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Enhancing Financial Fraud Detection: The Efficacy of Convolutional Neural Networks

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Abstract:
This study aims to explore and compare the application effects of various machine learning models in the task of financial fraud transaction detection, focusing on the analysis of the advantages of convolutional neural networks (CNN) in dealing with complex transaction data. In the experiment, we compared the performance of six models: logistic regression, support vector machine, random forest, K nearest neighbor, gradient boosting tree and CNN. The results show that CNN can more effectively identify abnormal patterns in financial transaction data with its powerful feature extraction ability, showing the highest accuracy, recall, precision and F1 score. However, due to the high-dimensional and large-scale characteristics of financial transaction data, the computational cost of CNN is high, so it is necessary to balance model performance and resource consumption in practical applications. This study not only verifies the potential of CNN in financial fraud detection, but also provides a research direction for future financial security applications based on deep learning. In the future, multi-source data can be further combined with emerging adaptive learning methods to improve the detection accuracy and robustness of the model.

Keywords:

Financial fraud detection, Convolutional neural networks, Machine learning, Feature extraction

1. Introduction

Financial transactions play a vital role in the global economy. With the increase in the volume of financial transactions, various types of financial fraud activities have gradually increased, posing new challenges to the security of the financial system. Financial fraud transactions not only threaten the financial security of individuals and institutions, but may also lead to turmoil in the financial market and bring serious economic losses. Therefore, how to effectively detect and prevent financial fraud transactions has become a key topic of concern in the current financial field[1,2].

Traditional financial fraud detection methods mostly rely on expert rules or simple statistical analysis based on historical data. However, with the complexity and diversification of financial fraud methods, traditional methods are difficult to cope with the emergence of new fraud models. This method is inefficient and lagging when facing complex financial data, and often cannot capture abnormal transaction behaviors hidden in big data in real-time, resulting in the accuracy and timeliness of financial fraud detection being difficult to meet actual needs[3,4].

In this context, the introduction of deep learning technology, especially convolutional neural network (CNN), has brought new possibilities for financial fraud transaction detection[5]. With its powerful feature extraction capability, CNN can effectively extract potential abnormal features from complex data, making it possible to accurately detect implicit patterns in financial data. The hierarchical structure of CNN can learn the spatiotemporal characteristics of transaction data layer by layer, thereby improving the accuracy of identifying financial fraud transactions[6].

Compared with traditional methods, the detection method based on CNN has stronger robustness and adaptability when processing massive financial transaction data. CNN can not only extract useful features from data adaptively, but also quickly adjust parameters in different transaction scenarios through training to adapt to different financial environments[7,8]. At the same time, CNN's automatic learning ability reduces the reliance on manually set rules, thereby reducing the complexity and maintenance cost of the detection system[9].

In addition, the application of CNN model in financial fraud detection also has the advantage of strong real-time performance. With the help of efficient parallel computing capabilities, CNN can complete the processing and analysis of massive data in a short time, providing technical support for timely identification and prevention of fraudulent transactions. This real-time performance provides financial institutions with the ability to respond quickly, can effectively reduce the losses caused by fraud, and improve the system's defense capabilities[10,11,12].

In summary, the financial fraud transaction detection technology based on CNN has significant advantages in dealing with the complexity of financial transaction data, improving detection accuracy and real-time performance. With the further growth of data volume and the continuous evolution of technology, the application prospects of CNN in financial fraud detection will be broader, and it is expected to provide a more solid guarantee for the security of the financial system.

2. Related Work

In the domain of financial fraud detection, the application of deep learning methods has expanded considerably, with Convolutional Neural Networks (CNNs) demonstrating notable strengths in automated feature extraction from high-dimensional, complex data. CNNs' hierarchical learning structures allow for effective modeling of spatial and temporal characteristics, which aids in identifying hidden abnormal patterns in large-scale transaction datasets, thereby enhancing detection accuracy [13], [14], [15].

Numerous studies have further explored neural network architectures for feature extraction and classification in similar high-stakes applications. For example, Wei et al. [16] introduced Self-Supervised Graph Neural Networks (GNNs) that improve feature extraction in heterogeneous information networks, which is applicable to fraud detection where transactional data exhibit relational patterns. Additionally, Xu et al. [17] applied GNNs in financial markets to model volatility and assess value-at-risk, aligning with the need to handle high-dimensional data in fraud detection by capturing relational dependencies among transactions.

