

# Graph Neural Network-Based Cross-Domain Fault Prediction for Smart Manufacturing Systems

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**Abstract.** The Internet of Things in smart manufacturing and Industry 4.0 is rapidly developing, changing the way traditional factories operate. These changes have brought new issues related to proactive equipment upgrades and real-time fault monitoring. Traditional machine learning methods cannot effectively address issues related to domain differences or variations across different regions. It still cannot manage distributed domains. This paper proposes a new method based on Graph Neural Networks (GNN) for cross-domain fault prediction in smart manufacturing facilities. Based on the aforementioned findings, this study has developed a new architecture called RGN-FCN. The study proposes an innovative method that combines Graph Neural Network (GNN) technology with Fast RPN for target recognition. The empirical analysis of this study shows that the GNN-based method outperforms traditional methods such as CNN and LSTM; it is also applicable under non-traditional conditions beyond simple input distributions. Adding explicit structural connections and domain-independent representation learning improves cross-domain generalization ability; accurately identifying less common or complex faults. Introduce how this framework helps deploy the next generation of AI-based, scalable, and resilient smart factory operation and maintenance systems. The future research goal is to further reduce the impact of high domain differences on performance and deepen causal interpretability, so that it can be applied in commercial environments.

**Keywords:** *Graph Neural Network, Cross-Domain Learning, Fault Diagnosis, Industrial Internet of Things, Predictive Maintenance*

Received on 30 October 2024, Accepted on 23 February 2025, Published on 13 March 2025

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## Introduction

The rapid development of smart manufacturing systems based on the Industrial Internet of Things (IIoT) has completely transformed people's perceptions of reliability, efficiency, and autonomy in the era of Industry 4.0. Next-generation factories densely connect production assets thru extensive automation systems, various protocols, and complex processes. By using high-performance sensors, original equipment, and robots to quickly obtain time series datasets of multiple physical and logical parameters, real-time analysis can be conducted [1]. Diverse and multi-domain data sources lack the ability to predict fault outcomes and fault locations. Due to changes in factory configuration, machine lifespan, and operating conditions, data distribution undergoes inconsistent changes over time. The transfer of knowledge or cross-domain learning has become more difficult [2,3]. The issue of "cross-domain transfer" still exists, and the predictive models have defects due to insufficient generalization ability [4].

Due to research in machine learning (ML) and deep learning, industrial reliability prediction models have entered a new era. Thru models such as Support Vector Machines, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), many domain tasks with rich datasets on a single factory or platform have already surpassed human levels [5,6]. In practical cross-site applications, or when products belong to different process flows or instrument applications, their predictability significantly decreases. Due to this defect, quality will be lost over long-term use. The common physical and logical dependencies in factory operations, such as the

complex networks between personnel, subsystems, and equipment, are often difficult to identify using traditional methods [7]. Existing methods assume that training and deployment data are independent and identical. In certain industrial applications, such as sudden domain shifts or lack of labels, this often does not hold true [8,9]. Changes in label quality, imbalanced class distribution, and variable working modes are issues that cannot be resolved thru traditional transfer learning and adaptation methods [10].

This paper proposes a paradigm shift by using Graph Neural Networks (GNNs) to predict cross-domain failures in smart factories. Since GNNs can naturally handle structured and interconnected data and encode local relationships, they can simultaneously capture global context. GNNs can help accurately predict by constructing a relational graph of industrial plants composed of devices, sensors, or process subunits and their interconnections (e.g., functional relationships, information exchange, etc.) to identify invariant domains. Based on this, a domain adaptation GNN framework is proposed for integrating distribution alignment, relation learning, and graph construction. In order to achieve cross-domain fault knowledge transfer, alignment is necessary. Contributions were made in the following areas: principled relational graph generation techniques; structure-distribution joint alignment based on multi-domain GNN. Extensive empirical experiments were conducted on various industrial datasets. A comprehensive ablation study on multiple parameters was conducted to observe the changes of each parameter during the experimental process. The remainder of this paper will be organized as follows: Section 2 reviews the progress in fault diagnosis and graph learning research based on cross-domain prediction; Section 3 describes the issues and proposed methods for knowledge graph-based predictive maintenance in this study; Section 4 introduces the evaluation metrics, discusses ablation and transfer analysis; and Section 5 will cover key findings and future developments.

## Related Work

### Cross-Domain Learning in Fault Prediction

Due to the diversity of factory structures and working conditions, cross-domain learning has become a hotspot in industrial fault identification research. Traditional machine learning models usually perform better when reused in the same environment. However, generalization in different environments (such as different factories, machine settings, and operating conditions) becomes more challenging. Domain adaptation methods aim to reduce the statistical property differences between the source domain and the target domain or align feature representations thru methods such as adversarial learning or feature matching [11, 12]. Domain-Adversarial Neural Networks (DANNs) aim to improve performance and reduce domain differences in large data discrepancy problems [13]. "Meta-learning" has recently been considered to have made significant progress. In the presence of sufficient labeled samples, even minor adjustment factors such as anomalies or fault labels during industrial maintenance will not affect the adaptability to new environments [14,15]. There are some drawbacks. In actual production systems, the impact ranges from obvious distribution changes to noisy data, missing data, and overlapping label spaces [16]. Cross-domain models still have many shortcomings in terms of scalability, reliability, and robustness [17].

