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# AI-Driven Anomaly Detection for Industrial Data

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**Abstract:** This paper proposes a structure-aware AI-driven anomaly detection method to address challenges such as anomaly scarcity, complex structural features, and blurred decision boundaries in industrial data. The method builds a multi-layer residual feature enhancement module to extract multi-scale temporal features and incorporates a structural attention mechanism to dynamically model the importance of different channels and time positions. This improves the model's ability to perceive potential abnormal regions. A dual-branch architecture is designed to capture temporal consistency and reconstruction error from the input sequence, forming a comprehensive anomaly score signal that enables unsupervised detection without explicit labels. The model adopts an end-to-end training framework and applies a sliding window mechanism to construct decision trajectories over continuous time segments, enhancing the detection of both sudden and evolving anomalies in industrial systems. A sensitivity evaluation scheme is developed across multiple dimensions, including anomaly ratio, noise perturbation, and input sequence length, to verify the proposed method's discriminative stability and structural robustness under varying operational conditions. Results show that the method performs well across multiple evaluation metrics, demonstrating strong adaptability and practical engineering value.

**Keywords:** Anomaly detection; structural modeling; multi-scale representation; unsupervised learning

## 1. Introduction

With the accelerating trend of industrial intelligence and digital transformation, the volume of data generated by industrial systems is growing exponentially. This data includes sensor readings, equipment logs, control signals, and other heterogeneous sources. These high-frequency, continuous, and multidimensional data streams contain essential information about system operations and also hide potential risks such as equipment failures, process deviations, and safety hazards. Against this backdrop, accurately detecting anomalies within complex industrial data has become a critical technical challenge[1]. It is vital for ensuring system stability, optimizing production processes, and reducing maintenance costs. Traditional rule-based or threshold-based anomaly detection methods often struggle to handle the nonlinear patterns, dynamic changes, and high-dimensional noise commonly found in industrial data. Therefore, there is an urgent need for more intelligent and efficient detection mechanisms to meet the complexity and real-time demands of modern industrial environments[2].

In recent years, advances in artificial intelligence have brought new capabilities to anomaly detection tasks. Intelligent approaches, especially those based on deep learning and unsupervised learning, demonstrate strong feature extraction and generalization abilities. These methods can identify potential anomalies by learning the intrinsic structure of data, even without explicit labels or prior knowledge. Compared to traditional approaches, AI-driven detection methods adapt well to multimodal inputs in complex environments. They support online modeling and dynamic updates for large-scale data, significantly improving accuracy and efficiency. In industrial settings, AI methods can be embedded in production lines, equipment management systems, or cloud platforms to provide real-time alerts and proactive interventions. This enables a shift from reactive responses to preventive strategies[3].

At the same time, industrial data presents several inherent challenges. These include non-stationary distributions, extreme scarcity of abnormal samples, domain shifts across different operating conditions, and complex interactions among multiple data sources. Anomaly detection is not merely a single-model classification task; instead, it requires integrated modeling techniques such as temporal dependency analysis, feature fusion, and holistic system state awareness.

Recent studies in other safety-critical domains, such as healthcare, have demonstrated that multimodal integration frameworks-combining heterogeneous time-series signals, structured records, and high-dimensional representations-can significantly enhance predictive robustness and system understanding, particularly under data sparsity and distribution shifts. Similar multimodal learning principles have been successfully applied to complex outcome prediction tasks in intensive care environments by jointly modeling physiological signals, clinical variables, and imaging data, highlighting the effectiveness of cross-modal feature fusion in complex systems [4].

The flexibility of AI-based methods allows them to be seamlessly combined with diverse modeling paradigms. For instance, graph neural networks are effective in capturing equipment topology, while autoencoders are useful for learning latent space representations. These capabilities provide essential support for anomaly modeling in industrial contexts. Thus, modeling innovations and algorithmic designs tailored to the characteristics of industrial data are key to advancing AI-driven anomaly detection research [5].