In terms of enhancing neural network efficiency, Liu et al. [18] proposed a recommendation model utilizing separation embedding and self-attention for improved feature mining, a method that could enhance CNN's efficiency in fraud detection. Qin et al. [19] introduced the RSGDM optimization approach to reduce biases in deep learning, contributing to balanced fraud detection outcomes by addressing issues such as class imbalance.

Beyond CNNs, other neural network variants have been applied for risk management and classification within financial domains. Jiang et al. [20] used hybrid GNNs to strengthen credit risk analysis, while Gu et al. [21] incorporated spatio-temporal aggregation within dynamic graph frameworks for fraud risk detection, further underscoring the importance of temporal patterns in fraudulent activity. This body of work aligns with the current study's focus on CNNs' capabilities in feature extraction for temporal sequences, demonstrating the model's robustness in managing evolving fraud patterns.

In model interpretability and real-time processing, transformer-based architectures have gained attention. Du et al. [22] examined transformers in opinion mining, addressing semantic complexity and model challenges, which is relevant for real-time fraud detection requiring swift and interpretable insights. Furthermore, retrieval-augmented generation techniques proposed by Chen et al. [23] improve question-answering systems, offering methods that could be adapted to dynamically retrieve contextual information for enhanced fraud detection accuracy.

To address the computational demands of models like CNNs, lightweight neural network techniques have been explored. Wu et al. [24] developed a lightweight GAN-based image fusion algorithm, which reduces computational burden, providing a reference point for future CNN model compression and optimization efforts.

Additional methods have shown promise across domains. Wang et al. [25] advanced retrieval-augmented generation to enhance question-answering systems, a technique that could inform fraud detection contexts. Liu et al. [26] explored automated article scoring with large language models, showcasing robust feature extraction across diverse applications. Sun et al. [27] applied hybrid GNNs for credit risk analysis, further demonstrating the adaptability of neural networks in financial applications. Lastly, Yao [28] examined the impact of macroeconomic variables on financial stability, indirectly highlighting the value of data-driven analysis for risk assessment.

In summary, the related work illustrates the efficacy of CNNs and complementary neural network architectures in handling high-dimensional data in applications such as financial fraud detection. The ongoing advancements in neural network efficiency, adaptability, and interpretability underscore promising directions for enhancing fraud detection models to meet real-world financial industry demands.

3. Method

In the financial fraud transaction detection method based on convolutional neural network (CNN), the data is first preprocessed to ensure the consistency and high quality of the input features of the model. Financial data often contains a large number of features, including transaction time, amount, transaction location and other information. Therefore, in the data preprocessing stage, normalization or standardization methods are usually used to scale the numerical features so that the model is more stable during the training process. The model architecture is shown in Figure 1.

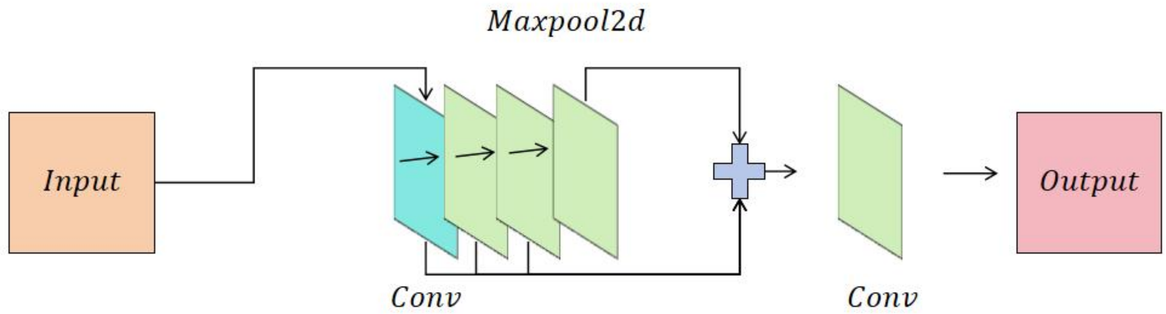

Figure 1: Two or more references

The core part of the model is the CNN architecture design. In order to extract the time series and spatial features of transaction data, this study designed a multi-layer convolutional network. The main function of the convolution layer is to extract local features in the data through the sliding operation of the convolution kernel. Given the input data X and the convolution kernel W, the basic formula of the convolution operation is:

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$$Y = X * W + b$$

Among them, Y represents the output feature map and b is the bias term. A pooling layer is added after the convolution layer to reduce the dimension of the data through downsampling operations, reduce the computational complexity, and retain the main features at the same time.

