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Financial Fraud Detection with Self-Attention Mechanism: A Comparative Study

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Abstract:

Financial fraud detection has always been an important research topic in the financial industry. With the increasing complexity of financial transactions, traditional detection methods have gradually become incapable of dealing with large and complex data. This study proposes a model based on the self-attention mechanism to improve the recognition accuracy of financial fraud transactions. The self-attention mechanism can effectively capture long-distance dependencies and global information in financial data, thereby improving the model's ability to identify fraudulent behavior. By comparing with a variety of common models such as decision trees, MLP, XGBoost, and CNN, the experimental results show that the model based on the self-attention mechanism outperforms other models in terms of accuracy, recall, precision, and F1-Score, especially in terms of recall and F1-Score. This study provides a new idea for financial fraud detection, especially when dealing with complex and heterogeneous data, and has strong application potential. Future research can further optimize the model and combine it with other deep learning techniques for multimodal learning to improve the accuracy and efficiency of fraud detection.

Keywords:

Self-attention mechanism, financial fraud detection, deep learning, model comparison

1. Introduction

In recent years, with the rapid development of the financial industry, financial fraud has become more complex and hidden, causing huge losses to financial institutions and customers. Traditional financial fraud detection methods rely on rules and manual feature extraction. Although these methods are effective in some cases, they are often unable to adapt to new fraud methods and are inefficient when processing large-scale and complex data. With the development of big data technology and deep learning, more and more research has begun to focus on fraud detection through intelligent algorithms, especially the application of self-attention mechanism in this field, which has gradually become a hot topic of research. The self-attention mechanism can effectively capture the relationship between different parts of the input data, especially when dealing with financial fraud detection tasks, it can extract potential related information from complex data, which helps to improve the accuracy and robustness of detection[1,2].

The self-attention mechanism first achieved remarkable results in natural language processing (NLP), especially in the Transformer architecture. The self-attention mechanism can effectively capture the dependency between different features by weighting the input data, solving the information loss problem of traditional convolutional neural networks (CNN) and recurrent neural networks (RNN) when processing long sequence data. In the task of financial fraud detection, financial transaction data usually contains a large amount of time series information and complex nonlinear relationships, and traditional models often have difficulty in handling these characteristics. The introduction of the self-attention mechanism enables the model to more flexibly capture the long-range dependencies in the data, providing more powerful technical support for financial fraud detection[3.4].

At present, the challenges of financial fraud detection are mainly reflected in the high dimensionality of data, the imbalance of samples, and the complexity of features. Financial fraud behaviors often show concealment and complexity, resulting in the number of fraud samples being much lower than normal transaction samples[5,6]. This imbalance makes the model more likely to predict normal samples, resulting in poor detection results. The self-attention mechanism can help the model focus more on important feature information by weighted combination of different features, effectively alleviating the negative impact of data imbalance. In addition, the self-attention mechanism can further improve the model's ability to identify different types of financial fraud by dynamically adjusting the importance of each feature[7].

In recent years, deep learning models based on the self-attention mechanism have been increasingly used in the field of financial fraud detection, especially when processing complex financial transaction data, and have achieved good results. Compared with traditional machine learning methods, deep learning models can automatically learn features from a large amount of raw data, reducing the complexity of artificial feature design[8,9]. In this context, deep neural networks combined with self-attention mechanisms have gradually become the mainstream method in financial fraud detection. The introduction of the self-attention mechanism enables the model to effectively learn the potential global information in the data, not just the local features, thereby improving the comprehensiveness and accuracy of detection. This ability makes the self-attention network particularly suitable for financial fraud detection tasks[10].

At the same time, with the continuous advancement of technology, more and more financial institutions have begun to try to use deep learning models for financial fraud detection[11]. For example, using the self-attention mechanism combined with graph neural networks (GNNs) or graph convolutional networks (GCNs) for financial fraud detection can further improve the performance of the model. Financial transaction data is essentially a complex network structure with various correlations between transactions. Graph neural networks can better process this structured data, while the self-attention mechanism helps the network better focus on the dependencies between key nodes. Through this combination, the model can better understand and predict global transaction patterns while capturing local features in transaction data, thereby improving the accuracy of fraud detection[12].

