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Capsule Network-Based AI Model for Structured Data Mining with Adaptive Feature Representation

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Abstract: This paper proposes a classification-based data mining algorithm that integrates a feature enhancement mechanism with Capsule Networks. The method is designed to address the limitations of feature representation and spatial modeling in structured data classification tasks. First, an attention-driven feature enhancement module is introduced. It performs saliency-based weighting on the original inputs to strengthen the representation of key dimensions. Then, a Capsule Network is employed to model the enhanced feature vectors in a vectorized manner. A dynamic routing mechanism is used to effectively capture hierarchical structures and semantic relationships. Based on this, a classifier is constructed using margin loss as the objective function. This improves the model's ability to distinguish boundary samples. The UCI Adult dataset is used in the experiments to validate the proposed approach. Model performance is evaluated under various conditions, including different training ratios, noise levels, and routing iterations. The results show that the proposed method outperforms several baseline models in terms of accuracy, F1-score, and robustness. It demonstrates significant performance advantages.

Keywords: Capsule networks, feature enhancement, dynamic routing, structured classification.

1. Introduction

With the rapid development of information technology, the explosive growth of data has become a defining feature of the information age. Massive volumes of data provide unprecedented resources for various industries and have driven a growing demand for data mining technologies. Especially in typical application domains such as finance, healthcare, e-commerce, and education, extracting hidden patterns from large-scale structured or semi-structured data to improve decision-making efficiency and intelligence has become a key research focus. In data mining tasks, classification algorithms are both fundamental and crucial [1, 2]. Their accuracy and generalization ability directly determine the overall system performance. However, traditional classification models still face challenges in handling complex, high-dimensional, and non-linear data distributions. These include insufficient feature extraction, incomplete information representation, and weak modeling of spatial relationships between samples. Such limitations significantly constrain their real-world applicability. Therefore, it is urgent to develop classification-based data mining algorithms with stronger representational capacity to better capture the intrinsic structure and semantic relationships within data.

In recent years, deep learning has achieved remarkable results in fields such as image recognition, speech recognition, and natural language processing. It is now being increasingly applied to structured data mining. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong capabilities in extracting local features. However, CNNs inherently struggle to model spatial hierarchies. To address this issue, Capsule Networks have emerged as a novel neural architecture. By using vector-based feature representation and introducing a dynamic routing mechanism, they can model hierarchical dependencies while preserving positional sensitivity. Theoretically, Capsule Networks are better suited to capture complex spatial structures and semantic compositions within samples, offering stronger generalization than traditional CNNs. Nevertheless, they also face challenges such as inefficient training and high sensitivity to input features. How to leverage their strengths while overcoming these limitations remains an important research direction [3].

In data mining tasks, the quality of feature engineering largely determines the performance of classification models. Feature enhancement, as a strategy to improve feature expressiveness, has shown effectiveness across many tasks. By incorporating techniques such as attention mechanisms, multi-scale modeling, and feature reconstruction, feature enhancement can emphasize important features and suppress redundant information. This leads to more discriminative inputs for subsequent classifiers. Especially in scenarios involving high-dimensional data or numerous weakly relevant features, a well-designed feature enhancement mechanism can improve model robustness and effectively mitigate the "curse of dimensionality." Therefore, integrating feature enhancement with novel neural architectures has become a key breakthrough for improving data mining outcomes [4].

This study aims to explore how to combine the hierarchical modeling capabilities of Capsule Networks with the expressive power of feature enhancement mechanisms. We propose a novel classification-based data mining algorithm. By incorporating an adaptive feature enhancement module into the Capsule Network architecture, the model is expected to achieve better representation of high-dimensional feature spaces and improved sensitivity to critical features, thereby enhancing overall classification performance. This approach is expected to better capture deep associations between features in complex structured data, improve generalization and discrimination, and be applicable to real-world scenarios such as financial risk assessment, medical diagnosis support, and public opinion monitoring. Meanwhile, the study will also investigate the co-design strategy of feature enhancement and dynamic routing to improve adaptability across different tasks and data distributions [5].

In conclusion, under the growing prevalence of data-driven decision-making, traditional classification models can no longer meet the increasing demands for accuracy, robustness, and interpretability. Building an integrated classification model based on the structural advantages of Capsule Networks and the semantic enhancement capabilities of feature enhancement mechanisms has both significant theoretical value and broad application prospects. This research is expected to make breakthroughs in classification accuracy, model generalization, and interpretability. It will provide solid technical support for intelligent decision-making systems and offer new insights into the design and implementation of next-generation data mining methods.