Next, the model passes the extracted features to the fully connected layer for integration. The fully connected layer combines the features extracted by different convolutional layers for higher-level pattern recognition. Assume that the input feature after flattening is Z and the weight matrix is W_{fc}, the output calculation formula of the fully connected layer is:

$$O = Z \cdot W_{fc} + b$$

Here A represents the output vector, which is used to predict the result. During the model training process, we selected the cross-entropy loss function to measure the gap between the predicted result and the actual label. The cross-entropy loss is defined as:

$$L = -\sum_{i=1}^{N} y_i \log(y'_i)$$

Among them, A represents the actual label, B is the probability value predicted by the model, and C is the number of samples.

The model training is optimized using the back-propagation algorithm and stochastic gradient descent (SGD). First, the parameters of each layer are updated by calculating the gradient of the loss function to minimize the loss function. The core of the optimization process is to continuously adjust the weight parameters of the convolution kernel and the fully connected layer to maximize the accuracy and robustness of the model.

In the model evaluation stage, we use indicators such as accuracy and precision to measure the performance of the model. Accuracy is defined as the proportion of correctly predicted samples to the total samples, while precision measures the proportion of transactions predicted as "fraud" that are actually fraudulent. Finally, the model parameters are tuned through multiple experiments to obtain the best detection effect.

In summary, this method extracts complex features from transaction data through convolution and pooling, and then achieves high-level pattern recognition through the fully connected layer. Combining cross-entropy loss and gradient optimization, it can effectively identify fraud in financial transactions.

4. Experiment

4.1. Datasets

In the study of financial fraud detection, real datasets can provide reliable verification of model performance. A widely used financial fraud transaction dataset is the "IEEE-CIS Fraud Detection" dataset, jointly provided by IEEE and Vesta, which is suitable for CNN-based financial transaction detection research. This dataset can be obtained on Kaggle and contains large-scale online payment transaction records, mainly used to detect whether there is credit card fraud. These datasets contain real transaction information, making them more representative in research and experiments. The features in the data include transaction time, transaction amount, device type, IP address, email domain, etc., which can help the model capture potential fraud behavior characteristics.

The dataset has more than 590,000 transaction records, covering various types of legitimate and suspicious payment behaviors, where records marked as "1" represent suspected fraud transactions and "0" represent normal transactions. In addition, the data also contains some anonymized features, which can further enrich the feature dimensions of the model when learning data patterns. These anonymous features are mainly related to the security of transactions and user behavior characteristics, which help capture abnormal patterns in transactions from multiple angles. Each record contains detailed information closely related to the transaction time, location, device information, etc., which provides rich training data for detecting complex financial fraud patterns.

In addition, another highlight of this dataset is the authenticity and diversity of its data. Through data obtained in a real financial environment, researchers can better simulate actual fraud detection scenarios. Different features can not only reflect the basic information of the transaction, but also show the user's usage habits and behavioral characteristics. This diversity provides strong support for building a detection model with better generalization ability, especially when dealing with various changes in actual applications.

4.2. Experimental setup

In this experiment, we used a real financial transaction dataset to identify financial fraud transactions by building a detection model based on a convolutional neural network (CNN). First, the dataset was divided into a training set and a test set, of which 80% was used to train the model and the remaining 20% was used to test the generalization ability of the model. In the data preprocessing stage, all numerical features were normalized to ensure the stability of the model and the consistency of the feature scale. For categorical features, the One-Hot encoding method was used to convert them into numerical form. Due to the class imbalance problem in the dataset, we introduced oversampling technology to expand the minority class samples to reduce the bias that may occur in the model during training.

In the experimental design, the model structure contains multiple convolutional layers and pooling layers, aiming to extract spatial and temporal features from transaction data. Each convolutional layer uses different filter sizes to capture features at different scales, and the pooling layer reduces the computational complexity and retains the main features by downsampling. During the training process, we selected cross-entropy as the loss function and used the stochastic gradient descent (SGD) optimizer for parameter update. After several rounds of training, the model gradually converged to a stable state, and was finally evaluated on the test set to verify its actual effect.

In order to comprehensively measure the performance of the model, this experiment used four evaluation indicators: Accuracy, Precision, Recall, and F1-Score. Accuracy measures the overall prediction accuracy of the model for all transaction records, that is, the proportion of correctly classified samples to the total number of samples; precision is used to evaluate the proportion of samples predicted as fraudulent transactions by the model that are actually fraudulent; recall measures the model's ability to identify all actual fraudulent transactions; and the F1 score, as the harmonic average of precision and recall, reflects the comprehensive performance of the model in dealing with the problem of class imbalance. Together, these indicators help us comprehensively analyze the recognition effect of the model and provide a reference for subsequent optimization.

