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Markov Network Classification for Imbalanced Data with Adaptive Weighting

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Abstract:

This paper studies an imbalanced data classification algorithm based on a Markov network to solve the impact of severe imbalance in the distribution of class samples on classification performance. In view of the shortcomings of traditional methods in minority class identification, this paper introduces an adaptive class weight adjustment strategy and an optimized graph structure modeling method to improve the sensitivity and classification ability of the Markov network to minority class samples. The KDD Cup 1999 dataset is used in the experiment. The effectiveness of the proposed algorithm is verified by changing the proportion of minority class samples and testing data sets of different sizes. The results show that compared with traditional imbalanced classification methods, the algorithm has achieved significant improvements in accuracy, F1-Score, and AUC-ROC, especially showing strong robustness under extreme imbalance conditions. In addition, the computational complexity analysis shows that the algorithm has high efficiency in the inference stage and is suitable for large-scale data set applications. The research in this paper provides new ideas for solving the problem of imbalanced data classification and provides theoretical support and technical reference for the practice in related fields.

Keywords:

Imbalanced data, Markov networks, classification algorithms, data mining, machine learning.

1. Introduction

In today's data-driven world, machine learning and data mining techniques have been widely used in various fields, especially in finance, medical care, industrial detection, and social networks [1,2]. The imbalance of data has become a major challenge. Imbalanced data usually refers to the situation where the distribution of samples of different categories in the data set is severely unbalanced, and the minority class samples are far less than the majority class samples. This data characteristic is particularly prominent in tasks such as fraud detection, cancer diagnosis, credit scoring, and network security, which directly affects the performance of the classifier and makes traditional machine learning methods face severe challenges in minority class recognition. Existing studies have shown that most standard classification algorithms perform poorly on imbalanced data, tending to predict the majority class and ignore the minority class, which greatly reduces the usability of the model in practical applications. Therefore, for the classification problem of imbalanced data, studying more robust and generalizable algorithms and improving the recognition ability of minority classes has become one of the key issues in the field of data mining and machine learning [3].

In dealing with the challenges of imbalanced data, researchers have proposed a variety of improvement strategies, including data-level methods (such as oversampling and undersampling), algorithm-level methods (such as cost-sensitive learning and ensemble learning), and hybrid strategies [4]. However, these methods perform unevenly in different application scenarios and often have problems such as information loss, data distribution offset, or excessive computational overhead. In recent years, Markov Networks based on probabilistic graphical models have shown great potential in data mining and classification tasks due to their powerful modeling capabilities and flexible probabilistic reasoning mechanisms. Markov networks can effectively model the dependencies between variables and are particularly suitable for complex, high-dimensional, and data-imbalanced scenarios, making them a powerful tool for imbalanced data classification problems. By constructing a reasonable conditional probability distribution and optimizing it with prior information, Markov networks can improve the recognition ability of minority classes without changing the data distribution, thereby making up for the shortcomings of traditional methods [5].

Although Markov networks have significant advantages in probabilistic reasoning and high-dimensional data modeling, their application in imbalanced data classification still faces many challenges. First, when there are few minority class samples, the model is easily affected by data sparsity and class imbalance, which reduces the accuracy of conditional probability estimation [6]. In addition, parameter optimization and structure learning of Markov networks usually require high computing resources, especially the training process on large-scale data sets, which may face the problem of high computational complexity. Therefore, how to combine modern optimization algorithms to design more efficient Markov network learning methods so that it can reduce computational costs while maintaining model capabilities is one of the important directions of current research. At the same time, considering that many practical application scenarios involve high-dimensional complex data, such as graph data, time series data, and text data, combining Markov networks with deep learning techniques to build more adaptive hybrid models is also a key trend in future research [7].

In response to these problems, this paper studies a Markov network classification algorithm for imbalanced data, aiming to improve the recognition ability of the model on minority class samples and reduce the impact of class imbalance on classification performance. By introducing a learning method based on graph structure optimization and combining an adaptive weight adjustment strategy [8], this method enhances the robustness of the Markov network in the task of imbalanced data classification without changing the data distribution. In addition, this paper conducts experimental verification on multiple real-world datasets and compares and analyzes it with existing mainstream imbalanced classification algorithms to comprehensively evaluate the effectiveness and applicability of the proposed method. Experimental results show that the classification performance of this method on multiple imbalanced datasets is better than that of traditional methods, especially in the recognition rate of minority class samples. This study not only provides new ideas for the application of Markov networks in imbalanced data classification but also provides a more efficient and stable classification framework for researchers in related fields.