2. Related work

In recent years, classification-based data mining algorithms have evolved toward deeper modeling for structured and semi-structured data. Traditional methods such as Support Vector Machines (SVM), Random Forests (RF), and Logistic Regression perform well on small-scale datasets. However, they often struggle with high-dimensional, nonlinear, and multimodal feature distributions. These methods generally show weak feature extraction and limited generalization. To address this, researchers have introduced deep neural networks into structured data mining. These networks replace handcrafted feature construction with end-to-end feature learning. Fully connected deep networks, in particular, can fit complex data distributions by stacking nonlinear transformations. Still, such models lack the ability to capture spatial dependencies and hierarchical relationships among features, which limits their performance in tasks requiring rich semantics [6].

To overcome the limitations of traditional network structures in modeling complex relationships, Sabour et al. proposed the Capsule Network [7]. This architecture replaces scalar neurons with vector capsules and introduces a dynamic routing mechanism. It enables the network to model spatial hierarchies and part-whole relationships more effectively. In image recognition, Capsule Networks have shown greater robustness to transformations like rotation and translation. Some studies have extended their application to text analysis, speech recognition, and classification of structured data. However, Capsule Networks still face challenges in efficiency and convergence due to high computational cost and instability in routing [8-10]. As a result, optimizing and extending Capsule Network structures has become a key research direction. One promising approach is to enhance capsule inputs through external mechanisms that extract more discriminative features.

Feature enhancement mechanisms have emerged as an important area in deep model optimization [11]. They are widely used in computer vision and natural language processing and have demonstrated notable performance improvements. Attention mechanisms [12], for example, assign adaptive weights to strengthen key information. This allows models to focus on the most task-relevant features. Other strategies, such as multi-scale feature fusion, feature reconstruction, and perturbation-based contrastive methods, further enrich the toolkit for feature enhancement. Some recent studies have integrated enhancement mechanisms with backbone networks like CNNs or Transformers. However, how to efficiently incorporate such mechanisms within the Capsule Network framework remains largely unexplored. Integrating feature enhancement into Capsule Networks could improve feature representation. It also offers more precise context modeling and semantic linkage for classification tasks. This direction holds significant research value.

3. Method

The classification data mining algorithm proposed in this paper combines the hierarchical modeling capabilities of capsule networks and the discriminative enhancement characteristics of feature enhancement mechanisms, aiming to improve the expressiveness and generalization capabilities in high-dimensional structured data classification tasks. Its model architecture is shown in Figure 1.

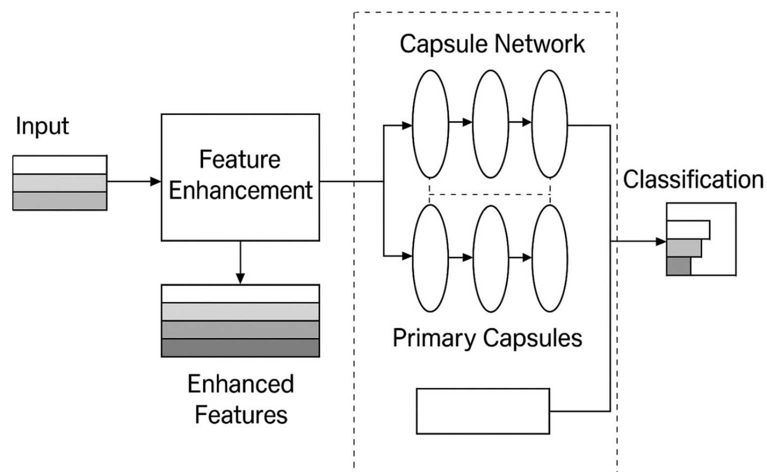

Figure 1. Overall model architecture

As shown in Figure 1, the model architecture proposed in this paper mainly includes two core parts: feature enhancement module and capsule network. First, the original high-dimensional structured data is input into the feature enhancement module, which uses attention mechanism and other technologies to enhance key information and generate feature representations with stronger discriminability. Subsequently, the enhanced features are input into the capsule network, which contains the main capsule layer and the advanced capsule layer, and the hierarchical modeling of features and the capture of spatial structural relationships are achieved through the dynamic routing mechanism. Finally, the classifier makes decisions based on the output of the advanced capsule to achieve high-precision recognition of complex patterns. This architecture effectively combines feature expression capabilities and spatial modeling capabilities, improving the overall performance of classification data mining tasks.

