)$$

In Equation (8), $Pop\_Bias_{i,j}$ represents the difference in demand degree between parts i and j. An example of the recommended system data graphic is obtained as shown in Fig. 4.

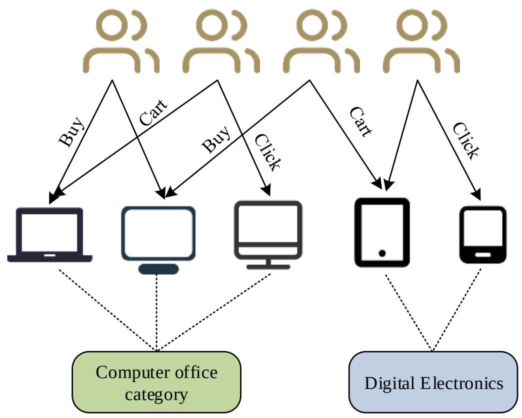


Figure 4: Recommended system data graph example

As illustrated in Fig. 4, the nodes represent users and projects, while the edges represent the users' preferences or interactions with projects. The figure demonstrates a variety of interaction modes, encompassing both direct user-project interactions and indirect interactions through other user nodes, thereby reflecting social influence. After changing the basic data of the recommender system to GSD, the complex relationship between users and items can be captured more clearly and the items can be categorized by attributes. Meanwhile, the complex interactions between users and items can form different types of edges, reflecting the preference intensity or interest patterns of different users for mechanical engineering parts. These edges link user nodes and item nodes, which form the graph structure of the recommender system [19]. This graphical representation method makes complex user project relationships intuitive and easy to understand. The GNN learning method based on graph results has advantages in mining the relationship between nodes and improving data utilization. The GNN schematic is shown in Fig. 5.

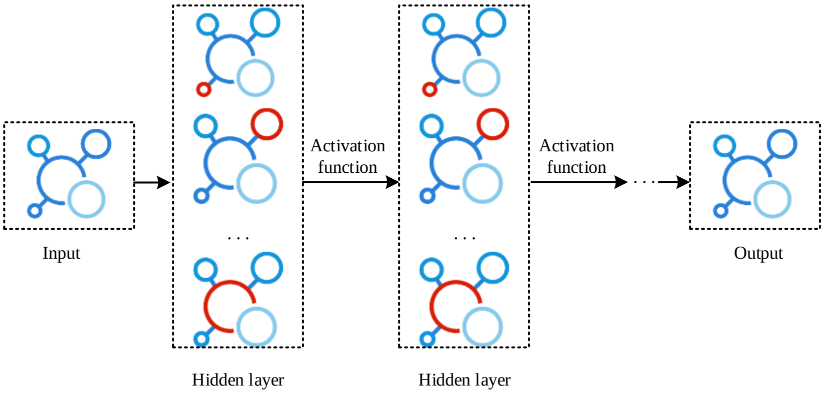


Figure 5: Diagram of neural network

In Fig. 5, each node in the GNN is forced by the learnt function mapping to aggregate data from its nearby nodes in order to gather the neighboring nodes' feature information. The information transfer path in this case points from the target node to the neighbor node. The representation of the node is then updated based on the information obtained from the aggregation and the node's own features. During the iteration process, the node representations will gradually stabilize, thus capturing the structural information of the graph and the complex relationships between the nodes. The GNN can deeply explore and utilize the complex and high-order connectivity information in the user-item interaction graph through its unique structural design, and it can also mine and disseminate more diversified items for users [20]. The propagation rule is shown in Equation (9).

$$h_i^{l+1} = \sigma(W \cdot AGG(h_k \mid \forall k \in N(i)) + b) \quad (9)$$

In Equation (9), $Pop\_Bias_{i,j}$ represents the propagation of GNN. σ represents nonlinear activation function. W and b are weights and bias vectors. $AGG(\square)$ represents the aggregation function. h_k is the node association information within the region. $N(i)$ represents the set of nodes within the range of node i. In order to mine the data features more fully for extraction, the study uses graph encoder to extract the data features. Each node is represented as a feature vector, and edges represent the relationships between nodes. GNN aggregates information from neighboring nodes through a message passing mechanism. At each layer, nodes collect features from their neighbors and integrate this information through max-pooling. The aggregated features are transformed by nonlinear activation functions to learn advanced representations of nodes. Finally, by stacking multiple GNN layers, the model can capture the multi-hop neighbor information of nodes and learn complex graph structural features. The general structural formula of graph encoder is Equation (10).