In general, the financial fraud detection method based on the self-attention mechanism provides a new idea for solving the shortcomings of traditional detection methods in terms of accuracy and efficiency. Self-attention networks can not only improve the model's ability to process complex data, but also demonstrate greater robustness in the face of the variability and concealment of financial fraud. In the future, with the increase in data volume and the continuous development of model technology, models based on self-attention mechanisms may occupy a more important position in financial fraud detection. By combining other advanced technologies such as transfer learning and generative adversarial networks (GANs), these models are expected to further improve the accuracy and efficiency of detection and provide more powerful support for risk management in the financial industry.

2. Related Work

In recent years, deep learning has made significant advancements in the field of financial fraud detection, with technologies such as self-attention mechanisms and graph neural networks (GNNs) becoming areas of focus. The self-attention mechanism initially demonstrated remarkable success in the field of natural language processing (NLP), particularly through the Transformer architecture, which effectively captures long-range dependencies and global relationships in data, offering new solutions for complex financial fraud detection tasks [13]-[15]. Sun et al. [13] proposed a bank risk prediction model based on time-series transformers, improving the accuracy of financial stability assessments. Similarly, Yao et al. [14] utilized masked autoencoders for self-supervised credit scoring, addressing data gaps and enhancing robustness against noise. Wang et al. [15] investigated the synergy between convolutional neural networks (CNNs) and transformers, demonstrating the effectiveness of this approach in risk-based applications, which holds significant value for financial fraud detection tasks.

Deep learning applications in financial fraud detection continue to expand through the adoption of diverse network architectures and training strategies. Feng et al. [16] introduced collaborative optimization methods using deep learning and ResNeXt, achieving significant accuracy improvements in financial data mining tasks. Yu et al. [17] developed a deep learning framework for anomaly detection in anti-money laundering systems, focusing on the identification of irregular patterns in cross-border transactions. Jiang et al. [18] leveraged generative adversarial networks (GANs) to address data imbalance in financial market supervision, enhancing the detection accuracy of rare fraudulent samples. Wu et al. [19] combined CNN and gated recurrent units (GRU) to propose an integrated sentiment analysis model for market risk prediction and early warning systems, contributing to fraud detection and risk management.

Graph neural networks (GNNs) have demonstrated powerful modeling capabilities for complex financial transaction data. Zhang et al. [20] developed a robust GNN framework for stability analysis in dynamic networks, showcasing its potential in financial fraud detection. Yao et al. [21] further employed hierarchical graph neural networks for stock type prediction, illustrating the adaptability of GNNs across various financial applications. The combination of GNNs with self-attention mechanisms enhances fraud detection systems by capturing intricate transaction relationships, improving model accuracy and interpretability.

Efficient data optimization and learning methods are essential for the real-time deployment of fraud detection models. Hu et al. [22] proposed an enhanced LoRA fine-tuning algorithm, optimizing large language models (LLMs) to improve efficiency and robustness, which can be applied to financial fraud detection. Wang et al. [23] explored feature alignment-based knowledge distillation, effectively compressing large models to reduce computational overhead while maintaining performance. Li et al. [24] introduced a matrix logic approach for efficient frequent itemset discovery in large datasets, contributing to the identification of hidden patterns in large-scale transaction data. Jiang et al. [25] applied Q-learning for dynamic risk control and asset allocation, providing insights into the potential of reinforcement learning in financial fraud detection.

Artificial intelligence-driven strategies for financial derivatives risk control and asset allocation have also been explored. Huang et al. [26] applied deep learning and ensemble models to improve risk assessment in financial derivatives trading. Xu et al. [27] proposed a multi-source data-driven long short-term memory (LSTM) framework to enhance stock price prediction and volatility analysis. Additionally, Jiang et al. [28] investigated the use of GANs in financial market supervision to balance datasets, addressing the challenge of detecting rare fraudulent transactions. Hu *et al.* [29] introduced few-shot learning with adaptive weight masking in conditional GANs, improving model generalization and performance in financial data analysis. Wang et al. [30] proposed dynamic scheduling strategies for resource optimization in computing environments, which play a critical role in managing large-scale financial transaction data.