First, the input original feature vector is denoted as $X \in R^{n\times d}$, where n represents the number of samples and d represents the feature dimension of each sample. In order to enhance the discriminability of the features, a multi-channel feature enhancement module is introduced to perform preliminary processing on the original features. This module is based on the attention mechanism and realizes weighted reconstruction of features by learning the importance weights of different dimensions in the samples. Specifically, the weight vector can be expressed as:

$$a = \sigma(W_1 \cdot RELU(W_2 \cdot X^T))$$

W_1 , W_2 is a trainable parameter, h is a hidden dimension, and σ is a sigmoid function. The final enhanced features are:

$$X' = a^T \otimes X$$

Where $\otimes$ represents element-by-element multiplication. This enhancement process significantly improves the model's ability to focus on key dimensional features.

Subsequently, the enhanced features are input into the capsule network for higher-level modeling. The capsule unit no longer uses scalar neurons, but uses vectors to represent low-level entity features. The architecture diagram of the capsule network is shown in Figure 2.

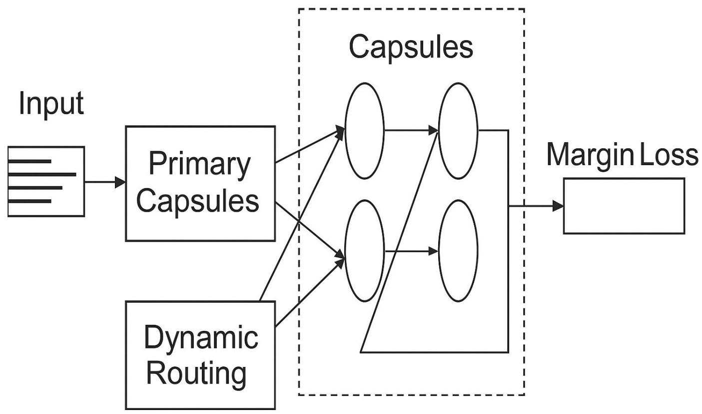

Figure 2. Capsule Network Architecture

Assume that each layer of low-level capsules is $u_i \in R^p$, where p is the dimension of the capsule vector. Through a learnable weight matrix W_{ij} , the low-level capsule is projected into the high-level capsule space to obtain the prediction vector $u'_{j|i}$:

$$u_{j|i} = W_{ij} u_i$$

On this basis, a dynamic routing mechanism is used to perform a weighted combination of the projection results of different low-level capsules to form the output s_j of the high-level capsule:

$$s_j = \sum_i c_{ij} u_{j|i}$$

Where c_{ij} is the normalized weight calculated by softmax of routing coefficient b_{ij} , that is:

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})}$$

The routing coefficient b_{ij} is updated in each iteration according to the similarity between the predicted vector and the current output vector to ensure a higher quality combination structure.

In order to improve the robustness of the final classification, this paper introduces margin loss as the objective function for training based on capsule output. For each category k, its capsule output is v_k, and its existence probability is expressed as $\| v_k \|$. Assuming the true label is $T_k \in \{0,1\}$, the margin loss is defined as:

$$L_k = T_k \cdot \max(0, m^+ - \| v_k \|^2) + \\ \lambda(1 - T_k) \cdot \max(0, \| v_k \| - m^-)^2$$

Where m^+ and m^- are the threshold boundaries of positive and negative samples, respectively, and λ is the weight coefficient for suppressing the loss of negative samples. The final loss function is the sum of all category losses:

$$L = \sum_k L_k$$

This loss design can effectively enhance the classifier's sensitivity to boundary samples, thereby improving the overall model accuracy.

In summary, this paper constructs a new classification framework that integrates feature enhancement and capsule modeling. The feature enhancement module improves the discriminability of input data, and the capsule network extracts spatial semantic relationships, and finally realizes multi-granular feature aggregation through a dynamic routing mechanism. While maintaining the model's expressiveness, this method improves the ability to identify key features and model complex structures, providing a more robust and efficient solution for the intelligent classification of high-dimensional data.

