Proceedings of the 3rd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/2025.28886

Retail Fraud Transaction Detection Based on Machine Learning Algorithms

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Abstract. This paper aims to improve the accuracy of fraudulent transaction detection in the retail industry to ensure its healthy and sustainable development. An innovative optimization model, BiTCN LSTM, is proposed to enhance long short-term memory networks with bidirectional temporal convolutional networks. Aiming at the limitations of existing models, this study systematically compares the performance of various mainstream classification algorithms in fraud detection tasks, including K-nearest neighbor (KNN), back propagation neural network (BP neural network), support vector machine (SVM), and logistic regression. The evaluation system comprehensively covers key indicators such as accuracy, recall, precision, F1 score, and area under the curve (AUC). The experimental results show that among the comparative models, logistic regression has the highest prediction accuracy, reaching 76.2%, followed by BP neural network (70.6%), while both KNN and SVM have accuracy below 70%. In sharp contrast, the BiTCN LSTM model proposed in this paper shows excellent performance in fraud detection tasks with an accuracy of up to 99.1%, which is significantly better than the best comparison model (logistic regression) by 22.9 percentage points. In addition, the model achieved the best results on all other core evaluation metrics such as recall, accuracy, F1 score, and AUC, fully demonstrating its ability to effectively identify fraudulent transactions while accurately distinguishing fraudulent and non-fraudulent samples, achieving high-precision classification of fraudulent transactions. The successful application of this model has significantly improved the security level of retail transactions, and provided strong technical support for curbing fraud, reducing economic losses, maintaining market order, and ultimately promoting the healthy, stable and sustainable growth of retail industry.

Keywords: Retail industry, accuracy of fraud transaction detection, machine learning

1. Introduction

With the explosion of e-commerce and the increasing diversification of payment methods, the retail industry is facing an unprecedented risk of fraudulent transactions [1]. Fraudsters continuously use technical loopholes, stolen identity information, and sophisticated money laundering methods to launch attacks, resulting in retailers suffering huge direct economic losses, bearing high transaction processing and investigation costs, and seriously damaging consumer trust and brand reputation [2]. In the fierce market competition, there is a sharp contradiction between consumers' pursuit of

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convenient payment experience and transaction security protection [3]. Any payment friction or data breach caused by fraud can lead to customer churn. At the same time, increasingly stringent financial regulatory requirements also require retailers to establish effective anti-fraud systems. The traditional rule-based detection system, due to its rigidity, outdated updates, and difficulty in coping with new fraud patterns, especially when processing massive, high-dimensional and rapidly changing transaction data, has high false positive rate and false positive rate and low efficiency, which can no longer meet the urgent demand of modern retail industry for accurate and real-time risk prevention and control [4]. Therefore, the development of more intelligent and adaptive fraud detection technologies has become a key infrastructure to ensure the healthy and sustainable development of the retail industry [5].

Machine learning algorithms, with their powerful data-driven learning and pattern recognition capabilities, have become the core force revolutionizing fraudulent transaction detection. This kind of algorithm can efficiently process and analyze the massive heterogeneous data generated every second in retail scenes, and automatically mine the complex and nonlinear fraud patterns hidden in it, far beyond the cognitive limits or simple rules of the human brain. The supervised learning model uses historically labeled data to train a classifier to accurately identify transactions that are similar to known fraud characteristics; Unsupervised learning is good at detecting abnormal suspicious transactions that deviate from normal behavior patterns without prior labeling, effectively solving "zero-day fraud"; Semi-supervised learning combines a small number of labels with a large number of unlabeled data, alleviating the problem of high labeling costs [6]; Deep learning is able to better handle time dependencies and high-dimensional feature interactions in transaction sequences [7]. The real-time stream processing capability of machine learning model enables it to complete risk assessment in milliseconds, realize real-time interception before transaction authorization, and automatically update the model according to the continuous evolution of fraud strategy, significantly improving detection accuracy, greatly reducing false alarm rate, reducing manual audit cost, optimizing the payment experience of legitimate customers, building a dynamic and intelligent security protection network for retailers, ensuring revenue and consolidating user trust. In this paper, a long short-term memory network model based on bidirectional temporal convolutional networks is optimized for fraudulent transaction detection, aiming to ensure the healthy and sustainable development of the retail industry.

2. Data set sources and data analysis

The dataset used in this article is an open-source dataset sourced from Kaggle （ https://www.kaggle.com/datasets/samayashar/fraud-detection-transactions-dataset/data ） This dataset contains multiple transaction data, each recording indicators such as transaction amount, transaction type, transaction date, device, failed transaction count in the past 7 days, and average transaction amount of users in the past 7 days. The target variable is whether it is transaction fraud (1 represents yes, 0 represents no), which can be used to develop advanced transaction fraud detection models. Select some data for display, as shown in Table 1.