### Graph Neural Networks for Industrial Applications

Graph neural networks have achieved success in modeling and analyzing relational industrial data. GCN and GAT are the initial versions that can iterate information from one node to another in the network thru neighborhood topology [18, 19]. Inductive models like GraphSAGE have expanded the application scope of feature aggregation to address the generalization problem of unvisited nodes in the network [20]. GNNs are increasingly being applied in many areas of the Internet of Things, such as industrial processes, manufacturing plants, equipment, and sensor networks. In the system diagram at the factory level, equipment or process units are considered nodes. Directed acyclic graphs (DAGs) also depict connections or interdependencies. Compared to completely data-driven methods, this formalization aids in root cause analysis, event propagation, and anomaly localization [21,22]. Equipment anomaly detection, predictive maintenance planning, production system optimization, and ensuring system resilience are all common applications [23]. Most modern GNN-based technologies are primarily used for static single-factory system identification. For industrial applications with time-varying changes in a distributed operation-data environment, the effectiveness and adaptability of transmitting factory-

specific knowledge across heterogeneous networks in various fields have not yet been fully addressed in the literature [24,25].

### Predictive Maintenance Paradigms

Predictive maintenance (PdM) is a continuously expanding concept in industrial automation. Originating from alarm thresholds or rule-based systems, it now includes artificial intelligence in time series analysis capabilities and feature learning environments. Initially, feature sets were constructed based on expert intuition and manual drawing; however, in the face of complex environments or large amounts of data, these feature sets are not applicable. With the widespread adoption of high-performance sensor technology and big data, end-to-end learning paradigms based on deep neural networks are becoming increasingly popular. Transformers and Long Short-Term Memory networks have become the core architectures of many PdM systems, excelling in fault sequence prediction and early anomaly detection. These AI systems have the capability to capture time-related changes and identify subtle deterioration features, but they also have significant issues. Most models are highly sensitive to the quality and representativeness of the training data, especially when there are distribution changes, rare fault types appear, or operational conditions change. Compared to deep learning in the "black box," the workflows of engineers and operators will become opaque. This is an explainable issue. In order to directly read or write Excel files, it is necessary to install additional libraries, such as xlrd and xlwt. These issues have greatly stimulated the development of graph-based domain adaptation strategies, which aim to enhance relational modeling capabilities and cross-domain generalization.

## Proposed GNN-based Framework for Cross-Domain Fault Prediction

### Problem Definition and Motivation

When there are significant changes in processes, equipment, and sensors, cross-domain fault prediction in advanced manufacturing requires a model with good generalization capability. This situation can be described as: learning a predictive function that can effectively transfer diagnostic information from a labeled source domain to an unlabeled or partially labeled target domain. Let each source domain provide sets of sample pairs, represented as  $(x_i^s, y_i^s)$ , where  $x_i^s$  denotes the raw observation from the  $i$ -th source instance-including fused sensor readings, process context, or operational time series-and  $y_i^s$  indicates its ground truth fault label. The target domain, conversely, comprises  $x_j^t$  with typically unknown or weakly supervised fault annotations.

Create a function that integrates the observations from the source and target into the latter to reliably predict the fault state; specifically:

$$f_{\text{cross}} : \left( \{x_i^s, y_i^s\}_{i=1}^{N_s}, \{x_j^t\}_{j=1}^{N_t} \right) \rightarrow \{y_j^t\}_{j=1}^{N_t} \quad \text{Eq.(1)}$$

where  $N_s, N_t$  are sample counts. The map should still be effective, including operational changes and statistics between different areas.

Besides making adjustments in sensor technology integration, scheduling, and hardware selection, there will still be an unsolvable domain-specific issue that arises afterward. This difference can be described as:

$$d_{\text{div}} = \sup_{\mathcal{H}} \left| \mathbb{E}_{x \sim P^s(x)} [h(x)] - \mathbb{E}_{x \sim P^t(x)} [h(x)] \right| \quad \text{Eq.(2)}$$

where  $P^s(x)$  and  $P^t(x)$  are the marginal distributions in source and target, and  $\mathcal{H}$  is a set of bounded discriminators.

Traditional i.i.d. vector-based machine learning models have failed because they cannot extract the potential structure or nature of interactions from the raw input data. Due to factors such as the network topology of distributed devices and task synchronization, process failures in the real world can lead to a chain reaction. When dealing with industrial transfers, methods based on clearly representing multi-scale structures and the interactions between scales are more suitable for addressing domain-specific issues. Applying graph neural networks within the scope of this system is both theoretically and practically enlightening.

### Relational Graph Construction in Smart Factories

In order to leverage relationship-based learning and adapt to various domains, it is necessary to abstract the complex smart factory environment into concise diagrams. This begins with automatic construction of a multi-relational attributed graph  $G^{(d)} = (V^{(d)}, E^{(d)}, X^{(d)}, R^{(d)})$  for each domain. Here, node set  $V^{(d)}$  encapsulates heterogeneous entities: machines, sensors, or process sub-units. Edge set  $E^{(d)}$  details concrete interactions, which may include physical couplings (e.g., conveyor links), syntactic flows (e.g., control signals), or resource dependencies (e.g., shared cooling circuits), while  $R^{(d)}$  defines multiple edge types reflecting the multiplex nature of industrial connectivity.