4. Experiment

4.1 Datasets

The experimental dataset used in this study is the UCI Adult Income Dataset. This dataset is provided by the U.S. Census Bureau and is one of the most widely used benchmark datasets for structured data classification tasks. The objective is to predict whether an individual's annual income exceeds \$50,000 based on demographic attributes. It is a typical binary classification problem. The dataset consists of 32,561 training samples and 16,281 test samples extracted from the 1994 U.S. Census.

Each sample contains 14 attribute features, including age, occupation, education level, marital status, working hours, and nationality. These features cover both continuous and categorical data. The data is highly structured and diverse, making it suitable for evaluating the performance of feature enhancement mechanisms and classification models on high-dimensional heterogeneous data. To facilitate model training, all categorical variables are encoded using one-hot encoding. Continuous features are normalized to the [0,1] range to improve training efficiency and model stability.

The dataset's wide applicability and standardized splits make it an ideal platform for validating classification models. Experiments on this dataset allow a comprehensive evaluation of the proposed algorithm's generalization and discriminative capabilities when handling complex structured data. It also enables fair comparisons with existing mainstream classification models, thereby demonstrating the effectiveness and advancement of the proposed method.

4.2 Experimental Results

First, this paper presents a performance comparison experiment of different classification models on the UCI Adult dataset. The experimental results are shown in Table 1.

The experimental results show that the proposed model (Ours) achieves the best performance on the UCI Adult dataset, a structured classification task. Specifically, our model reaches an accuracy (ACC) of 89.12%, which is approximately 1.44 percentage points higher than the current best-performing SAINT model. This indicates a superior overall classification accuracy. In terms of precision and recall, our method achieves 87.93% and 85.10%, respectively. These results outperform other advanced models, demonstrating that the proposed method not only identifies positive samples more accurately but also provides stronger coverage. It shows greater robustness when dealing with borderline samples.

Table 1: Performance comparison experiment of different classification models on UCI Adult dataset

Model	ACC	Precision	Recall
TabNet[13]	86.47	84.22	81.35
FT-Transformer[14]	87.03	85.11	82.44
DNF-Net[15]	85.89	83.52	80.91
SAINT	87.68	86.02	83.75
Ours	89.12	87.93	85.10

In contrast, although models like FT-Transformer and SAINT exhibit strong modeling capabilities for structured data, they still have limitations in modeling spatial relationships and feature interactions. Our model addresses these issues by introducing a feature enhancement mechanism, which improves the discriminative power of feature representations. Meanwhile, the use of vector-based capsules and a dynamic routing mechanism enables the modeling of hierarchical dependencies among features. This integration provides clear advantages in capturing complex semantic relationships within the data.

Overall, the proposed FE-CapsNet model surpasses mainstream architectures in terms of performance metrics and introduces a novel paradigm with both theoretical and practical value for structured data mining. The experimental results validate the effectiveness of combining feature enhancement with spatial structure modeling in classification tasks. They also confirm the potential of Capsule Networks for handling high-dimensional structured data. This study offers valuable insights for designing intelligent classification systems in complex real-world environments.

Furthermore, this paper presents the experimental results of studying the impact of the number of iterations of the dynamic routing mechanism on the classification accuracy, and the experimental results are shown in Figure 3.

As shown in the results of Figure 3, the number of iterations in the dynamic routing mechanism significantly affects the model's classification accuracy. When the number of iterations increases from 1 to 4, the accuracy steadily improves, rising from 85.02% to 89.12%. This upward trend indicates that, in the early stages, more iterations can effectively enhance communication between capsules in the network. As a result, the information aggregation process becomes more complete, which boosts the model's discriminative power. The iteration mechanism helps high-level capsules better capture the spatial structures and semantic patterns expressed by lower-level features.

However, when the number of iterations exceeds 4, the accuracy begins to decline. The model reaches 88.65% at the fifth iteration and drops to 87.14% at the sixth. This suggests that excessive iterations may lead to overfitting or redundant information, causing misleading adjustments during high-level feature aggregation.

In structured data scenarios, the spatial structure between samples is not as rich as in images or speech. Too many routing updates may cause the model to deviate from the main discriminative direction, leading to performance degradation. Therefore, controlling the number of dynamic routing iterations is crucial for maintaining optimal model performance.