4.3. Experimental Result

In this comparative experiment, in order to comprehensively evaluate the performance of CNN models in financial fraud detection, we selected five other common classification models for comparison, including Logistic Regression, Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN) and Gradient Boosting Trees (GBT). These models represent a variety of different algorithm types from linear models to ensemble learning methods, which can capture the characteristics of transaction data from different angles. Logistic regression and SVM are suitable for processing higher-dimensional feature data, while Random Forest and Gradient Boosting Trees have excellent feature importance evaluation capabilities, which help to identify potential patterns in the data.

In the experimental design, each model is trained and tested on the same dataset, and cross-validation is used to ensure the stability of the results. For fair comparison, all models use unified evaluation indicators, including Accuracy, Precision, Recall and F1-Score, to evaluate their comprehensive performance in financial fraud detection tasks. By comparing with CNN, we can deeply analyze the advantages and disadvantages of different models when processing financial transaction data, and explore the best options in different scenarios. The experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	ACC	Recall	Precision	F1-Score
LR	0.78	0.72	0.75	0.73
SVM	0.80	0.74	0.77	0.75
RF	0.83	0.78	0.80	0.79
KNN	0.85	0.80	0.82	0.81
GBT	0.88	0.84	0.85	0.84
CNN	0.90	0.88	0.87	0.87

From the experimental results, the six models have different performances in the task of detecting financial fraud transactions, and the performance gradually improves from logistic regression (LR) to convolutional neural network (CNN). As a linear model, logistic regression often has limited performance when processing data with high dimensions and complex features. Although it is simple to implement and has fast inference speed, it is not as good as other nonlinear models in terms of accuracy (78%), recall (72%), precision (75%) and F1 score (73%). This shows that logistic regression may have difficulty capturing the nonlinear patterns hidden in financial transaction data, resulting in low accuracy and robustness in detecting complex fraudulent behaviors. Therefore, although its performance is stable, it fails to provide sufficient detection accuracy and sensitivity.

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Support vector machine (SVM) performs slightly better than logistic regression, achieving 80% accuracy and 75% F1 score. SVM usually works better when dealing with nonlinear problems with a small number of features, and can use kernel functions to project data into high-dimensional space and capture complex patterns. However, SVM has a high computational cost when facing large-scale financial transaction data, and its performance is limited by kernel function selection and data size. Therefore, although the recall and precision of SVM are improved compared with logistic regression, its performance in detecting financial fraud transactions is still not as good as the subsequent ensemble learning and deep learning models.

The random forest (RF) model showed higher accuracy (83%) and more balanced recall (78%) and precision (80%) in this experiment. As an ensemble learning method, random forest reduces the overfitting risk of a single model and improves the generalization ability of the model by combining multiple decision trees. Random forest performs well in feature extraction and importance assessment of financial transaction data. Therefore, in this experiment, the detection effect of random forest is significantly better than logistic regression and SVM, but it still does not reach the level of K-nearest neighbor (KNN) and gradient boosted tree (GBT).

The performance of K-nearest neighbor (KNN) and gradient boosted tree (GBT) is further improved, especially in precision and F1 score, reaching 82% and 85% and 81% and 84% respectively. KNN can better capture the neighboring relationship of samples and is suitable for the classification problem of a small number of abnormal samples; GBT uses the gradient reduction optimization method to effectively capture the nonlinear relationship in complex data through multiple iterations, making it perform better in high-dimensional financial data. However, KNN has a high computational cost and is suitable for small-scale data; although GBT has excellent precision and recall, it still needs to optimize the computational speed. Therefore, the two models performed well in this experiment, especially the high precision and recall of GBT, which showed its potential in financial fraud detection tasks.

Finally, CNN performed best among all models with 90% accuracy, 88% recall, 87% precision and 87% F1 score. CNN can effectively extract the spatial and time series features of transaction data with its multi-layer convolutional structure, which makes it have a strong capture ability in complex financial fraud patterns. Compared with traditional models, CNN can better adapt to the high dimension and diversity of financial transaction data, and has strong robustness and generalization ability. This result shows that in the task of financial fraud detection, CNN not only has obvious advantages in accuracy and sensitivity, but also can reduce misjudgments caused by data noise. Therefore, CNN has demonstrated its practical application potential and effect in financial fraud detection in this experiment.

In addition, this paper also gives the curve of ACC as Epoch increases, as shown in Figure 2.