In order to achieve graph-based modeling, each node is assigned a set of feature vectors that integrate various process metrics, such as dynamic health signatures, process state parameters, and derived operational metrics:

$$X^{(d)} = [x_1^{(d)}, x_2^{(d)}, \dots, x_{|V^{(d)}}^{(d)}] \quad \text{Eq.(3)}$$

with each  $x_i^{(d)}$  a high-dimensional descriptor adaptable by task or context.

The third-order adjacency matrix is used to encode various edge relationships:

$$\mathcal{A}^{(d)} \in \mathbb{R}^{|V^{(d)}| \times |V^{(d)}| \times |R^{(d)}|} \quad \text{Eq.(4)}$$

where  $\mathcal{A}_{i,j,r}^{(d)} = 1$  if a relationship of type  $r$  exists between node pair  $(i, j)$ .

Due to the differences in topology and meaning between the target and source factories, normalization and alignment processes are required. Alignment is needed. This is how to establish:

$$g_{\text{align}} : (X^{(d)}, \mathcal{A}^{(d)}) \rightarrow (\bar{X}, \bar{\mathcal{A}}) \quad \text{Eq.(5)}$$

where  $g_{\text{align}}$  harmonizes node/edge representations across factories, enabling model parameter sharing and cross-domain supervision in the downstream relational learning process.

As shown in Figure 1, converting the original operational data and factory topology into a cross-domain multi-relational graph is the foundation of this proposal.

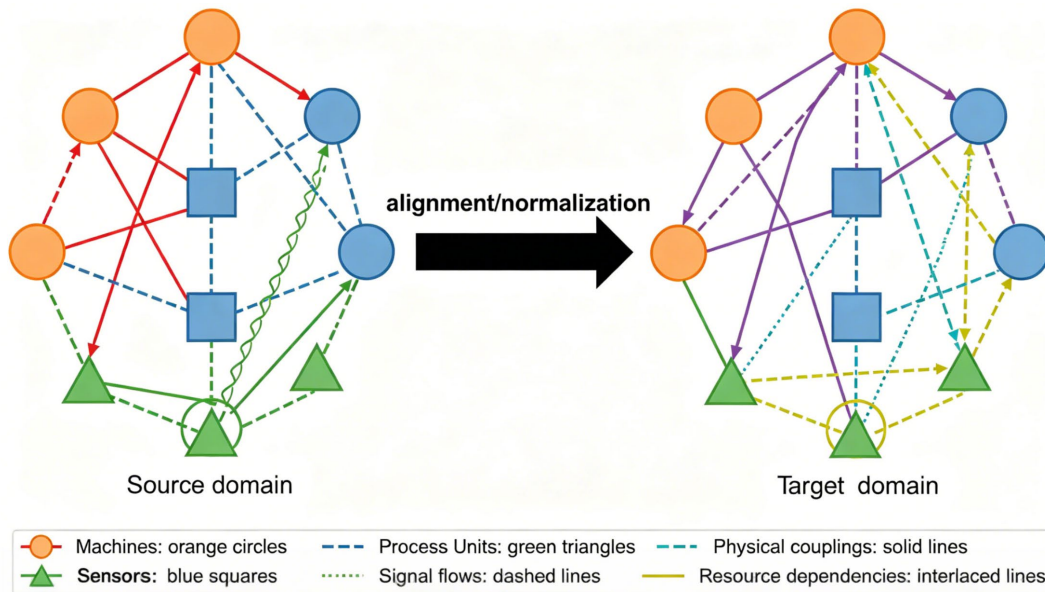


Figure 1. Schematic of Cross-Domain Multi-Relational Graph Construction for Smart Factories

### GNN Model Architecture

To ensure the stable transmission and interpretable diagnosis of heterogeneous industrial systems, the core model constructs a stack-based relational GNN structure, which is based on a unified graph abstraction. The unified node features and adjacency tensors of multiple relationships obtained from factory data constitute the input of the network. Using an embedding layer to project all input attributes into a common latent space:

$$H^{(0)} = \sigma(W_0 \bar{X} + b_0) \quad \text{Eq.(6)}$$

where  $W_0$  and  $b_0$  are parameters learned to maximally preserve predictive structure, and  $\sigma$  is a pointwise activation.

Core relational reasoning is achieved thru relation-aware message passing and iteration:

$$H_i^{(l+1)} = \phi \left( \sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_i^r} \alpha_{ijr}^{(l)} W_r^{(l)} H_j^{(l)} + W^{(l)} H_i^{(l)} \right) \quad \text{Eq.(7)}$$

This formulation ensures that information propagates according to both edge semantics and learned attention coefficients, with  $\alpha_{ijr}^{(l)}$  encoding relevance of node  $j$  for node  $i$  through edge type  $r$ .

Achieving domain adaptation at the representation level is key. Different encoders-or domain-specific subspaces-map source and target graph signals to embeddings  $Z^s$  and  $Z^t$ . A discrepancy regularizer is integrated as follows:

$$\mathcal{D}_{\text{align}}(Z^s, Z^t) = \|\mathbb{E}_{z \sim Z^s}[\psi(z)] - \mathbb{E}_{z \sim Z^t}[\psi(z)]\|^2 \quad \text{Eq.(8)}$$

where  $\psi(\cdot)$  is a nonlinear differentiable feature mapping (often a kernel embedding). It can remain unchanged under model conversion to penalize distribution misalignment, thereby reducing domain generalization errors.