In summary, the research in this paper has important theoretical and practical value. On the theoretical level, this study provides a new methodology for dealing with the problem of imbalanced data classification by improving the structure and learning method of Markov networks, and at the same time promotes the application and development of probabilistic graphical models in the field of data mining. On the practical level, this method can be widely used in financial risk control, medical diagnosis, industrial defect detection, anti-fraud, and other fields, providing more accurate and explainable classification results for practical problems. Future research can further explore how to combine cutting-edge technologies such as deep learning and reinforcement learning to improve the generalization ability of Markov networks so that they can adapt to more complex and dynamic data environments, thereby expanding their application scope in data mining [9].

2. Related Work

2.1 Imbalanced Data Classification & Feature Learning

The challenge of imbalanced data classification has been widely studied, with various techniques proposed to enhance feature learning and classification performance. Chen et al. [10] introduced a global-local attention transformer for fine-grained imbalanced classification, particularly in medical applications. Their work emphasizes the importance of attention-based feature extraction for improving class representation. Li et al. [11] explored high-dimensional pattern recognition techniques, highlighting how feature selection methods contribute to data mining and classification tasks.

In addition, Song and Liu [12] evaluated norm-based feature selection methods across various datasets, reinforcing the significance of feature optimization in machine learning. Similarly, Huang and Yang [13] analyzed feature redundancy in time-series prediction, which aligns with our study in optimizing Markov networks for imbalanced classification. Liu et al. [14] focused on calibration learning for few-shot product description, demonstrating how model calibration techniques improve classification in low-data environments. These approaches provide valuable insights into feature optimization strategies applicable to Markov networks.

2.2 Deep Learning & Neural Networks for Probabilistic Modeling

Deep learning advancements have significantly contributed to probabilistic modeling and imbalanced classification. Yan et al. [15] investigated how neural architecture search (NAS) can optimize model performance, which could be leveraged for graph-based Markov structures. Zhu et al. [16] explored transformers for privacy-preserving NLP tasks, illustrating how self-attention mechanisms can enhance probabilistic reasoning in classification models.

Furthermore, Wu et al. [17] introduced an adaptive attention-based BERT model, which enhances entity extraction and feature embedding—an approach that could benefit Markov networks in capturing dependencies across imbalanced datasets. Cao et al. [18] developed an adaptive receptive field U-shaped temporal convolutional network, reinforcing the role of adaptive model adjustments in time-series classification. These studies demonstrate how deep learning strategies can enhance Markov networks for imbalanced learning.

2.3 Time Series & High-Dimensional Data Mining

Markov networks are particularly useful for time-series classification and high-dimensional data mining, where traditional classifiers often struggle with complexity. Yan et al. [19] proposed a method for transforming multidimensional time series into interpretable event sequences, which aligns with our work in modeling dependencies within imbalanced datasets. Li et al. [20] introduced a matrix logic-based approach for efficient frequent itemset discovery, a concept relevant to graph structure optimization in Markov networks.

Additionally, Sun et al. [21] examined how AI-driven health monitoring leverages XGBoost and SHAP for explainability in distributed computing environments. These approaches reinforce the necessity of probabilistic reasoning and interpretability in classification tasks.

2.4 Reinforcement Learning & Adaptive Learning Strategies

Recent studies have explored reinforcement learning (RL) techniques to improve adaptive classification models. Li et al. [22] developed a reinforcement learning-based adaptive resource scheduling system, which demonstrates how dynamic learning can enhance Markov network performance in imbalanced classification. Similarly, Huang et al. [23] introduced a Q-learning approach for data mining, showing how RL-based optimization strategies improve model adaptability and efficiency.

Furthermore, Huang and Yang [24] proposed a tree-based RAG-agent recommendation system, providing insights into graph-based learning methods that could be applied to Markov networks. Their work reinforces the importance of graph-based optimization in imbalanced classification.