3. Method

In the task of financial fraud detection, we used a deep learning model based on the self-attention mechanism. The self-attention mechanism calculates the correlation between different positions in the input data, allowing the model to automatically learn the global dependencies between various features. This mechanism is particularly suitable for processing financial data, because the time series information in financial data and the complex relationships between different features are usually difficult to model using traditional machine learning methods. The core idea of the self-attention mechanism is to assign different weights to each element of the input data, so that the model can "focus" on key feature information during processing, thereby improving the ability to identify fraudulent behavior. Its network architecture is shown in Figure 1.

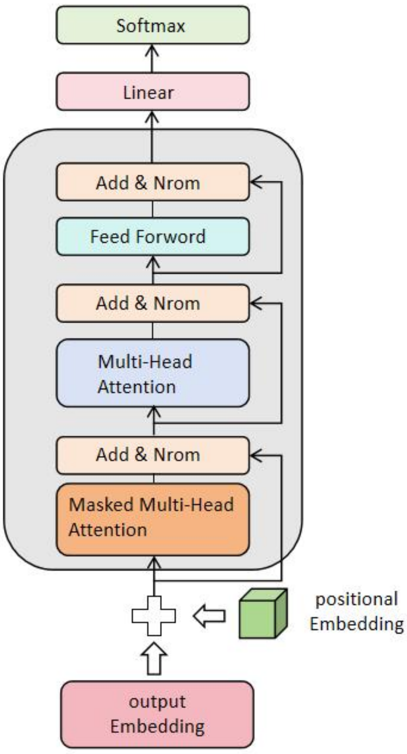

Figure 1: Network architecture diagram

Specifically, the input data is first processed by a multi-layer self-attention mechanism. At each layer, the self-attention module forms a weighted representation of each position by calculating the correlation between each position in the input sequence. The key to the self-attention module lies in the attention weights it calculates, which determine the importance of each feature in the output. In order to calculate the attention weights, we first need to perform a linear transformation on the input features, and then obtain the correlation between the features through an inner product operation. Given an input sequence, the attention weight can be calculated by the following formula:

$$Attention(Q,K,V) = soft\max(\frac{QK^T}{\sqrt{d_k}})V$$

Among them, Q, K and V represent the query vector, key vector and value vector respectively, and $\sqrt{d_k}$ is a constant used for scaling. In this way, the model can dynamically assign a weight coefficient to each input, so that in subsequent calculations, more attention is paid to those features that are critical to identifying fraud.

Next, after multiple self-attention layers, the model passes these weighted feature representations to the fully connected layer for further processing. Through multiple layers of stacking, the self-attention mechanism can capture multi-level dependencies from the data, thereby improving the ability to identify complex fraudulent behaviors. Finally, through an output layer, the model generates a result for judging whether it is fraudulent or not. The self-attention mechanism enables the model to better focus on the key features of fraudulent transactions, avoid excessive loss of information, and cope with the common time series and dependencies in financial transaction data.

In this study, we trained financial transaction data with such a self-attention mechanism model and compared it with other traditional machine learning models. The advantage of the self-attention mechanism is that it can dynamically adjust the weights and focus on the most critical parts of the data, thereby improving the accuracy and robustness of fraud detection. Through such deep learning methods, the model can not only effectively identify complex financial fraud behaviors, but also maintain high performance in the face of data imbalance and noise.

4. Experiment

4.1. Datasets

In this study, the publicly available Kaggle Credit Card Fraud Detection Dataset was selected as the experimental dataset. This dataset contains credit card transaction records of European cardholders in September 2013. The dataset contains 284,807 transaction records, of which about 0.17% are fraudulent transactions. These data are highly representative, covering multiple categories of transaction information and containing some hidden fraud transaction features. This dataset has been widely used in the study of credit card fraud detection, providing a valuable experimental basis for academia and industry.

The features of this dataset include 30 anonymized numerical variables (V1 to V28), which are obtained by transforming the original financial features using PCA (Principal Component Analysis) technology. In addition, it also includes two non-numerical variables: Time (indicating the time when the transaction occurred) and Amount (indicating the transaction amount). The label of the dataset is Class, where 0 represents normal transactions and 1 represents fraudulent transactions. Since there are relatively few fraudulent transactions, this dataset has a serious class imbalance problem, which makes it a classic dataset in fraud detection tasks. In order to avoid the bias of the model caused by imbalanced data, various data preprocessing methods such as oversampling and undersampling were used in the study.