Linear read and softmax are used to predict the classification of the target node. The high-level state of the target node is mapped to the estimated fault probability as follows:

$$\hat{y}_i^t = \text{softmax}(W_{\text{out}} H_i^{(L)} + b_{\text{out}}) \quad \text{Eq.(9)}$$

Model training uses a combination of losses to monitor, adjust the domain, and regulate model complexity:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{cls}} + \lambda_1 \mathcal{D}_{\text{align}} + \lambda_2 \mathcal{L}_{\text{reg}} \quad \text{Eq.(10)}$$

Here, the classification loss  $\mathcal{L}_{\text{cls}}$  is ordinarily the categorical cross-entropy over the source, while the regularization term  $\mathcal{L}_{\text{reg}}$  constrains model complexity or encourages sparsity as appropriate to the application.

The training process alternates between reducing the classification loss of the labeled source and gradually reducing the feature distribution difference thru domain adaptation. This is usually achieved by using stochastic gradient descent with a small amount of mixed-domain data.

In considering the overall end-to-end design of node message passing and domain-agnostic learning, as shown in Figure 2: from the original graph to uncoordinated features; thru multi-layer relational propagation + explicit domain distribution alignment; then outputting classifications for different target domains.

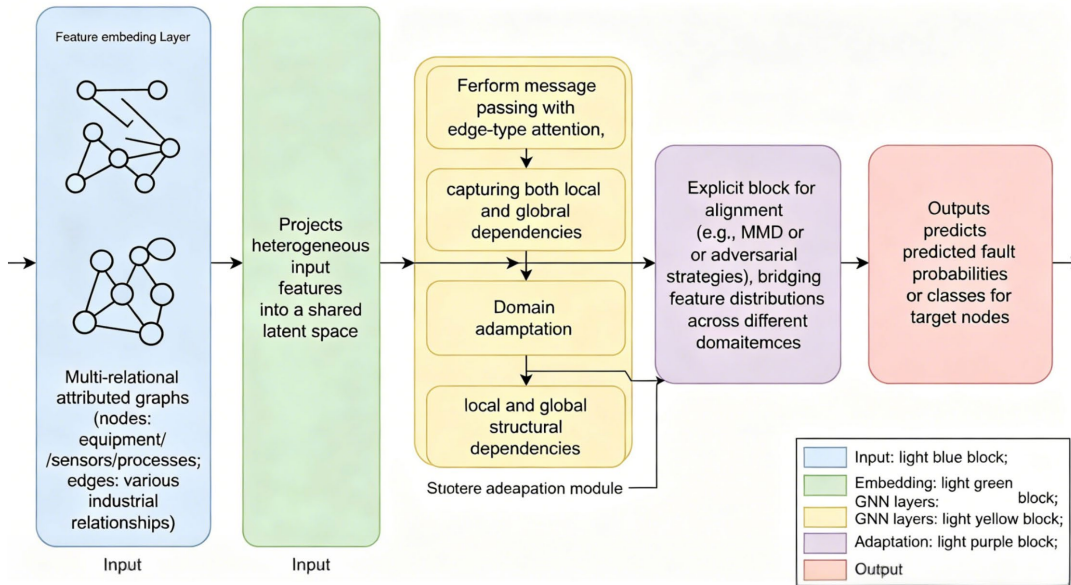


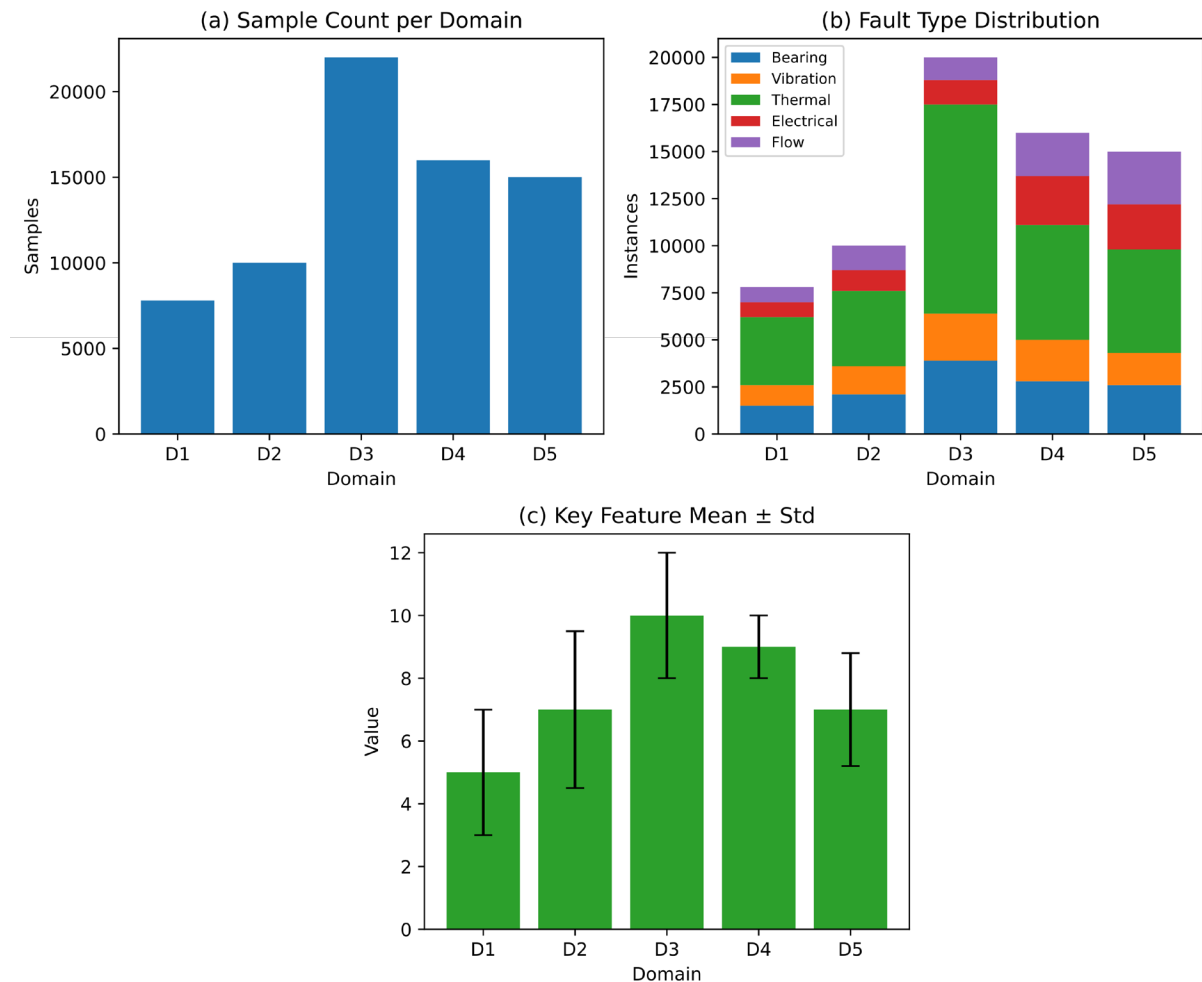
Figure 2. End-to-End GNN-Based Cross-Domain Fault Prediction Architecture

## In-Depth Empirical Analysis and Cross-Domain Validation

### Dataset Description and Preprocessing

Create an evaluation environment that includes five independent real industrial datasets, corresponding to the factories and operating conditions of D1-D5. After thorough cleaning, the number of labels in each domain ranges from 7,800 to 22,000. The sensor data and process status information of the 43 modalities are represented by indices in the spatial domain. D1 mainly exhibits the characteristics of mechanical components; D3 has highly automated and complex feedback loops; D5 requires a large amount of power for control and faces various issues such as electrical instability and flow blockage, all of which are true representations of industrial heterogeneity. The statistical distribution of key process parameters such as peak current, vibration amplitude, and temperature gradient deviation shows significant domain differences. Before fairly evaluating the model, strict standardization and matching processes must be conducted.