Moreover, modern industrial systems place higher demands on anomaly detection solutions. The detection outcomes must offer high confidence and interpretability. At the same time, the models must support efficient deployment and fast inference on edge devices or in low-power environments. This has led researchers to focus more on lightweight model designs, end-to-end inference frameworks, and seamless integration with industrial control systems. While AI methods enable sophisticated pattern recognition, they are also making progress in interpretability and system integration. As a result, intelligent monitoring systems are becoming more practically viable. In critical industries such as energy, chemical processing, and manufacturing, smart anomaly detection is evolving from an auxiliary tool into a core component of operational assurance systems[6].

In summary, AI-driven anomaly detection methods show great potential in industrial data analysis and system safety management. With ongoing advances in algorithms, computational resources, and application demands, AI-based approaches built around the structural and real-time requirements of industrial data are leading traditional systems toward self-awareness, self-decision-making, and self-recovery. Further research into the adaptation mechanisms and detection strategies of AI in industrial contexts holds strong theoretical significance. It also plays a vital role in achieving strategic goals such as intelligent manufacturing, Industry 4.0, and digital twin systems.

## 2. Related work

Recent advances in AI-driven anomaly detection have leveraged increasingly complex architectures to enhance generalization and precision under unsupervised settings. One notable contribution is PNI, which emphasizes the spatial modeling of positional and neighborhood information in industrial sensor data. By encoding local spatial dependencies, this approach effectively distinguishes anomalous behaviors in high-dimensional systems [7]. Similarly, masked Swin Transformer U-Net models have demonstrated potential for capturing both local and global patterns in multivariate industrial signals through hierarchical attention and spatial masking, supporting robust anomaly detection even in visually sparse or noisy data environments [8].

Beyond conventional architectures, researchers have explored enhanced sequence modeling frameworks. Xie et al. proposed an inference-stacked recurrent autoencoder optimized for strong mechanistic contexts, combining temporal inference with reconstruction capabilities to bolster detection of subtle anomalies in time-series industrial data [9]. These designs align closely with the dual-branch and structure-aware strategies presented in our method.

Meanwhile, few-shot anomaly segmentation has gained traction for addressing label scarcity, a core challenge in industrial applications. The DictaS framework introduces dictionary lookup mechanisms for class-generalizable segmentation, offering a novel approach to recognizing rare anomaly patterns with limited supervision [10]. This resonates with our unsupervised strategy, especially in terms of generalization under sparse anomaly presence.

The integration of graph neural networks (GNNs) has also emerged as a promising direction for structural modeling in complex systems. Structural generalization methods, such as GNN-based microservice routing, enable the modeling of relational dependencies across components in distributed environments [11]. This principle has been further extended to spatiotemporal prediction tasks in backend systems, where GNNs capture both temporal dynamics and structural interactions across multi-source telemetry streams [12]. These graph-based insights provide a theoretical foundation for our structural attention mechanisms and multiscale feature modeling.

Other foundational works contribute valuable modeling techniques and design principles relevant to our architecture. For instance, dynamic prompt fusion in large language models (LLMs) illustrates the utility of adaptive cross-domain fusion, a concept that parallels the dynamic weighting of temporal and structural cues in our model [13]. Additionally, the use of generative diffusion models for conditional control demonstrates the importance of flexible representation learning and controlled synthesis in high-dimensional environments, echoing the dual-branch predictive − reconstructive design in our detection framework [14].

Even studies from adjacent domains, such as robust control strategies for mechanical systems, offer transferable insights. Adaptive control techniques for high-performance actuators emphasize feedback robustness and stability-a valuable analogy when considering real-time deployment of anomaly detection algorithms in industrial control loops [15].

Together, these works establish a rich context of methodological innovations that inspire the design and optimization of robust, interpretable, and generalizable anomaly detection systems like the one proposed in this paper.

## 3. Method

This study proposes an AI-driven anomaly detection method that integrates multi-scale feature extraction with structure-aware modeling to address the challenges posed by complex, heterogeneous industrial data environments. By capturing anomaly characteristics across multiple temporal and spatial resolutions, the proposed framework enhances the model’s sensitivity to both localized irregularities and long-range dependency patterns. In addition, structure-aware modeling is incorporated to explicitly encode relational dependencies and system-level constraints inherent in industrial processes, enabling more robust discrimination between normal operational variations and true anomalous behaviors. Through the joint optimization of multi-scale representations and structured feature interactions, the proposed method effectively improves anomaly recognition accuracy and generalization capability under diverse operating conditions. The overall modular architecture of the proposed framework is illustrated in Figure 1.