$$E^{(l)} = H(E^{(l-1)}, G) \quad (10)$$

In Equation (10), $Pop\_Bias_{i,j}$ represents the node l layer embedding representation. H represents the encoder of IA. G represents the view after IA. The l th layer representation obtained through neighbor node layer embedding is Equation (11).

$$e_i^{c(l)} = \sum_{j \in N_i^c} \frac{1}{\sqrt{|N_i^c|}\sqrt{|N_j^c|}} e_j^{c(l)} \quad (11)$$

In Equation (11), $e_i^{c(l)}$ and $e_j^{c(l)}$ represent the embedding representations obtained by the neighbor nodes. N_i^c represents the set of all neighbors of part i in the part similarity graph with de-demand degree. N_j^c represents the set of all neighbors of part j in the part similarity graph with de-demanded degree. Then the final vectors of the parts are obtained using the multilayer information propagation aggregation layer as in Equation (12).

$$e_i^c = \sum_{l=0}^{L} \alpha_l e_i^{c(l)} \quad (12)$$

In Equation (12), e_i^c represents the final embedding vector. L represents all layers of GNN IA. $e_i^{c(l)}$ is the superposition result of the initial embedding. α_l represents the embedding representation weight parameter of l layer. The SSL is then combined with GNN to further enhance the intelligence of intelligent mechanical manufacturing, especially in anomaly detection and fault prediction. The derived optimization model architecture based on SSL and GNN intelligent manufacturing is shown in Fig. 6.

In Fig. 6, the integration of GNN and SSL began with the construction of a multi-behavioral interaction feature extraction mechanism. Among them, SSL is used to automatically learn feature representations from a large amount of unlabeled data from mechanical operations in order to identify abnormal patterns. Then, these feature representations and SsSs are used as inputs to GNN, which updates node representations by aggregating neighbor node information, captures high-order connectivity relationships between devices, and predicts potential failures. Among them, Bayesian personalized ranking BPR is a method for learning user preferences, while p, q, and n are embedded neural network data. Through the information propagation and aggregation mechanism of GNN, the model is able to capture higher-order connectivity between devices and thus identify abnormal behaviors that significantly deviate from normal patterns. The model greatly raises the degree of equipment intelligence and assists in anticipating maintenance needs in order to lessen the impact of malfunctions on output.