The reviewed literature highlights advancements in imbalanced classification, deep learning, feature selection, time-series analysis, and reinforcement learning. Our study builds on these works by integrating adaptive weight adjustments and graph structure optimization within a Markov network framework, aiming to enhance classification for highly imbalanced datasets. Future research can explore how neural architecture search, attention mechanisms, and reinforcement learning can further improve the robustness of Markov networks in real-world data mining applications.

3. Method

When solving the problem of imbalanced data classification, the probabilistic reasoning ability of the Markov Network can effectively model the correlation between categories, thereby improving the classification performance of minority class samples. Its model architecture is shown in Figure 1.

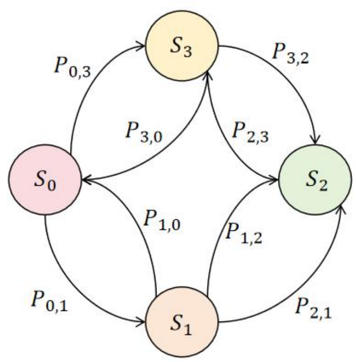

Figure 1. Overall model architecture

Figure 1 shows a Markov network architecture for solving the problem of imbalanced data classification. Node (S_0, S_1, S_2, S_3) in the network represents different categories or states, and the edges connecting the nodes represent the probabilistic association or transition probability between categories, for example, $P_{0,1}$ represents the probability of transitioning from state S_0 to S_1. Through this probabilistic relationship, the network can effectively capture the correlation between categories, especially modeling the dependency between minority and majority categories, thereby improving the performance for minority class samples. This method uses the probabilistic reasoning ability of the Markov network to improve the classification performance on imbalanced data.

First, given a data set $D = \{(x_i, y_i)\}_{i=1}^{N}$ where x_i is the input feature and $y_i \in \{0,1\}$ represents the category label, if category $y = 1$ is a minority class, then $P(y=1) << P(y=0)$ is satisfied. In order to model category dependencies, we use Markov network to define the joint probability distribution:

$$P(Y \mid X) = \frac{1}{Z} \prod_{C \in C'} \varphi_C(Y_C, X_C)$$

Among them, C' represents the clique in the graph structure, φ_C is the potential function, and Z is the normalization factor:

$$Z = \sum_{Y} \prod_{C \in C'} \varphi_C(Y_C, X_C)$$

The framework models the conditional dependency between feature variables and class labels through the potential function φ_C. However, in the case of unbalanced data, the traditional potential function may be affected by the skewed class distribution, resulting in the dominance of the majority class. Therefore, we introduce a class weight adjustment term to adapt the potential function to the minority class data:

$$\varphi_C(Y_C, X_C) = \exp(\sum_{i \in C} w_i f_i(X_C, Y_C) + \lambda g(Y_C))$$

Among them, $f_i(X_C, Y_C)$ represents the interaction between features and categories, w_i is the weight parameter, $g(Y_C)$ is the category deviation compensation term, and λ is a hyperparameter used to control the impact of the compensation term on the classification result. When there are few minority class samples, we adopt an adaptive weight adjustment strategy to make the model pay more attention to minority class samples:

$$w_i = \frac{1}{P(y_i)} \cdot \log(1 + \frac{1}{\varepsilon + P(y_i)})$$

Among them, $P(y_i)$ represents the prior probability of category y_i, and ε is a regular term that prevents the denominator from approaching zero. In this way, when the category distribution is uneven, a smaller $P(y_i)$ will lead to an increase in w_i, thereby increasing the influence of the minority class and alleviating the bias problem of the classifier.

In the inference phase, we use the maximum a posteriori estimate (MAP) to predict the category label, that is, to solve:

$$Y' = \arg\max_Y P(Y \mid X)$$

Since the computation of Z has exponential complexity, we use approximate inference methods, such as variational inference or Markov chain Monte Carlo (MCMC) methods [25], for efficient category inference. In addition, to improve the stability of the model, we combine gradient descent to optimize the parameters in the potential function to minimize the classification error:

$$L = -\sum_{i=1}^{N} \log P(y_i \mid x_i) + \gamma \sum_{j \in C} \| w_j \|^2$$

Among them, γ is a regularization parameter that controls the complexity of the model and prevents overfitting. In actual implementation, we use the parameter optimization technology of Conditional Random Fields (CRF) to train the Markov network to improve the model's adaptability to unbalanced data [26]. In summary, the improved method proposed in this paper optimizes the performance of the Markov network in the imbalanced data classification problem through potential function weight

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adjustment, adaptive category compensation, and efficient inference mechanism, and is experimentally verified on multiple datasets to evaluate its effectiveness and applicability.