In addition, the credit card fraud dataset provided by Kaggle has also been strictly processed in terms of anonymization and privacy protection, and the transaction data does not involve the personal information of specific users. Although the features in the dataset have been anonymized, the key attributes of the transaction, such as transaction time, amount, device, etc., are still retained, which can provide rich input for financial fraud detection models. The characteristics of this dataset are its high dimensionality, class imbalance, and noisy data, which makes it an ideal choice for testing the effectiveness and robustness of advanced deep learning methods such as self-attention mechanism models in financial fraud detection.

4.2. Experimental Result

In this study, in order to evaluate the performance of the self-attention mechanism model in the task of financial fraud detection, we selected several classic machine learning and deep learning models for comparative experiments. First, the decision tree (DT) was selected as one of the comparative models. The decision tree is a simple and intuitive supervised learning method that performs classification and regression tasks by recursively partitioning the data space. Its advantage is that it is easy to understand and explain, and the decision process can be intuitively displayed through the tree structure. However, the performance of the decision tree is greatly affected by data noise and is prone to overfitting, so its performance on complex data sets is usually not as good as that of the deep learning model. Secondly, the multilayer perceptron (MLP) as a basic artificial neural network model was also selected as a comparative model. MLP consists of multiple fully connected layers and introduces complex representation capabilities through nonlinear activation functions. It can capture nonlinear relationships in the data and show good results in relatively simple tasks. However, MLP usually requires large computing resources when facing high-dimensional and large-scale data, and it is difficult to effectively process long-distance dependencies and contextual information in the data. Despite this, MLP is still a widely used baseline model suitable for comparison with more complex deep learning models.

In addition, convolutional neural networks (CNNs) were also included in the comparative experiments. Although CNNs were originally designed for image processing, their powerful feature extraction capabilities and local perception mechanisms enable them to perform well in processing high-dimensional data. In the task of financial fraud detection, CNNs can automatically learn the key patterns in the data, especially when the data has spatial or local features, CNNs can extract important feature information through convolutional layers. However, CNNs are relatively weak in capturing long-distance dependencies of time series data and may not be able to fully adapt to the complex patterns in financial transaction data. Finally, XGBoost (Extreme Gradient Boosting), as an ensemble learning method based on gradient boosting trees, is widely used in classification and regression tasks. XGBoost improves the accuracy of the model by integrating multiple decision trees, and is particularly suitable for structured data. Its advantage is that it can handle missing values, noisy data, and class imbalance problems. XGBoost has strong generalization capabilities and is efficient when processing large-scale data. However, compared with deep learning methods, XGBoost is insufficient in capturing the global relationship between complex features, so its performance in some tasks may not be as good as deep learning methods such as self-attention mechanisms. The comparative experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	ACC	Recall	Precision	F1-Score
DT	0.82	0.76	0.78	0.77
MLP	0.84	0.78	0.80	0.79
XGBoost	0.86	0.81	0.83	0.82
CNN	0.89	0.83	0.85	0.82
Ours	0.92	0.90	0.93	0.91

From the experimental results, it can be seen that there are obvious differences in the performance of different models in the task of financial fraud detection. First, as a traditional machine learning model, although the decision tree (DT) has certain interpretability, it has limited performance when processing complex data. The accuracy of the decision tree is 0.82, the recall rate is 0.76, the precision is 0.78, and the F1-Score is 0.77. This shows that the performance of the decision tree in identifying fraudulent transactions is relatively weak, especially in terms of recall rate, showing a high false negatives, that is, many fraudulent behaviors are not correctly identified. Although the decision tree can provide an intuitive model structure that is easy to understand and explain, it is incapable of tasks such as financial fraud, which is more complex and has diverse data features, especially in capturing complex patterns and long-distance dependencies.

Among traditional machine learning models, the multi-layer perceptron (MLP) performs slightly better than the decision tree. The accuracy of the MLP is 0.84, the recall rate is 0.78, the precision is 0.80, and the F1-Score is 0.79. Compared with decision trees, MLP can capture complex nonlinear relationships in data through multiple fully connected layers and nonlinear activation functions, which improves the learning ability of the model, especially in the processing of higher-dimensional data. However, although MLP improves classification performance to a certain extent, its ability to capture temporal and global dependencies in data is weak, which is particularly critical in financial fraud detection tasks. Although MLP performs relatively well, it still fails to effectively balance recall and precision, resulting in limited improvement in F1-Score.