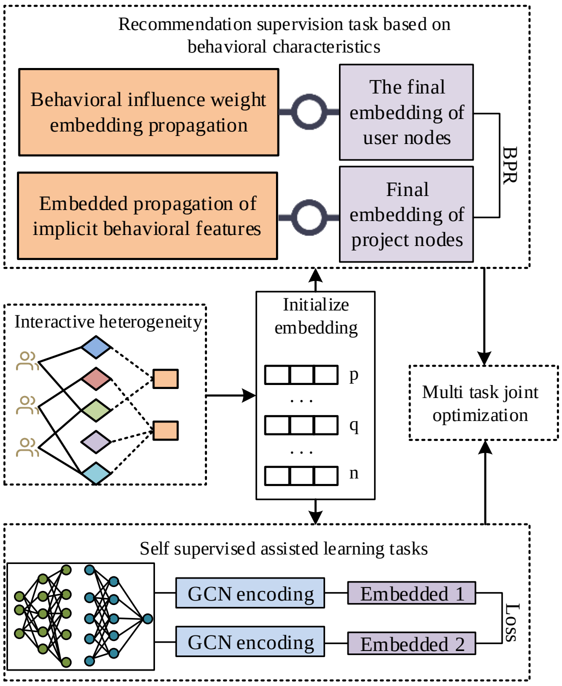


Figure 6: Intelligent manufacturing optimization model architecture

4 Effectiveness analysis of SSL and GNN in intelligent mechanical manufacturing

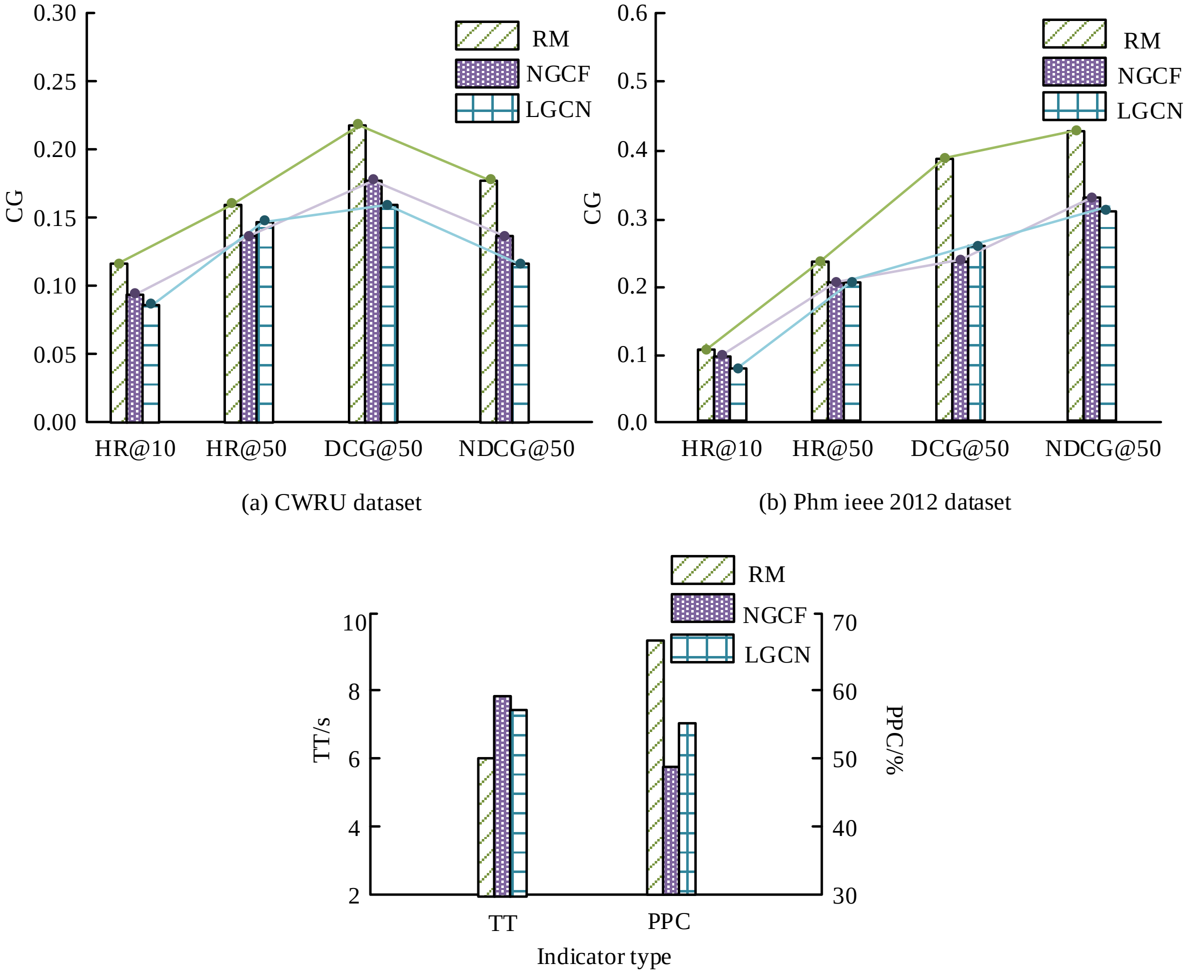
4.1 Comparative experimental analysis of graph SSL algorithms based on intelligent manufacturing