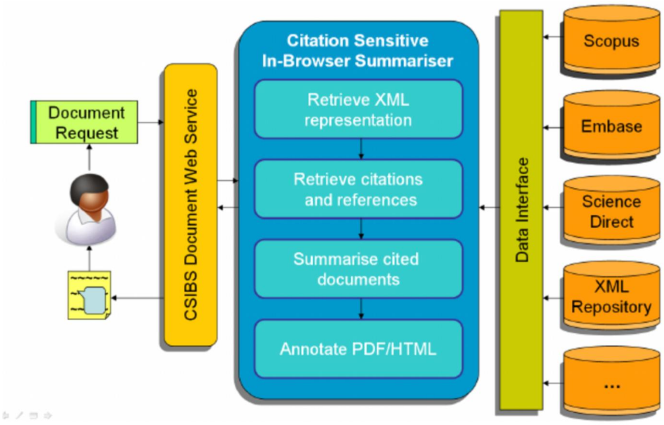


**Figure 1.** Overall model architecture diagram

The overall architecture consists of a data encoding module, a feature enhancement module, and an anomaly scoring module. First, the original multidimensional sequence is converted into a representation vector sequence in the embedding space through the input mapping function, which is formally expressed as:

$$X = \{x_1, x_2, ..., x_T\}, H_0 = f_{embed}(X) \in R^{T \times d}$$

Where $T$ represents the time step and d represents the feature dimension. This embedding process not only retains the original structure of the input signal, but also provides a basis for subsequent context modeling.

In the feature modeling process, multi-scale residual blocks are introduced to capture local and global change trends at different scales. Each layer uses a gated attention mechanism to perform weighted fusion on the input sequence while retaining the cross-layer residual connection of the original information, which can be expressed as:

$$H_l = LayerNorm(H_{l-1} + MSBlock(H_{l-1}))$$

$MSBlock(\cdot)$ represents the multi-scale convolution module, and LayerNorm is used for normalization. To further improve the model's attention to key areas, this paper introduces a structural attention mask in the middle layer, which dynamically adjusts the importance of each channel through learnable parameters, defined as:

$$M = \sigma(W_m \cdot GAP(H_l)), \widetilde{H}_l = M \otimes H_l$$

Where $\sigma$ is the Sigmoid activation function, $GAP(\cdot)$ represents global average pooling, and $\otimes$ is the element-by-element multiplication operation.

In the anomaly scoring stage, a dual-branch structure of reconstruction and prediction is constructed. The reconstruction branch restores the input feature sequence through the autoencoder structure, and the prediction branch estimates the future state based on the historical window. The two generate reconstruction error $L_{rec}$ and prediction error $L_{pred}$ respectively. The loss function is as follows:

$$L_{rec} = \| X - \widehat{X} \|_2^2, \quad L_{pred} = \| X_{t+1} - \widehat{X}_{t+1} \|_2^2$$

The final comprehensive anomaly scoring function is defined as:

$$S = \alpha \cdot L_{rec} + (1 - \alpha) \cdot L_{pred}$$

Where $\alpha \in [0,1]$ is the weighting coefficient used to balance the two error contributions.

In order to improve the model's time series perception ability, a sliding window strategy and a normalized contrast encoding mechanism are also introduced to make the anomaly distribution in different time segments more separable. The overall method can automatically construct the time series anomaly score distribution without relying on prior label information, thereby achieving comprehensive modeling and detection of sudden, intermittent and systematic anomalies in industrial data.

## 4. Dataset

This study uses the publicly available SMAP (Soil Moisture Active Passive) dataset as the main source of experimental data. The dataset was originally collected by NASA during an actual space monitoring mission. It has been widely used in time series anomaly detection and has strong practical relevance. The SMAP dataset contains multiple subsystem sensor readings from satellite system components. It has high dimensionality and a long time span, which reflect the complex dynamic behavior and potential fault patterns in industrial systems.