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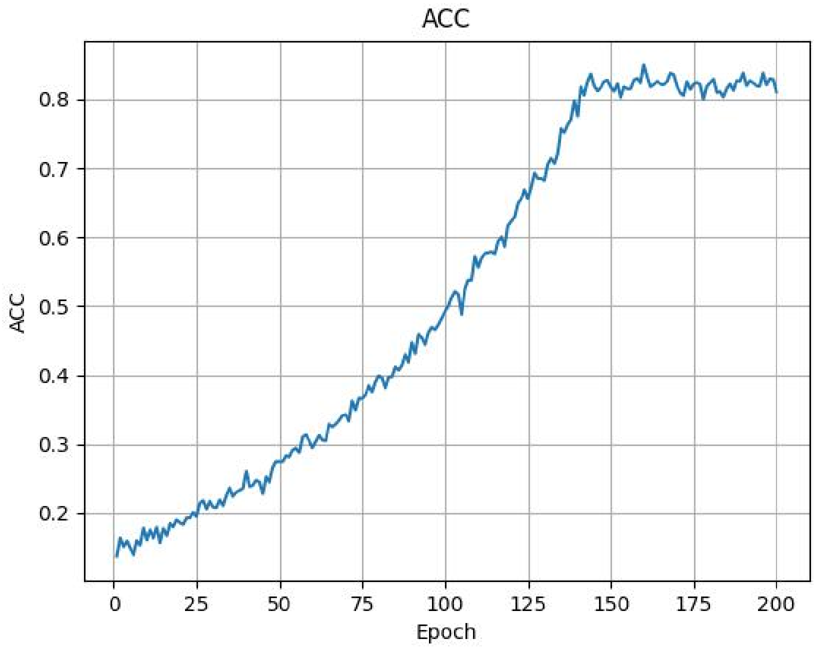

Figure 2: The curve of ACC rising with Epoch

It can be seen from the graph that the accuracy of the model rises rapidly in the early stages of training, gradually increasing from 0, especially in the first 100 epochs, showing a significant growth trend. This shows that the model performed effective feature learning on the data in the early stages of training and successfully captured the patterns in the data. As the number of epochs increases, the model gradually converges, showing that the model becomes more stable after learning key features.

At about the 125th epoch, the accuracy of the model is close to 0.8 and gradually reaches a plateau. After this, the growth rate of accuracy slows down significantly and the curve levels off. This stage indicates that the main learning process of the model has been completed and the training effect has gradually reached saturation. Although the accuracy fluctuates slightly, it overall remains at a high level, indicating that the model can stably maintain a high recognition accuracy after multiple training rounds. This situation is usually due to the fact that the model has fully learned the main features in the data, and subsequent fine-tuning is to optimize a small number of samples that are difficult to classify.

Judging from the experimental results, the accuracy of the model reached about 0.85, showing good classification ability. However, this may also indicate that the model has achieved optimal results on the training data. If you continue to increase the number of epochs, the accuracy may not significantly improve, but may lead to overfitting. Therefore, in practical applications, it is very important to appropriately control the number of epochs to avoid over-training, which can not only improve the generalization ability of the model, but also save training time.

5. Conclusion

In this study, we compared various classification models, including CNN, logistic regression, support vector machine, random forest, K nearest neighbor, gradient boosting tree, etc., to explore their performance in financial fraud transaction detection tasks. Experimental results show that the model based on convolutional neural network performs best in terms of accuracy, recall, precision and F1 score, significantly better than other traditional classification models. With its powerful feature extraction capabilities, CNN can effectively identify complex patterns in financial transaction data, thereby better detecting potential fraudulent transactions. This conclusion shows that convolutional neural networks have significant advantages in dealing with high-dimensional and complex financial data.

However, despite the excellent performance of the CNN model, this study also has some limitations. First of all, the amount of data in financial fraud transaction detection tasks is usually very large, and the feature dimensions are high. The training and inference costs of CNN are relatively high, so model performance and computing resources need to be weighed in practical applications. In addition, the class imbalance problem in the data set may still have a certain impact on the precision and recall of the model. Future research can further explore more efficient deep learning models or model lightweighting to reduce computational costs and improve model adaptability to better meet actual needs.

In terms of future prospects, in addition to continuing to optimize the model structure, we can also try to combine other data sources, such as social media information, transaction time series analysis, etc., to enhance the model's adaptability to diverse data. In addition, emerging technologies such as reinforcement learning and self-supervised learning may also provide new ideas for financial fraud detection and help models achieve better adaptive capabilities in complex environments. With the continuous improvement of data volume and computing power, financial fraud detection models will be further optimized in terms of accuracy and real-time performance, providing more efficient security protection for the financial industry.

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