To analyze the effectiveness of the application of intelligent mechanical manufacturing based on SSL and GNN designed by the study, the superiority and reliability of the research methodology is mainly verified. The study uses Case Western Reserve University (CWRU) and Phm ieee 2012 dataset of publicly available datasets as experimental data. The CWRU dataset is a well-known dataset used for bearing fault diagnosis that contains bearing operating data under various operating conditions and can represent the reliability of the entire system. However, some types of faults have fewer samples, which can lead to data imbalance problems. The Phm IEEE 2012 dataset is a maintenance prediction and health monitoring dataset that contains operational data of various mechanical equipment and can reflect various conditions that may occur during actual operation of the equipment. However, the data dimension is relatively large. Both types of data have good representativeness and public availability. For the CWRU dataset, the study removed all samples containing missing values and standardized the features. The PHM IEEE 2012 dataset has been normalized to ensure that the eigenvalues are located on the same scale. The cross-validation method is used to train and test the model effect. There are three graph encoder layers and a 40-entity embedding dimension. The selection of three GNN layers is based on experimental results and provides a good balance between model performance and computational efficiency. A reduced number of layers might not entirely capture the intricacies of the graph structure, while an increased number of layers could result in overfitting. The 40-dimensional embedding space is large enough to capture rich feature representations while avoiding the curse of dimensionality. The experimental environment is shown in Table 2.

Table 2: Intelligent mechanical manufacturing experimental environment

Environment entry	Environmental parameters
Operating system	Linux CentOS7
Development language	Python3.7
Developing deep learning frameworks	Tensorflow1.14
Hard disk	1T
Memory	16G
GPU	GeForce RTX 2080 SUPER
CPU	Intel(R) Xeon(R) Silver 4215R CPU @ 3.20GHz

The GNN layers was set to 4, and the number of feature-based part-similar neighbors sampled was set to 50. The initial data and user embedding are set to 80, and the regularization parameter is set to 0.005. The initial weight is set to 1/4, and the learning rate is adjusted to 0.001. The Top-N recommendation hit rate (HR) is used as the evaluation index, and the specific comparison of each recommender system is made between the cumulative gain (CG), discounted cumulative gain (DCG), normalized discounted cumulative gain (NDCG) and training time (TT) and parallel processing capability (PPC). The single-behavior neural graph collaborative filtering (NGCF), light graph convolutional network (LGCN), multi-behavior model efficient heterogeneous collaborative filtering (EHCF) and the proposed model of the study are compared for experimental validation. Among them, CG can intuitively display the performance of recommendation systems at different ranking depths. DCG is capable of simulating the user experience while browsing recommendation lists in a realistic manner. NDCG possesses the capability to directly compare the performance of disparate recommendation systems or users. TT and PPC are capable of evaluating the computational efficiency and scalability of the model. The model evaluation performance is shown in Fig. 7.