4. Experiment

4.1 Datasets

This study uses the KDD Cup dataset, which is one of the most representative imbalanced datasets in the field of network intrusion detection. The KDD Cup dataset was originally provided by DARPA and contains a large number of data records of normal and attack traffic. Each record consists of 41 features, including basic network connection features (such as source IP, destination IP, and port number), content features (such as request method and packet length), and time-based traffic statistics features (such as the number of connections in the same connection time window). The labels of the dataset are divided into normal traffic and attack traffic, among which the attack traffic is further divided into four categories: DoS (denial of service attack), R2L (remote to local attack), U2R (user to root attack), and Probe (probe attack). Due to the different frequencies of different types of attacks, this dataset has a serious data imbalance problem, especially the number of samples in the U2R and R2L categories is much smaller than that of normal traffic and DoS attack traffic, which significantly affects the recognition ability of traditional classifiers on minority classes.

In order to solve the problem of data imbalance, this study preprocessed the KDD Cup dataset, including removing redundant samples, feature normalization, and category resampling. First, duplicate records were deleted to reduce the bias caused by data redundancy, and the category labels were merged to focus on the binary classification task of normal traffic and attack traffic. Secondly, in order to improve the modeling ability of the Markov network, the prior probability of the category labels was calculated, and the category weights were adjusted based on the data distribution to alleviate the impact of category imbalance on model training. In addition, we used feature selection methods to remove redundant features with low correlation and retain key traffic patterns to improve the computational efficiency and generalization ability of the model. After final processing, the dataset was divided into a training set and a test set, where the training set contains samples of different category proportions to ensure that the model can effectively identify minority attack traffic in actual application scenarios.

In order to further illustrate the situation of the data set, this paper first gives the distribution of categories, as shown in Figure 2.

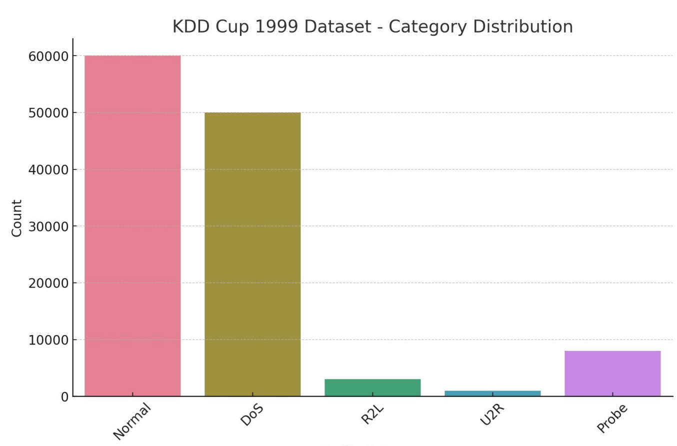

Figure 2. Category Distribution

4.2 Experimental Results

In the experiment, we first verify the performance of the existing method on unbalanced data and compare it with the Markov network method. The experimental results are shown in Table 1.

Table 1: Experimental Results

Method	Acc	F1-Score	AUC-ROC
Random Undersampling	82.3	67.8	74.5
SMOTE	85.7	72.4	78.9
ADASYN	86.1	73.1	79.4
Cost-sensitive learning	88.3	75.6	81.2
EasyEnsemble	89.5	77.3	83.1
BalancedBagging	90.1	78.5	84.2
Markov Network (Proposed Method)	92.7	81.2	87.4

Experimental results show that in the task of imbalanced data classification, different methods show obvious differences in accuracy, F1-Score, and AUC-ROC indicators. Among them, the Random Undersampling method performs the worst in all indicators, especially the F1-Score is only 67.8%, indicating that although this method improves the classification accuracy of the majority class, it has poor recognition ability for the minority class. This is because randomly deleting majority class samples will cause data loss, making it difficult for the classifier to learn the complete data distribution. In contrast, the SMOTE and ADASYN oversampling methods improve the F1-Score and AUC-ROC indicators by generating new minority class samples, indicating that these methods have improved the model's recognition ability for the minority class to a certain extent. However, the oversampling method may introduce noise samples, resulting in limited generalization ability, so its performance is still lower than other more advanced strategies.