To prepare the data for relational and temporal analysis, all-time series were resampled into fixed 500 -sample windows and missing sensor channels were imputed using linear interpolation. For each window, statistical features-including mean, standard deviation, skewness, and spectral entropy-were concatenated with process meta-tags. The profound heterogeneity and class imbalance across these domains are visually summarized in Figure 3, which is described and analyzed below.



**Figure 3.** Multi-Source Dataset Statistics: (a) Comparison of sample counts across domains D1-D5; (b) Aggregated proportion of five fault/health states; (c) Distributions (mean  $\pm$  variance) of primary process features across domains

Figure 3 shows the shortcomings that need to be addressed when building a reliable cross-domain diagnostic system. Due to the uneven distribution of samples among different groups, there may be considerable bias; it cannot be universally applicable to everyone. There are significant differences between the primary keys in

different regions and their corresponding adjustment values; advanced technology should be used during the matching and updating process. An efficient cross-domain prediction system must be designed in the following aspects: robust normalization, precise feature selection, and method adaptability for learning functions. These dataset features directly lead to the use of graph-based models and domain adaptation techniques in the next phase of the experiments.

### Implementation Details

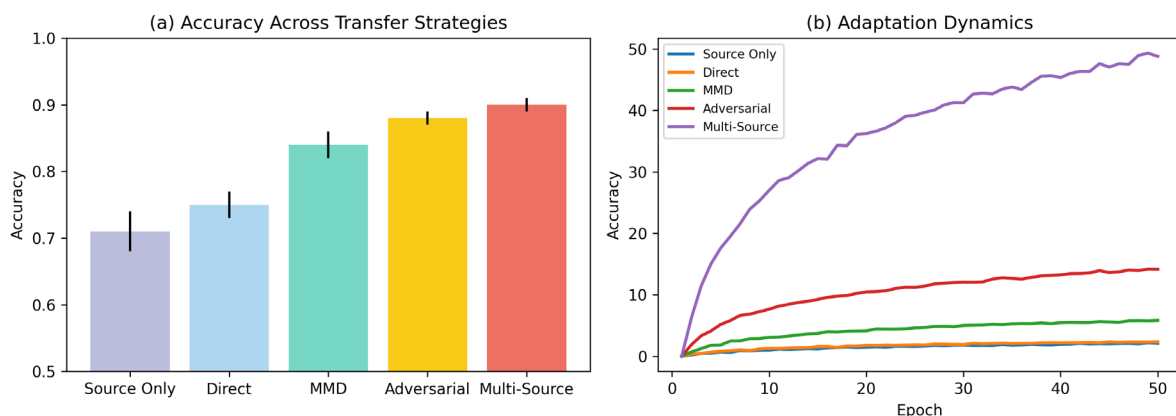
All experiments utilized dual NVIDIA RTX 4090 GPUs and 384 GB RAM, with software built on PyTorch 2.2 and DGL for graph computation. The proposed GNN was implemented as a four-layer relational encoder, using 256 hidden units and ReLU activations. A dropout of 0.35 was consistently applied for regularization, and the Adam optimizer with 0.001 learning rate and batch size 128 was used; dynamic learning-rate schedule facilitated rapid and stable convergence over 320 training epochs.