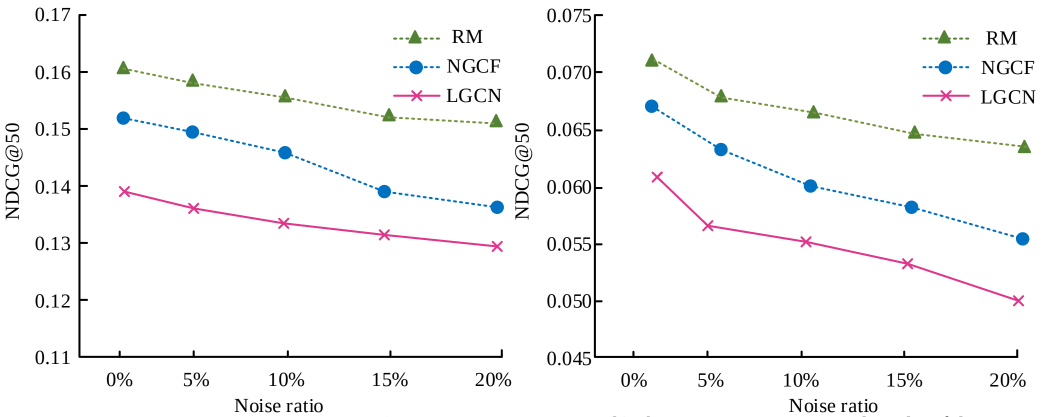
(a) CWRU dataset

(b) Phm ieee 2012 dataset

(c) CWRU dataset+Phm ieee 2012 dataset

Figure 7: Model evaluation performance

Fig 7 compares the performance of different recommendation models on two datasets, including HR, discount cumulative gain (DCG), normalized discount cumulative gain (NDCG), as well as TT and PPC. In Fig. 7, the research model performs significantly better on both CWRU and Phm ieee 2012 datasets. In Fig. 7(a), on the CWRU dataset, the research model outperforms the single-behavior NGCF model by 5.6%, 6.4%, and 4.8% for HR, DCG, and NDCG, respectively. It demonstrates that the study model is more accurate at forecasting objects that users might come into contact with later on. It also improves 10.8%, 8.5%, and 6.3% over the HR, DCG, and NDCG of the multi-behavioral model EHCF, respectively. In Fig. 7(b), the performance comparison of the research model on the Phm ieee 2012 dataset is similar to that on the CWRU dataset. In Fig. 7(c), the TT of the model decreased by 2.4% and 1.8%, respectively, compared to the other two. PPC increased by 16.4% and 10.2%, respectively. As the complexity of the dataset increases, the performance improvement of the research model becomes more significant. It indicates its strong robustness in handling complex user behavior data. Overall, by combining SSL and GNN, the research models can more deeply explore complex features and patterns in data, including subtle differences in user behavior and complex relationships between items, to better understand and predict user preferences. Moreover, it performs well in terms of computational efficiency and scalability. To further evaluate the effect of the model in the practical application of intelligent mechanical manufacturing, the study selects NGCF and EHCF models and the research model to conduct noise robustness anti-interference experiments. Adding Gaussian noise with a mean of 0 and an adjustable standard deviation to the dataset can simulate the random error of the sensor readings. Then gradually control the noise level and observe the performance changes of the system at different noise levels. The noise robustness results of intelligent mechanical manufacturing practical application are shown in Fig. 8.



(a) CWRU experimental results of dataset (b) Phm ieee 2012 experimental results of dataset

Figure 8: Comparison experiment results of noise robustness

In Fig. 8, the practical application of the model under both datasets displays an obvious decreasing trend with the increase of the noise intensity during mechanical fabrication. In Fig. 8(a), on the CWRU dataset, the research model shows a gain of 5.36% and 6.27% in the NDCG metrics over the NGCF and EHCF models, respectively. In Fig. 8(b), on the Phm ieee 2012 dataset, the study model has a gain of 4.26% and 5.85% in NDCG metrics over the NGCF and EHCF models, respectively. The experimental result data show that the research model is more effective in maintaining the accuracy and relevance ranking of the recommendation results in a complex and variable noise environment. This reflects its superior data processing capability and feature extraction strategy. It is proved that the research model has wide adaptability and stability in dealing with different sources and types of noise, which can provide more reliable recommendation services in the practical application of intelligent mechanical manufacturing. To demonstrate the contribution of individual components of SSL and GNN to the overall performance, the study conducted an ablation experiment analysis. The proportion of relevant items in the top 10 items of the recommendation list is denoted as Precision@10. The proportion of items successfully recommended by the recommender system among all relevant items is denoted as Recall@10. The reconciled average of Precision and Recall is compared with the F1-Score@10 which measures the overall performance of the model. The results are shown in Table 3.

Table 3: Results of ablation experiment table

Performance indicators	SSL model only	GNN model only	SSL+GNN model
HR@10	0.60	0.65	0.75
NDCG@10	0.45	0.50	0.60
Precision@10	0.55	0.60	0.70
Recall@10	0.50	0.55	0.65
F1-Score@10	0.52	0.57	0.67

According to Table 3, the complete model outperforms models using SSL or GNN alone in all performance metrics. The integration of SSL to learn useful feature representations of data and GNN to capture and utilize complex relationships in graph structured data furnishes a potent instrument for intelligent mechanical manufacturing. To further validate the superiority of the model, the experimental section is expanded to benchmark new models beyond NGCF and EHCF. The model includes sparse aggregation of graph convolutions for inductive learning of node representations (GraphSAGE), graph convolutional network (GCN), and graph isomorphism network (GIN) used for inductive learning of node representations. The benchmark test results are shown in Table 4.

Table 4: Model benchmark test table

Performance indicators	GraphSAGE	GCN	GIN	SSL+GNN model
HR@10	0.58	0.62	0.70	0.75
NDCG@10	0.48	0.52	0.58	0.60
Precision@10	0.52	0.57	0.63	0.70
Recall@10	0.48	0.52	0.60	0.65
F1-Score@10	0.50	0.54	0.61	0.67

In Table 4, the SSL+GNN model outperforms other baseline models in all key performance indicators. This indicates that the SSL+GNN model can more effectively support decision-making, optimize resource allocation, and improve production efficiency in practical applications.