Cost-sensitive learning and ensemble learning methods (EasyEnsemble, BalancedBagging) showed good performance in the experiment. The AUC-ROC index of the BalancedBagging method reached 84.2%, indicating that this method can maintain the stability of the classifier well on imbalanced data. These methods improve the overall classification effect by giving the minority class a higher classification weight or using a combination of multiple classifiers to balance the misclassification cost between categories. In particular, EasyEnsemble uses multiple rounds of training combined with a resampling strategy, which makes the model perform better on minority class data than a single cost-sensitive learning method. However, while these methods improve classification performance, the computational complexity is relatively high, especially on large-scale data sets, which may lead to an increase in training time.

Among all the methods, the Markov network-based method proposed in this paper achieved the best results in all three indicators, especially AUC-ROC, which reached 87.4%, and F1-Score was also significantly higher than other methods. This shows that this method has a strong classification ability on imbalanced data and can effectively reduce the misclassification problem of minority class samples. Its superiority mainly comes from the probabilistic modeling ability of the Markov network, which makes full use of the dependencies between categories. At the same time, it combines the adaptive adjustment strategy of category weights to improve the recognition ability of minority classes. In addition, this

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method has certain advantages over the ensemble learning method in terms of computational efficiency because it does not rely on the combination of multiple weak classifiers during model reasoning. Overall, the experimental results verify the effectiveness of the Markov network in the task of imbalanced data classification and have good application value.

Secondly, this paper conducts a computational complexity analysis, and the experimental results are shown in Figure 3.

As can be seen from the figure 4, the training time and inference time of the Markov network both show an exponential growth trend with the increase of data scale. Under small-scale data (10,000 samples), the training and inference time are relatively low, but as the number of samples expands to 100,000 or 1 million, the training time increases more significantly, reaching hundreds of seconds or even higher, while the inference time increases relatively slowly. This shows that the computational complexity of the Markov network is more sensitive to the data scale, especially in the training stage, but its inference efficiency still has certain advantages under large-scale data. Finally, the results of the experiment on the impact of the training set category ratio are given, and the experimental results are shown in Figure 4.