Comparative benchmarks included a twelve-filter CNN, a two-layer LSTM (each cell: 128 units), and a VGG-adapted architecture—all of which were tuned using grid search for optimal hyperparameters within each domain. No labeled target data was exposed to any model during training—the models operated under a strict source-to-target domain adaptation regime. Complete configuration and preprocessing scripts, as well as random seeds, have been published for reproducibility.

To ensure the robustness and reproducibility of our results, each experiment was repeated five times with different random seeds, and average metrics were reported. All data preprocessing, model training, and evaluation pipelines were automated using custom Python scripts. During hyperparameter tuning, early stopping based on validation loss was implemented to avoid overfitting. Model checkpoints and performance logs were systematically archived for further analysis. Additionally, all source code and dataset partitions have been made available upon request, supporting open science practices and facilitating further research in cross-domain industrial fault detection.

### Cross-Domain Transfer Effectiveness

The central objective of the following ablation studies is to elucidate the effect of various domain adaptation strategies on fault prediction performance in highly heterogeneous manufacturing scenarios. We benchmarked five distinct transfer paradigms: (i) source-only, with models trained solely on labeled source data and directly evaluated on the target without adaptation; (ii) direct transfer, involving naively re-training with a limited number of target samples; (iii) Maximum Mean Discrepancy (MMD)-based adaptation; (iv) adversarial domain alignment; and (v) mixed-source adaptation, integrating multiple source domains in different proportions to target. For each, the same GNN backbone was deployed with rigorously held-out target domains, and all results are reported as mean accuracy across five transfer tasks.



**Figure 4.** Cross-Domain Transfer Strategy Analysis: (a) Accuracy of five adaptation strategies across all domain pairs; (b) Loss and accuracy convergence for five representative transfer tasks

Figure 4(a) shows the results of various methods summarized for comparison across each domain pair. The results do not directly outperform the benchmark; distribution shift might be the issue. Mmd regularization

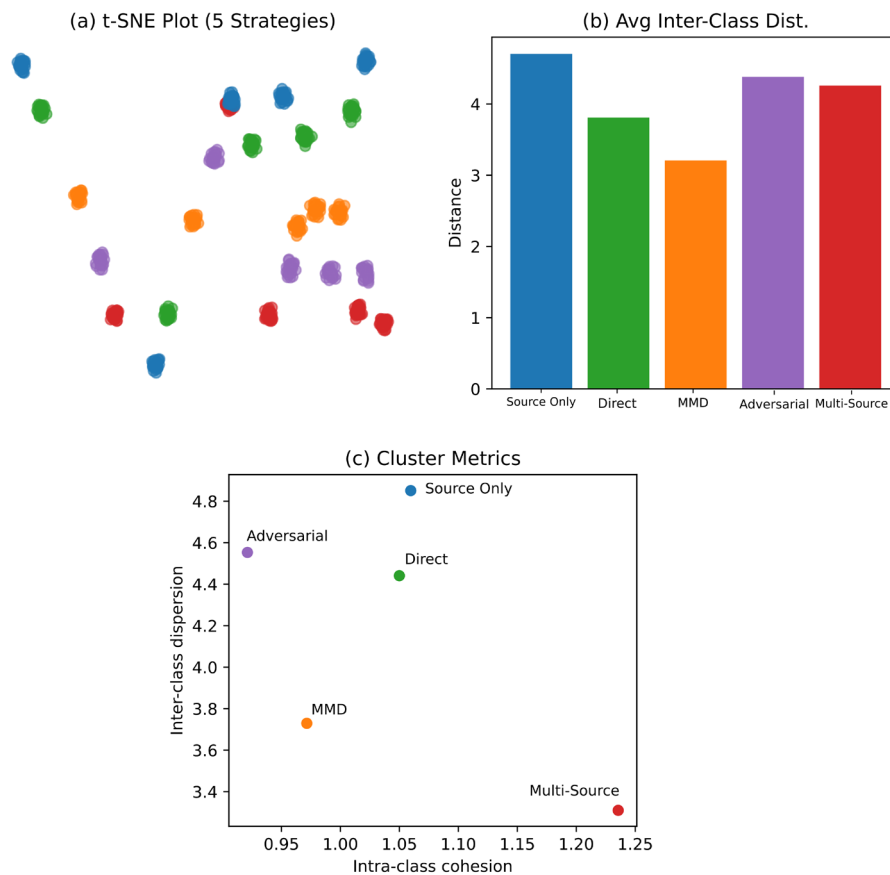
enhances the ability to identify sparse fault environments in cases of class imbalance or severe failures. Adversarial alignment is more accurate in almost all cases and has achieved its highest accuracy; mixed source adaptation has made negligible but significant progress using ideal weights in the cases with the greatest differences.