4.2 Experiments on parameter analysis of graph SSL algorithms based on intelligent manufacturing

The research model's performance can be better understood, its configuration can be optimized, and its capacity for generalization can be enhanced by conducting a thorough analysis of its key parameters following the conclusion of the model's numerous performance comparison trials. Among these are the number of GNN coding layers L, the number of SsSs K, and the SSL scale weight coefficient β. The L of layers 2-4 can achieve a good balance, while K needs to be determined through experimentation to find the optimal value. A smaller beta value emphasizes the importance of downstream tasks, while a larger beta value gives more weight to self-supervised tasks, usually set at 0.001. The experiments first set different values of β on Movielens-M, Last-FM and Book-Crossing datasets. It also keeps K and L constant, both set to 40. The key performance metrics such as NDCG, recall, etc. are recorded for each β-value. The impact of the obtained SSL scale weight coefficient β is shown in Fig. 9.

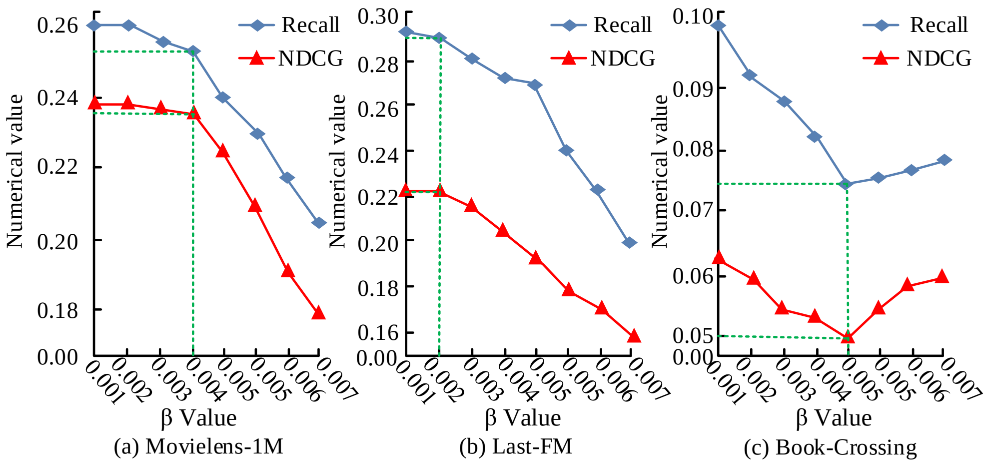


Figure 9: The influence of scale weight coefficient β on SSL

In Fig. 9, the larger the value of β is taken, the NDCG and recall performance of the model decreases. In Fig. 9(a), on the Movielens-M dataset, the model performance is best in comparison when the value of β is taken at 0.001. Its model performance decreases rapidly after taking a value of 0.004, while the recall value is always greater than the NDCG. In Fig. 9(b), on the Last-FM dataset, the model performance is best when β is taken at an initial value, and the model performance decreases after the value is increased to 0.002. In Fig. 9(c), on the Book-Crossing dataset, the model performance appears to decrease and then rebound as the value of β is increased. However, the rebound is small and far from the initial value. The results show that the research model is extremely sensitive to β, and the performance of the research model is close to the ideal state when β takes smaller values. In studying the effect of different SsS numbers K on the model, the value of L is set constant and β is set to 0.001. The obtained effect of SsS number K is shown in Fig. 10.

In Fig. 10, as the value of K grows, the research model performance shows a general trend of increasing and then declining, and the recall value is always bigger than NDCG. In Fig. 10(a), the model performance shows the most obvious trend of increasing and then decreasing on the Movielens-M dataset, where the optimal K value is 30. Meanwhile, the model performance is relatively stable on the other two datasets. The results show that the model performance varies most significantly on the Movielens-M dataset, and the characteristics of the dataset make the SsSs more sensitive to the model performance. Among them, the optimal K value enables the model to fully utilize the SsSs to enhance the learning effect of the main task. This reflects the important role of the model for intelligent mechanical manufacturing SSL. In studying the effect of different GNN coding layers L on the model performance, β is set to take a constant value and K is 30. The effect of GNN coding layers L obtained is shown in Fig. 11.