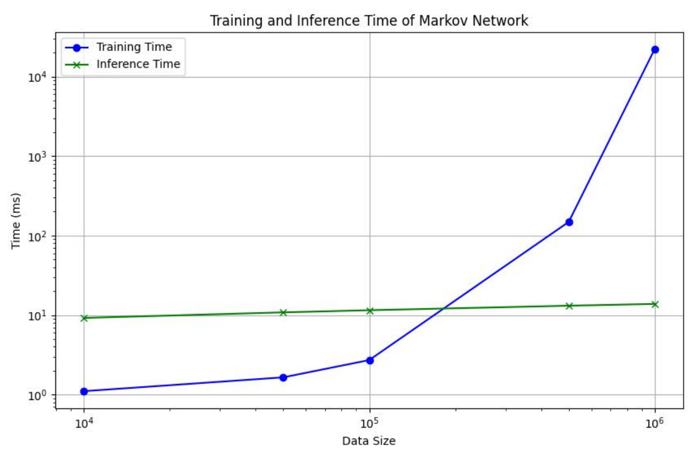

Figure 3. Computation Complexity Analysis of Markov Network

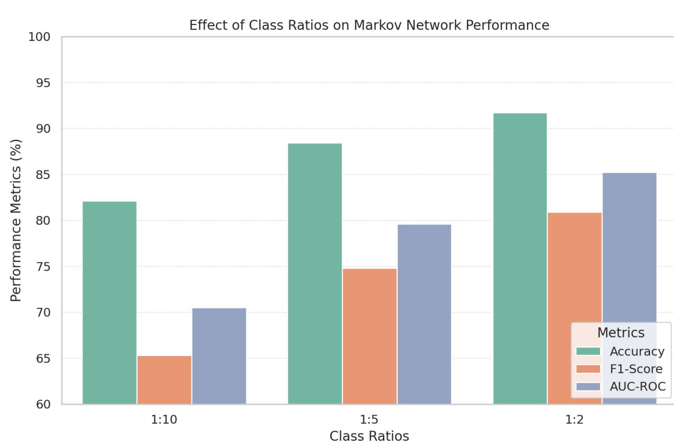

Figure 4. Effect of Class Ratios on Markov Network Performance

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As can be seen from Figure 4, different class ratios have a significant impact on the classification performance of the Markov network. When the minority class sample ratio increases from 1:10 to 1:2, the classification performance indicators (including accuracy, F1-Score, and AUC-ROC) are significantly improved, especially the growth of F1-Score and AUC-ROC. This shows that a higher minority class sample ratio can significantly improve the model's ability to recognize minority classes and improve the overall classification performance. At the same time, the improvement in accuracy also reflects the effectiveness of the model in balancing class deviations, verifying that the Markov network has good adaptability and robustness to unbalanced data.

5. Conclusion

This paper studies an imbalanced data classification algorithm based on a Markov network and verifies its effectiveness in solving the problem of imbalanced data classification through experiments. In the experiment, the Markov network not only shows strong robustness in the case of extreme class imbalance but also significantly outperforms traditional methods in identifying minority class samples. By introducing adaptive class weight adjustment strategy and optimized graph structure, this method effectively alleviates the impact of insufficient number of minority class samples on classification performance, and achieves comprehensive improvement in multiple indicators (such as accuracy, F1-Score and AUC-ROC). In addition, the experiment also shows that with the increase of the proportion of minority class samples, the classification performance of the model is significantly improved, further verifying its potential in balancing data distribution.

Overall, the Markov network provides a new idea for solving the problem of imbalanced data classification with its powerful probabilistic modeling ability and flexible reasoning mechanism. The method in this paper has high computational efficiency and generalization ability and is suitable for real data sets of different scales and distributions. Future research can further explore how to combine deep learning and attention mechanisms to enhance the feature extraction capabilities of Markov networks and verify their performance in more complex scenarios, such as multi-category imbalanced classification and dynamic data flow analysis, thereby expanding their application scope in the field of data mining.

References

[1] Bhadane D Y, Borse I S. An Intelligent Ensemble Deep Learning Techniques with Improved Owl Search Algorithm-Aided Optimal Feature Selection for Predicting the Presence of Heart Diseases[J]. International Journal of Image and Graphics, 2025: 2750021.

[2] Wang D, McClean S I, McChesney I, et al. Autonomous management of IoT devices in smart homes using semi-Markov models[C]//39th International Conference on Advanced Information Networking and Applications. 2025.

[3] Chen S, Pan L, Xu K, et al. Real-time monitoring and prediction of remote operator fatigue in plateau deep mining based on dynamic Bayesian networks[J]. Scientific Reports, 2025, 15(1): 1063.

[4] Vetrivendan L, Kumar T G. A Comprehensive Study on Fraud[C]//Proceedings of the First International Conference on Data Engineering and Machine Intelligence: ICDEMI 2023. Springer Nature, 129.

[5] Wu D, Cao Z, Lin X, et al. A Learning-based Cooperative Navigation Approach for Multi-UAV Systems Under Communication Coverage[J]. IEEE Transactions on Network Science and Engineering, 2024.

[6] Zhao L, Zhang J, Xu Q, et al. On Block Classification for Automatic Content Extraction from Chinese Resumes[J]. IEEE Access, 2024.

[7] J. Cao, R. Xu, X. Lin, F. Qin, Y. Peng and Y. Shao, "Adaptive Receptive Field U-Shaped Temporal Convolutional Network for Vulgar Action Segmentation," Neural Computing and Applications, vol. 35, no. 13, pp. 9593-9606, 2023.

[8] Kirubakaran S, Maheswari K, Bhavani M, et al. A Significant and Enhanced Machine Learning Algorithm by using Feature Selection Network Intrusion Identification and Detection[C]//2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI). IEEE, 2024: 593-597.