Figure 4(b) depicts the loss variations and adaptation methods for five typical tasks. The final loss values based on MMD and adversarial methods are smaller than those of other methods, with the highest stagnation accuracy. Compared to these fields, there has been almost no change; it cannot be said that every area has completely solved these problems.

Different transfer strategies have varying impacts on the generalization of models across domains with different characteristics. Domain-specific alignment methods outperform simple transfer learning in terms of accuracy and stability in the training evaluation of different target languages. Adaptive methods are more successful in this environment compared to other methods; they have already addressed the significant differences between domains or the imbalance between categories, helping to reduce the impact of the target domain on the prediction results. In some cases, performance improvements have reached a plateau, requiring continuous advancements to further enhance adaptive technologies. Domain adaptation-based methods are expected to improve the accuracy of industrial equipment fault detection.

### Visualization of Learned Representations

t-SNE projects the learned feature embeddings from all domains into a two-dimensional space and obtains qualitative visualizations of the top five representative methods to study the underlying structures imposed by various adaptation methods. As shown in Figure 5(a), after processing, training only on the source domain results in very clear cluster separation. MMD and adversarial techniques respectively tighten the clusters internally and the domain-invariant groups. Adversarial alignment results in minimal and category-discriminative clusters, which possess strong transferability.



**Figure 5.** Embedding Space Visualization and Metrics: (a) t-SNE distribution under five adaptation strategies; (b) Average inter-class distance for all methods; (c) Intra-class and inter-class aggregation metrics

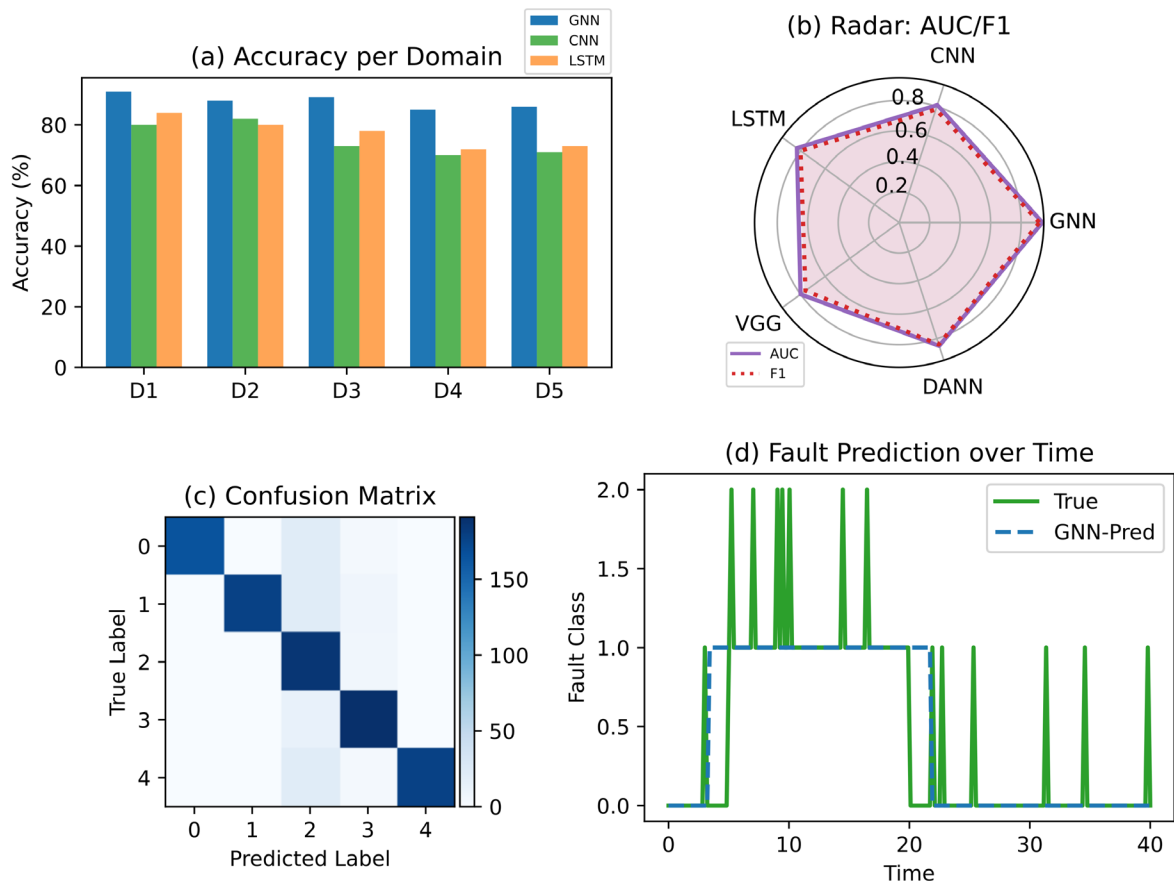
Figure 5(b) shows the average Euclidean distance between classes. The explicit method of domain alignment improves the average inter-class separability. Whether it is effective in actual industrial diagnostics needs empirical validation.