In Fig. 11, the recall and NDCG performance of the research model on all three datasets increases and subsequently drops as the value of L increases. In Fig. 11(a), on the Movielens-M dataset, the model performance increases to a maximum at L=2, but continues to decrease when L>3 and reaches a steady state at L=4. On the other two datasets, the model performance also maximizes at L=2 and continues to decrease afterward. The results show that the number of SsSs has a significant effect on model performance, and the right amount of SsSs can help the model learn more useful features. However, too many signals may introduce noise and lead to a decrease in model performance. In summary, the performance of the research model in the field of intelligent mechanical manufacturing is optimized when the parameters β=0.01, K=30, and L=2 is selected. Choosing β=0.01 means that the weight of SsSs in the overall objective function is low. It helps the model to focus on self-supervised tasks without overly relying on these signals, thus maintaining sensitivity to the final task. Choosing K=30 means that an appropriate amount of SsSs is used in model training. It helps the model capture complex structures and patterns in the data while avoiding overfitting. Choosing L=2 means that the model can capture key information about the graph structure while maintaining computational efficiency. This finding not only validates the effectiveness of SSL and GNN in complex industrial scenarios, but also demonstrates the importance of model performance that can be significantly improved by fine-tuning the model parameters.

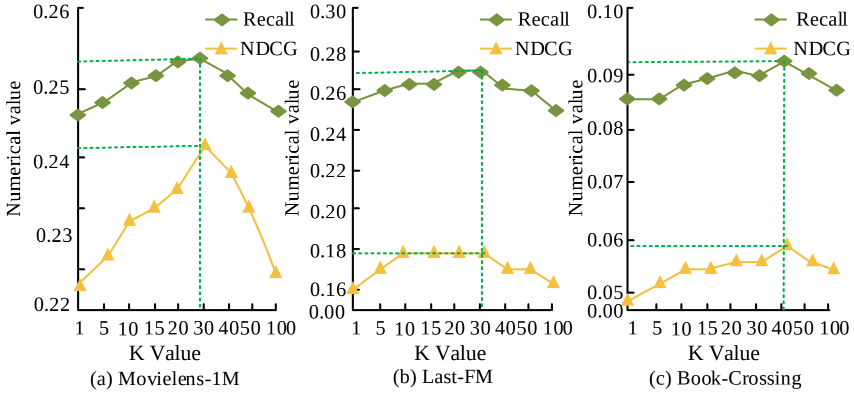


Fig. 10 The influence of the number of self-supervised signals K

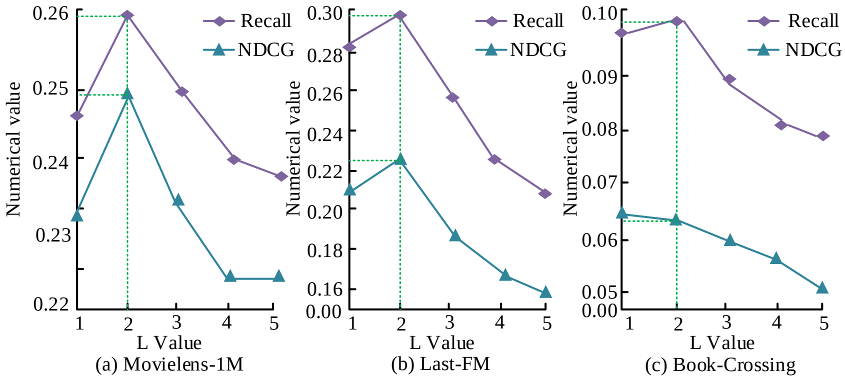


Figure 11: The influence of L encoding layers in neural networks

5 Discussion

The study used a fusion method of SSL and GNN to construct an intelligent manufacturing optimization model. Compared with the intelligent scheduling model obtained by Yang S. [10], this model could capture more complex data structures. The reason was that the model proposed in this article used a reasonable amount of SsSs. Compared with the detection method of Rani V et al. [12], the model proposed in this study had better robustness. The reason was that the feature extraction strategy of the model in this article could maintain the accuracy of the results. SSL automatically mined patterns from a large amount of unlabeled data through contrastive learning, and the test results on the CWRU dataset showed that the model's HR, DCG, and NDCG have improved by 5.6%, 6.4%, and 4.8%, respectively. This indicated that SSL could effectively identify potential faults in bearings under different operating conditions without relying on external labels for fault detection. Meanwhile, GNN enhanced the predictive ability of the model by capturing the complex interactions between devices. On the Phm IEEE 2012 dataset, the NDCG metrics of the model improved by 5.36% and 6.27% compared to the baseline model. It reflected the superior performance of GNN in processing high-dimensional data and predicted maintenance scenarios in real-world scenarios, accurately predicting possible equipment failures. Through experimental analysis, it was found that the model performance reaches its optimum when the parameters β =0.01, K=30, and L=2. This discovery not only validated the effectiveness of SSL and GNN in complex industrial scenarios, but also demonstrated that fine-tuning model parameters could significantly improve model performance. In the noise robustness experiment, the model was able to maintain a high NDCG index even after the addition of Gaussian noise, indicating that the model could maintain the accuracy and relevance ranking of recommendation results in noisy environments. In summary, the studied intelligent manufacturing optimization model had demonstrated significant performance improvement and advantages in practical applications by combining the technical features of SSL and GNN. The model had the capacity to automatically learn data features and capture complex relationships between devices. Furthermore, it could improve performance through parameter optimization, thereby providing an effective technical solution for the field of intelligent manufacturing.