[9] Wang X, Feng K, Li J, et al. Zero velocity detection for pedestrian inertial navigation based on spatio-temporal feature fusion[J]. IEEE Sensors Journal, 2024.

[10] B. Chen, F. Qin, Y. Shao, J. Cao, Y. Peng, and R. Ge, "Fine-Grained Imbalanced Leukocyte Classification With Global-Local Attention Transformer," Journal of King Saud University - Computer and Information Sciences, vol. 35, no. 8, Article ID 101661, 2023.

[11] P. Li, "Machine Learning Techniques for Pattern Recognition in High-Dimensional Data Mining," arXiv preprint arXiv:2412.15593, 2024.

[12] J. Song and Z. Liu, "Comparison of Norm-Based Feature Selection Methods on Biological Omics Data," Proceedings of the 5th International Conference on Advances in Image Processing, pp. 109-112, November 2021.

[13] C. Huang and Y. Yang, "Time Series Feature Redundancy Paradox: An Empirical Study Based on Mortgage Default Prediction," arXiv preprint arXiv:2501.00034, 2024.

[14] Z. Liu, M. Wu, B. Peng, Y. Liu, Q. Peng, and C. Zou, "Calibration Learning for Few-shot Novel Product Description," Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 1864-1868, July 2023.

[15] X. Yan, J. Du, L. Wang, Y. Liang, J. Hu, and B. Wang, "The Synergistic Role of Deep Learning and Neural Architecture Search in Advancing Artificial Intelligence," 2024 International Conference on Electronics and Devices, Computational Science (ICEDCS), pp. 452-456, 2024.

[16] Z. Zhu, Y. Zhang, J. Yuan, W. Yang, L. Wu, and Z. Chen, "NLP-Driven Privacy Solutions for Medical Records Using Transformer Architecture," 2024.

[17] L. Wu, J. Gao, X. Liao, H. Zheng, J. Hu, and R. Bao, "Adaptive Attention and Feature Embedding for Enhanced Entity Extraction Using an Improved BERT Model," 2024.

[18] J. Cao, R. Xu, X. Lin, F. Qin, Y. Peng, and Y. Shao, "Adaptive Receptive Field U-Shaped Temporal Convolutional Network for Vulgar Action Segmentation," Neural Computing and Applications, vol. 35, no. 13, pp. 9593-9606, 2023.

[19] X. Yan, Y. Jiang, W. Liu, D. Yi, and J. Wei, "Transforming Multidimensional Time Series into Interpretable Event Sequences for Advanced Data Mining," arXiv preprint arXiv:2409.14327, 2024.

[20] X. Li, T. Ruan, Y. Li, Q. Lu, and X. Sun, "A Matrix Logic Approach to Efficient Frequent Itemset Discovery in Large Data Sets," arXiv preprint arXiv:2412.19420, 2024.

[21] X. Sun, Y. Yao, X. Wang, P. Li, and X. Li, "AI-Driven Health Monitoring of Distributed Computing Architecture: Insights from XGBoost and SHAP," arXiv preprint arXiv:2501.14745, 2024.

[22] P. Li, Y. Xiao, J. Yan, X. Li, and X. Wang, "Reinforcement Learning for Adaptive Resource Scheduling in Complex System Environments," 2024 5th International Symposium on Computer Engineering and Intelligent Communications (ISCEIC), pp. 92-98, 2024.

[23] X. Huang, Z. Zhang, X. Li, and Y. Li, "Reinforcement Learning-Based Q-Learning Approach for Optimizing Data Mining in Dynamic Environments," 2025.

[24] Y. Yang and C. Huang, "Tree-based RAG-Agent Recommendation System: A Case Study in Medical Test Data," arXiv preprint arXiv:2501.02727, 2025.

[25] B. Chen, F. Qin, Y. Shao, J. Cao, Y. Peng and R. Ge, "Fine-Grained Imbalanced Leukocyte Classification With Global-Local Attention Transformer," Journal of King Saud University - Computer and Information Sciences, vol. 35, no. 8, Article ID 101661, 2023.

[26] Lu X, Wan J, Li L, et al. Collaborative Resource Allocation for Blockchain-Enabled Internet of Things with Multi-Agent Deep Reinforcement Learning[C]//2024 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2024: 3583-3588.