Additionally, Figure 5(c) quantifies both intra-class cohesion and inter-class dispersion by evaluating their respective metrics across strategies. Here, adversarial alignment achieves the lowest intra-class spread and highest inter-class margin, supporting the assertion that explicit regularization promotes both domain and category invariance.

These visualizations help assess whether the adaptation is effective and provide some reference for improving subsequent models. Analyze whether there is overlap or dispersion between categories; these situations may not yet be clearly defined and may require the introduction of further data augmentation strategies in this area. Quantitative improvements are accompanied by a feature space that is more interpretable and reliable. Achieving well-separated and clustered distribution embeddings will help improve the accuracy of faults in complex real-world production environments.

### Discussion

As shown in Figure 6, the cross-domain evaluation results indicate that the GNN-based model performs excellently across all five domains and fault types, while other models perform poorly. As shown in Figure 6(a), for each domain, the average accuracy of GNN reached 89.2%. The advantage of encoding relational context in mitigating the distribution gap between domains, compared to CNN and LSTM, shows an improvement ranging from 6% to over 15%.



**Figure 6.** Cross-Domain Fault Diagnosis Results: (a) Per-domain accuracy-GNN versus benchmarks; (b) Comparison of GNN, CNN, LSTM, VGG, and domain-adversarial models via AUC and F1; (c) Confusion matrix for five fault categories in D2; (d) Temporal trace of predicted and actual faults

The polar plot shows the performance of GNN, CNN, LSTM, VGG, and domain adversarial on AUC and F1 accuracy, as shown in Figure 6(b). Although GNN exhibits relatively stable high values in most dimensions, CNN and LSTM

show significant declines in the D4 and D5 dimensions, as these dimensions have fewer fault domains and temporal variation characteristics. GNN has good generalization ability in domains with domain heterogeneity.

Figure 6(c) shows the confusion matrix for predicting five types of faults on domain D2. GNN can not only identify mechanical or vibration faults that traditional models usually misjudge, but also distinguish between categories. Although there is slight confusion between electrical and thermal categories, the overall classification error rate is lower compared to sequence-based models. This indicates that the structural dependency theory proposed by GNN is correct.

As shown in Figure 6(d), the predicted values during different time periods are consistent with the actual state of the fault status labeled for that time period. GNN detects baseline delays or overreactions, as well as sudden changes and initial failures. Quick detection in practical maintenance applications

The proposed G-NN-based method can clearly reveal the overall interaction patterns of various industries in our society at different levels. Using GNN to improve classification accuracy and robustness under different conditions, including distribution changes, class imbalance, and abnormal environments, has shown good results compared to other methods; it is more suitable for practical application scenarios that include factory environments. This network can detect both frequent and occasional faults; the confusion matrix experiments showed a low classification error rate. Compared to CNN and LSTM, which significantly underperform under certain conditions, this highlights the shortcomings due to the lack of relational information and structural understanding. From the temporal prediction consistency of GNN, it can be seen that there is a certain application prospect in developing real-time monitoring systems to prevent equipment degradation thru timely alerts. It can be concluded that, in the context of Industry 4.0, combining topology and adaptive mechanisms is a necessary condition to ensure the effectiveness of predictive maintenance models; promising areas for industrial application exploration have also been identified.

## Conclusion

Introducing a cross-domain diagnostic framework based on graph neural networks, which has been rigorously tested on a large number of real industrial datasets. This paper effectively addresses the challenges of complex and dynamic manufacturing scenarios by combining relational feature model training with domain-invariant representation learning and transfer optimization. Based on the extensive feature representations learned from the graph, and combined with an operationally added domain adaptation alignment mechanism, to improve diagnostic accuracy under conditions of sample distribution changes and imbalance.

The system can adaptively identify high-level processes and specific factory anomalies. By combining these two methods, information can be transmitted between sensor-equipped systems rich in large amounts of data and small objects operating under uncertain conditions, thereby overcoming the persistent limitations of industrial artificial intelligence.

These features bring transformative practical value to the real-world application of smart factories. In the early stages of factory construction or during its development, the rapid implementation of predictive maintenance and anomaly detection systems will not affect diagnostic accuracy. Changes in system configuration, such as equipment adjustments or process shifts, will not affect diagnostic accuracy. This framework can support the implementation of large-scale, highly reliable AI operation and maintenance systems, which is crucial for making the industrial revolution with features such as digital twin technology and adaptive manufacturing a reality.

Several directions for future research. Current findings support transferability to some extent, but performance degradation becomes more pronounced when the distribution deviates significantly or new domains are introduced. In the future, more adaptive online methods may be attempted, and collaboration with multiple meta-learners could be pursued to address the issues more deeply. By introducing richer causal models and quantifying uncertainty, they become more trustworthy and interpretable in safety-critical and multimodal process environments.

## Author Contributions

Sebastian Płocharski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Robert Ostrowski contributes

to methodology, software, validation, analysis, investigation. All authors have read and agreed with the manuscript before its submission and publication.

#### Funding

This research received no specific financial support from any funding agency.

#### Institutional Review Board Statement

Not applicable.

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