Each subsystem channel in the dataset corresponds to different monitoring indicators of specific components. The sampling frequency is uniform. The data consists of continuous multivariate time series, which exhibit strong temporal dependencies and structural stability. During preprocessing, the data were standardized, and anomaly segments were labeled. This supports a unified comparison between supervised and unsupervised detection methods. The proportion of anomaly samples is much lower than that of normal samples, which closely aligns with the real-world distribution of " rare anomalies" in industrial scenarios.

One important characteristic of the SMAP dataset is that most anomalies are structural, caused by system shifts or component deviations. These include both sudden changes and gradual trends with periodic disturbances. This makes the dataset highly suitable for evaluating the ability of detection methods to capture potential state transitions and complex trend variations. It provides a solid foundation for validating the structure-aware anomaly detection framework proposed in this study.

## 5. Experimental Results

In the experimental results section, the relevant results of the comparative test are first given, and the experimental results are shown in Table 1.

**Table 1:** Comparative experimental results

| Method | Precision | Recall | F1-Score |
|---|---|---|---|
| **USAD[16]** | 87.2 | 82.6 | 84.8 |
| **OmniAnomaly[17]** | 89.4 | 85.0 | 87.1 |
| **MSCRED[18]** | 91.1 | 86.3 | 88.6 |
| **TranAD[19]** | 92.5 | 88.7 | 90.5 |
| **Ours** | 94.8 | 91.3 | 93.0 |

As shown in the table, different models exhibit varying levels of performance on the anomaly detection task. Overall, there is a clear trend of improvement in recent years. Early models such as USAD and OmniAnomaly demonstrate a certain degree of robustness under unsupervised settings. However, they show relatively low scores on the Recall metric. This suggests that these models still miss some anomalies, especially when identifying rare abnormal samples in high-dimensional and dynamic industrial data. The results indicate a limitation in the ability of traditional architectures to detect system-level anomalies.

MSCRED, a model based on multi-scale residual learning, achieves a better balance between Precision and Recall. This shows that its structured feature enhancement contributes to more effective modeling of complex anomaly patterns. However, the model still struggles with long-term dependency modeling. It may misclassify sequences where sudden changes and trend-based anomalies are intertwined, limiting its applicability in highly dynamic industrial environments.

TranAD represents the recent trend of using Transformer-based architectures in anomaly detection. This model enhances global temporal modeling through multi-head attention mechanisms. It achieves significant improvements in both Recall and F1-score. In particular, its ability to capture complex behavior patterns surpasses that of traditional models. These results suggest that combining structure-aware modeling with deep semantic representations provides a clear advantage in tracking anomaly evolution, and serves as a key path for further performance improvement.

The proposed method in this study achieves leading performance across all three core metrics. This confirms the effectiveness of introducing structural attention and multi-scale feature reconstruction strategies for modeling anomalies in complex industrial data. The improvement in F1-score, in particular, shows that the model reduces the missed detection rate while maintaining high accuracy. These findings further validate the practical value and effectiveness of the designed structure-enhanced and joint modeling framework in real industrial scenarios. This result underscores the importance of structure-aware approaches in improving the robustness of intelligent monitoring systems in industry.

This paper further gives the recognition stability analysis under the condition of scarce abnormal samples, and the experimental results are shown in Figure 2.