As a model based on ensemble learning, XGBoost's performance was further improved in this experiment, with an accuracy of 0.86, a recall of 0.81, a precision of 0.83, and an F1-Score of 0.82. XGBoost can effectively reduce overfitting and improve the generalization ability of the model by constructing multiple decision trees and optimizing them using the gradient boosting algorithm. In financial fraud detection, XGBoost improves the recognition ability of minority categories (fraudulent transactions) through weighted integration, which significantly improves the recall rate. The advantage of XGBoost is that it can show good computational efficiency when processing large-scale data, and it can automatically handle missing values and class imbalance problems. However, despite its excellent performance in most indicators, XGBoost still fails to achieve the effect of deep learning models in capturing long-distance dependencies of data, especially when dealing with financial data with complex patterns and contextual information.

Compared with traditional machine learning models, convolutional neural networks (CNNs) show obvious performance advantages, with an accuracy of 0.89, a recall of 0.83, a precision of 0.85, and an F1-Score of 0.82. The advantage of CNN lies in its powerful feature extraction ability, especially in image and sequence data, which can capture local features through convolution operations and automatically learn effective representations of data. In the task of financial fraud detection, CNN can automatically extract important features in transaction data and show strong pattern recognition capabilities. However, the limitation of the CNN model is that it mainly focuses on the extraction of local features and may not fully capture the global dependencies and contextual information in financial transaction data. Therefore, although CNN has achieved good results in accuracy and precision, it is still slightly insufficient in recall and F1-Score, and has not fully realized its potential.

In this experiment, the model based on the self-attention mechanism (Ours) performed best, with an accuracy of 0.92, a recall of 0.90, a precision of 0.93, and an F1-Score of 0.91. The self-attention mechanism can capture long-distance dependencies and global information by assigning different weights between each input data point and other data points, and is particularly suitable for processing financial data with long-term dependencies and complex contexts. Compared with other models, the self-attention mechanism can effectively improve the recall rate and reduce missed detections, thereby ensuring that more fraudulent behaviors are identified. In addition, since the self-attention mechanism can weight different features, it has significant advantages in processing the diversity and complexity of data, and can better adapt to the needs of financial fraud detection tasks. Therefore, the model based on the self-attention mechanism surpassed other models in all indicators in this experiment, showing stronger recognition and generalization capabilities.

In general, these comparative experimental results show that the self-attention mechanism has stronger global modeling capabilities and better performance than traditional machine learning models and deep learning models, such as CNN, especially in complex financial fraud detection tasks. The self-attention mechanism can effectively capture long-distance dependencies and contextual information in the data, thereby improving the prediction accuracy and recall ability of the model. Although models such as CNN and XGBoost have strong advantages in local feature learning and ensemble learning, they have certain limitations in global information processing and long-distance dependency modeling. Through the results of this experiment, it can be clearly seen that the application potential of the self-attention mechanism in financial fraud detection tasks can be further optimized and promoted in the future, especially when processing large-scale financial transaction data, it will be able to provide more accurate and efficient detection capabilities.

5. Conclusion

This study proposes a financial fraud detection method based on the self-attention mechanism, aiming to improve the recognition ability of fraudulent transactions in the financial field. By comparing with a variety of traditional machine learning methods and deep learning models, the results show that the self-attention mechanism shows significant advantages in the task of financial fraud detection, especially in terms of accuracy, recall, precision, and F1-Score. Through comparative experiments, it is found that traditional decision trees (DT), multi-layer perceptrons (MLP), and XGBoost have certain limitations when processing complex financial data, especially in capturing global dependencies and long-distance dependencies. The model based on the self-attention mechanism can effectively overcome these problems and make full use of the temporal and contextual information of financial data, thereby improving the overall performance. Future research can further explore how to optimize the computational efficiency of the self-attention mechanism and apply it to larger-scale financial data sets to improve the accuracy and real-time performance of fraud detection. In addition, combined with other advanced deep learning techniques, such as graph neural networks and generative adversarial networks, it may bring more innovative ideas to financial fraud detection.

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