6 Conclusion

Aiming at the problem of innovative application of intelligent mechanical manufacturing, the research conducted a fusion processing based on SSL and GNN methods. Among them, considering the comparative damage determination of intelligent machinery, a comparative SSL model was constructed to utilize the data to automatically identify and predict the abnormalities of the machinery during operation. Meanwhile, heterogeneous graph and meta-path were introduced to accurately express the structural relationship, path length and other factors in the intelligent network. Then on the basis of SSL, it was fused with GNN for optimization, and the propagation rules of GNN were described to improve the level of intelligence to form a recommendation system. Finally, the optimization model architecture based on SSL and GNN intelligent manufacturing was derived. The results indicated that the research model improved HR, DCG and NDCG by 5.6%, 6.4%, and 4.8% over the NGCF model on both datasets, respectively. It also improved each performance by 10.8%, 8.5%, and 6.3% over the EHCF model, respectively. In the practical application of intelligent mechanical manufacturing, the research model exhibited a gain of 5.36% and 6.27% in NDCG metrics over the NGCF and EHCF models, respectively. There was a gain of 4.26% and 5.85% over the NDCG metrics of the NGCF and EHCF models, respectively. The enhancement of NDCG exerts a direct influence on the efficacy of decision-making processes within the production context, facilitating the optimization of resource allocation and the mitigation of unanticipated downtime. DCG has been shown to enhance the efficiency and output of the production line. Improving HR performance helps reduce production costs, improve user experience, and make products more competitive in the marketplace. The results of the study show that the research model is superior compared to other models in terms of dataset performance and practical application, and has good intelligent mechanical manufacturing application value. Moreover, it has contributed to the performance of user classification and recommendation systems. Although the model performed well in experiments, its scalability may be limited by data quality, computational resources, and model generalization ability when implemented in actual industrial environments. The incompleteness of industrial data, noise, and environmental differences can lead to a decrease in model performance. In addition, the high computational requirements of GNN and SSL models can be a challenge in resource-constrained environments. Therefore, the model needs to be adapted and optimized in new environments to ensure its efficiency and accuracy in different industrial scenarios.

Funding

2023 Henan Province Key Research and Development and Promotion Project (Science and Technology Research Project): Research and Application of a Virtual Reality-Based Visualization Platform for Maintenance Safety Knowledge of Electromechanical Equipment (No. 232102321061)

Acknowledgement

2023 Henan Province Key Research and Development and Promotion Project (Science and Technology Research Project): Experimental Research on low-temperature Waste Heat Power Generation System based on radial inflow turbine (No. 232102320223)

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