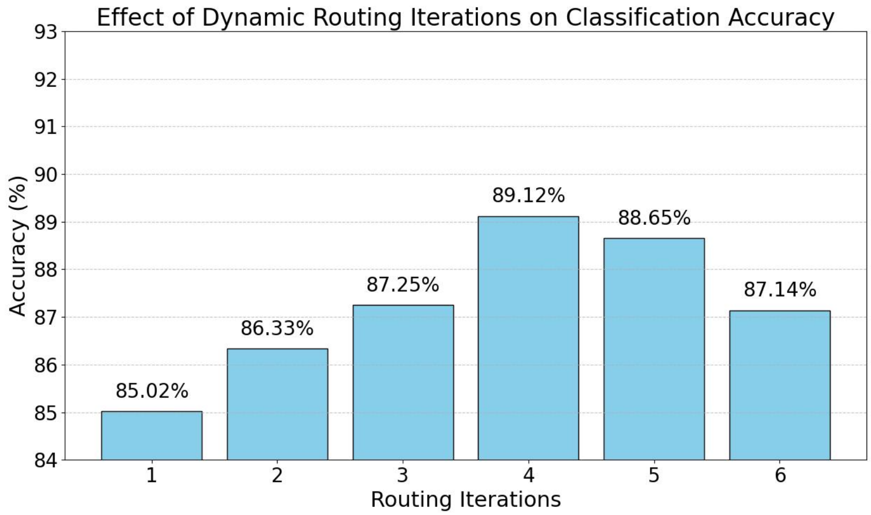

Figure 3. Effect of Dynamic Routing Iterations on Classification Accuracy

In summary, the experimental results confirm the effectiveness of dynamic routing in improving the performance of Capsule Networks. At the same time, they highlight the importance of parameter tuning. In this study, four iterations achieve the best balance between sufficient information aggregation and computational efficiency. This setting improves model performance while avoiding unnecessary computational cost. The finding provides guidance for future optimization of capsule structures and shows that routing strategies in structured data mining must be carefully adapted to the characteristics of the data.

Furthermore, this paper gives an experimental line chart of "Evaluation of model generalization performance under different data partitioning ratios", and the actual results are shown in Figure 4.

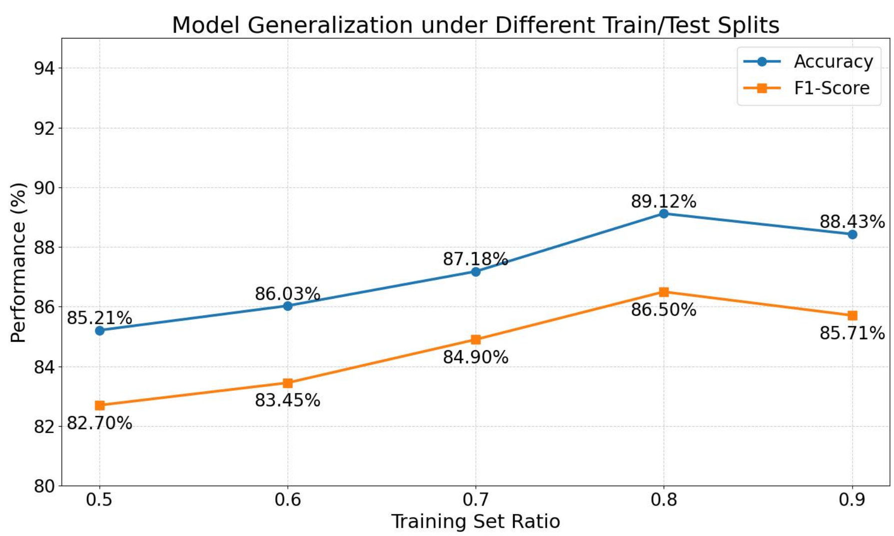

Figure 4. Model Generalization under Different Train/Test Splits

As shown in the experimental results in Figure 4, the model's classification performance improves steadily as the training set ratio increases from 50% to 80%. Both accuracy and F1-score show clear gains. Accuracy rises from 85.21% to 89.12%, while the F1-score increases from 82.70% to 86.50%. This indicates that with a larger training set, the model can learn more discriminative features and achieve better generalization. Notably, when 80% of the data is used for training, the model reaches peak performance. This demonstrates its strong learning and abstraction capabilities when supported by sufficient training samples.