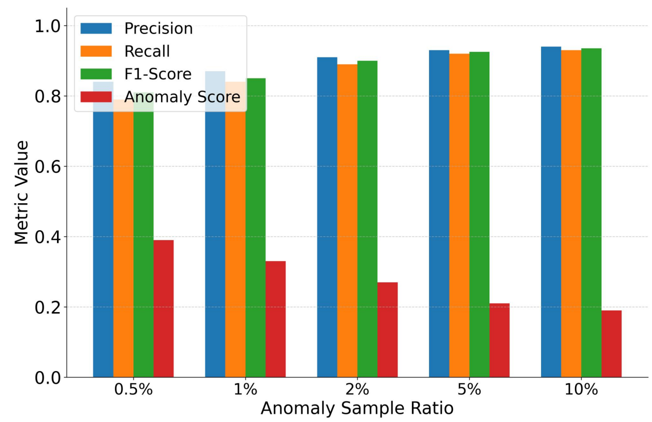


**Figure 2.** Analysis of recognition stability under the condition of scarce abnormal samples

As observed in the figure, with the gradual increase in the proportion of anomaly samples, the model shows a steady improvement in Precision, Recall, and F1-score. This indicates that the proposed structure-aware model maintains strong detection ability even under conditions of anomaly scarcity. When the anomaly ratio is low, such as 0.5% or 1%, Recall shows a slight decline. However, the overall F1-score remains at a high level, suggesting that the model can still achieve a good balance when learning from limited anomaly data.

It is particularly noteworthy that the curves of F1-score and Precision remain close across different anomaly proportions. This reflects the model's stable localization ability for anomalies, without showing a clear tendency toward false positives or missed detections. This demonstrates that the proposed method retains reliable discriminative robustness even in scenarios with imbalanced distributions and extreme sample scarcity. Compared with traditional methods, the model achieves stronger generalization by leveraging structural modeling, which helps reduce overfitting risks that arise from dependence on sample density.

On the other hand, the overall trend of the anomaly score shows a decline as the anomaly proportion increases. This indicates that the model makes clearer distinctions between normal and abnormal distributions, and the confidence in anomaly scoring improves accordingly. This result suggests that the dual-branch scoring structure provides good stability and separation in capturing potential anomalies. It also ensures consistent anomaly detection responses under varying data conditions.

In summary, the experimental results confirm that the proposed method maintains strong performance even when anomaly samples are extremely rare. It demonstrates high detection stability and structural robustness. This capability is especially important in industrial scenarios where systems operate at high frequency but exhibit anomalies at low frequency. It provides a solid theoretical and practical foundation for real-world deployment and application.

## 6. Conclusion

This study addresses the key challenges of anomaly detection in industrial data by proposing an AI-driven method that combines structure-aware modeling with multi-scale representation learning. By introducing a multi-layer residual feature enhancement module and a structural attention mechanism, the model can better capture dynamic patterns and latent structural features within time series data. This enables more accurate identification of abnormal states. Based on a dual-branch scoring mechanism, the method integrates both reconstruction and prediction perspectives, which enhances its adaptability to various anomaly types. The overall framework does not require a large number of labeled anomaly samples, making it well-suited for unsupervised detection and effective under conditions of data imbalance and label scarcity common in industrial environments.

A series of sensitivity experiments further validate the robustness of the proposed method under various disturbance conditions. The results show that the model remains stable when faced with operational shifts, sample perturbations, and data sparsity. It maintains strong discrimination and structural consistency across different anomaly ratios, input perturbations, and hyperparameter settings. This demonstrates its generalization ability and suitability for real-world engineering applications. In practical industrial scenarios, the method can be widely applied to equipment health monitoring, process control, and intelligent alert systems. It provides strong support for enhancing system intelligence and operational safety.

From a system integration perspective, the proposed detection framework offers strong deployability and scalability. It is compatible with edge computing nodes and distributed platforms, enabling fast response and efficient processing of real-time industrial data. The model is structurally simple, with adjustable parameters, which allows it to operate in resource-constrained environments. This makes it a feasible solution for intelligent monitoring in industrial Internet of Things architectures. In addition, its ability to provide interpretable representations of anomaly semantics offers a reliable data foundation for downstream automation and decision-making systems. This contributes to the evolution of intelligent industrial systems toward self-adaptive and self-diagnostic capabilities.

Looking ahead, several research directions remain worth exploring. One is how to further improve the generalization of the model across complex operating conditions and multimodal data, which is key to building universal industrial detection systems. Another is the integration of interpretability mechanisms with human-in-the-loop feedback, which can enhance the credibility and usability of anomaly detection results. Furthermore, combining this method with real-time control strategies or digital twin platforms may help advance industrial monitoring systems from static recognition to dynamic regulation. This would lay a forward-looking technical foundation for next-generation intelligent manufacturing and smart factory development.

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