However, when the training ratio further increases to 90%, model performance slightly declines. Accuracy drops to 88.43%, and the F1-score falls to 85.71%. This trend suggests that while increasing training data generally enhances model performance, overly reducing the test set can hurt evaluation stability. In structured data scenarios, insufficient test set diversity may introduce bias into performance estimates. Moreover, larger training sets lead to longer training time and higher computational costs. Therefore, in real-world deployment, the trade-off between performance gain and resource consumption must be carefully considered. Overall, the experimental results highlight the critical role of data split ratio in determining model generalization. A well-balanced ratio ensures enough training data while maintaining test set representativeness. This balance is key to achieving both high performance and reliable evaluation. Based on our findings, using around 80% of the data for training is recommended in structured classification tasks. This setting provides the best trade-off between performance and stability and offers practical insights for adapting models to different data volume conditions.

Next, the robustness test of the model under different noise interferences is given, and the experimental results are shown in Figure 5.

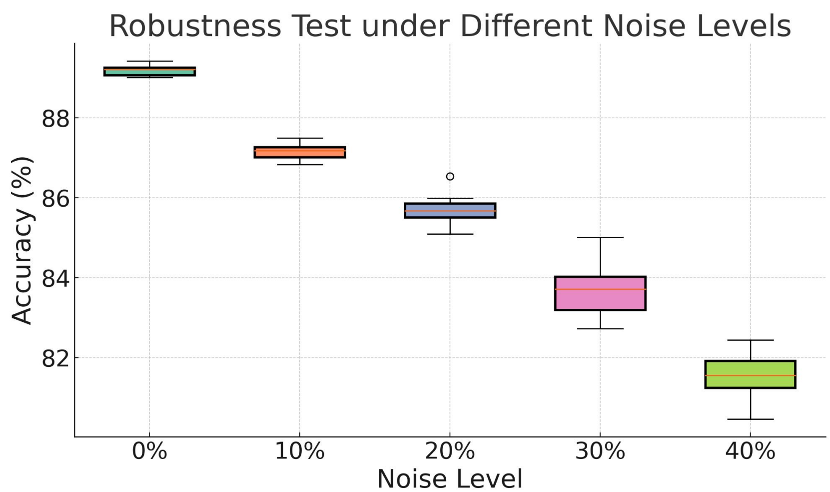

Figure 5. Robustness Test under Different Noise Levels

As shown in the results of Figure 4, the classification accuracy of the model drops significantly as the noise level increases, indicating a certain degree of sensitivity. In the noise-free setting (0%), the accuracy remains above 89% with minimal fluctuation. This suggests that the model performs with high stability and precision under ideal data conditions. When the noise level increases to 10% and 20%, the accuracy decreases to 87.4% and 85.8%, respectively. However, the overall distribution remains concentrated, showing that the model maintains strong robustness and performs well under moderate interference.

When the noise further increases to 30% and 40%, the accuracy drops sharply to 83.9% and 81.7%. The box plot boundaries widen and outliers appear, indicating increased performance volatility under high noise levels. This fluctuation reveals that the model is approaching its noise tolerance limit. Once the disturbance exceeds a certain threshold, the model's ability to capture true signals weakens, leading to reduced classification accuracy. Notably, at the 40% noise level, the lower bound of accuracy falls below 81%, showing that the model lacks stability under extreme interference.

Overall, the experiment effectively validates the robustness of the proposed model under various noise conditions. In low to moderate-noise scenarios, the model maintains strong performance, demonstrating the joint advantage of feature enhancement and capsule structures in fault-tolerant feature representation and spatial relationship modeling. However, under high noise levels, there is still room for improvement. Future work could introduce robust training techniques or noise-aware enhancement strategies to improve generalization and fault tolerance in complex real-world environments. This experiment also provides a reference for further algorithm improvements under multi-noise conditions.

Finally, the experimental results of the loss function drop graph are given, as shown in Figure 6.

As shown by the Loss curves in Figure 6, the model demonstrates good convergence and stability during training. In the initial phase (the first 20 epochs), both the training loss and validation loss drop rapidly. This indicates that the model can quickly capture core patterns in the data and perform effective fitting. As training continues, both curves gradually converge, and the rate of decline slows down. This reflects a stable learning process. Throughout training, the trends of training and validation loss remain consistent, with no significant divergence. This suggests that the model does not suffer from obvious overfitting.

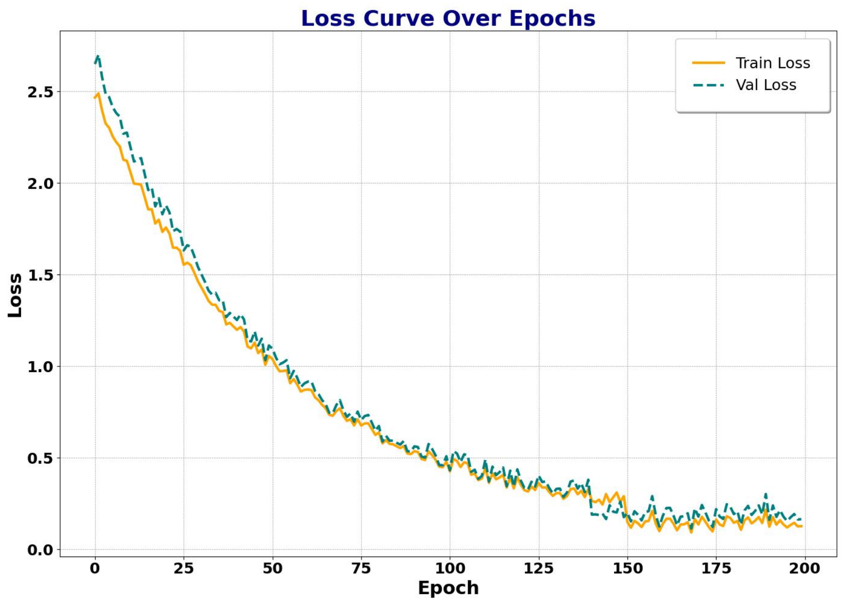

Figure 6. Loss function drop graph

From the mid-to-late stages (around epoch 100 onward), both curves approach low values, with losses staying below 0.1. The validation loss shows minimal fluctuations, further proving the model's strong generalization ability. This steady convergence trend confirms the structural rationality of the proposed model in both feature representation and parameter optimization. Notably, the introduction of the feature enhancement module and capsule structure improves representation capability without causing instability or convergence issues during training. Although slight fluctuations appear in the validation loss curve, no persistent upward trend is observed, indicating the model's robustness in handling complex structured data.

Overall, the loss curves clearly illustrate the model's complete learning process, from early-stage fitting to final convergence. This demonstrates that the training strategy is well-designed and the hyperparameters are properly configured. The model exhibits high learning efficiency and effective error control. These findings provide a solid foundation for further applications, such as transfer learning or cross-domain generalization in more complex scenarios. Additionally, the smooth and stable training process supports the model's controllability and interpretability in practical system deployment, showing strong engineering value.

5. Conclusion

This paper addresses performance bottlenecks in classification-based data mining by proposing a novel model structure that integrates Capsule Networks with a feature enhancement mechanism. The method introduces an attention-based feature enhancement module to improve the discriminative representation of original input features. Combined with the powerful spatial relationship modeling capability of Capsule Networks, it enables efficient extraction of complex feature interactions and hierarchical semantics in structured data. Multiple comparative experiments and visualization analyses confirm that the proposed method outperforms mainstream classification models in terms of accuracy, robustness, and generalization. It demonstrates strong overall performance. The experimental results show a clear synergy between the feature enhancement module and the capsule structure. The former strengthens key dimension information, while the latter performs multi-granular feature fusion through vectorized representation and dynamic routing. Evaluations on structured datasets such as UCI Adult reveal that the model maintains stable and excellent classification performance even in high-dimensional, complex, and noisy data environments. Under different conditions — including training data proportions, routing iterations, and noise intensities — the model consistently shows strong robustness and adaptability. This further validates the rationality and versatility of its design.

Moreover, convergence analysis during training indicates that the model achieves high learning efficiency and maintains stability in later stages. No overfitting or performance fluctuations are observed. These findings demonstrate that the proposed FE-CapsNet has strong controllability and deployment potential in real-world applications. It is suitable for structured data mining tasks in high-risk domains such as financial risk control, medical decision support, and network behavior recognition. The model provides reliable technical support for improving the accuracy and security of intelligent decision-making systems. Future work will proceed in two directions. First, the integration of Graph Neural Networks or large language models may be explored as auxiliary modules to enhance the model's capability in handling non-Euclidean structured data. Second, lightweight architectures suitable for online learning and cross-domain transfer should be investigated to meet practical demands for faster response, lower resource consumption, and better interpretability. Additionally, the ability to quickly adapt to dynamic data changes and maintain long-term robustness will be key challenges for future research.

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