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Table 1. A portion of the dataset

Transaction Amount	Transaction Type	Previous Fraudulent Activity	Daily Transaction Count	Failed Transaction Count	Card Age	Transaction Distance	Is Weekend	Fraud Label
39.79	POS	0	7	3	65	883.17	0	0
1.19	Bank Transfer	0	13	4	186	2203.36	0	1
28.96	Online	0	14	4	226	1909.29	0	1
254.32	ATM Withdrawal	0	8	4	76	1311.86	0	1
31.28	POS	1	14	4	140	966.98	1	1
168.55	Online	0	3	2	51	1725.64	0	0
3.79	POS	0	2	2	168	3757.19	0	0

3. Method

3.1. Bidirectional Time Convolutional Network

Bidirectional temporal convolutional network (BiTCN) is a dedicated deep network for timing modeling. It improves the sequence feature extraction ability by fusing bidirectional timing context information. The network structure is shown in Figure 1. Traditional one-way TCN only uses historical time series information to model. Although it meets the causality of time series, it can't use future context information, and feature extraction has limitations [8].

BiTCN adopts the parallel structure of both forward and reverse branches. The forward branch extracts the historical timing dependencies, and the reverse branch mines the future timing associations. Both branches are composed of multi-layer causal expansion convolution and residual connection. The convolution receptive field is expanded by exponentially increasing expansion coefficients, which can efficiently capture long-span time series dependencies, and effectively solve the problems of gradient disappearance and low computational efficiency when traditional convolution and RNN process long sequences.

The core advantage of BiTCN is bidirectional feature fusion. The double branch outputs historical and future context features at each time series node respectively, and fuses bidirectional information through channel splicing to construct a refined time series feature expression containing complete context in a concise and efficient way.

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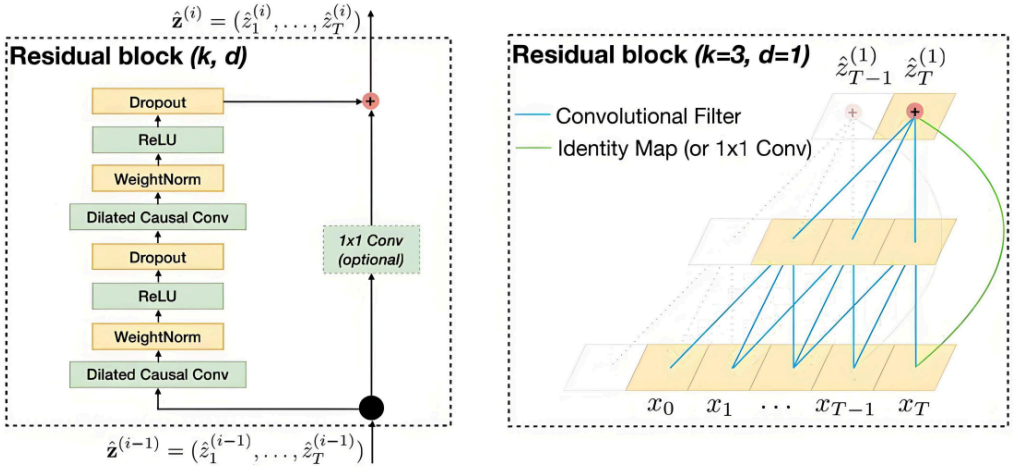

Figure 1. The network structure of the bidirectional time convolutional network

3.2. Long Short Term Memory Network

Long short-term memory network (LSTM) is an improved recurrent neural network, which is mainly used to solve the problems of gradient disappearance and gradient explosion in traditional RNN long-sequence modeling, and can stably learn long-term timing dependencies. The network structure is shown in Figure 2. The core design of LSTM is cell state transmission channel and three gating mechanisms of forgetting, input and output, which reconstructs the storage and updating mode of timing information.

Cell state transmits time series information in a linear manner, and the information loss is extremely low, which can realize the stable transmission of long-distance time series features. The three-gate control unit combines Sigmoid and Tanh activation functions to coordinately regulate the information according to the current input and historical hidden state, selectively complete memory forgetting, new feature update and feature output, and realize accurate screening and retention of timing information [9].

During the operation, the forgetting gate eliminates invalid history information; The input gate filters and updates valid new features; The output gate outputs the current moment hidden state based on the updated cell state. The whole gating mechanism allows LSTM to have powerful long-term timing-dependent modeling capabilities and adapt to long-sequence tasks.

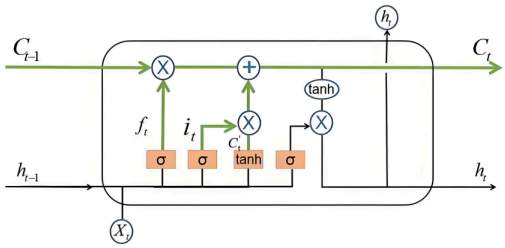

Figure 2. The network structure of the Long Short Term Memory Network

3.3. BiTCN optimized LSTM

The BiTCN optimization LSTM model takes BiTCN as the pre-feature extraction module, and combines the excellent local feature extraction ability of BiTCN with the long-term dependency

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modeling advantage of LSTM to achieve complementary network performance and improve the modeling efficiency and prediction accuracy of long-time series data [10].

BiTCN mines forward and backward features of time series data in parallel through bidirectional expansion convolution, which can not only accurately capture local details and short-term dependencies, but also rely on large receptive field to obtain long-distance context information. The feature preprocessed by BiTCN has low redundancy and high recognition, which can effectively filter the original data noise and simplify the sequence features.

Inputting the condensed high-quality features into LSTM can greatly reduce the computing overhead and modeling pressure of LSTM, so that it can focus on learning complex long-term time series dynamic features. This cascade structure makes up for the weak local feature extraction of LSTM and the long-term dependence of traditional convolutional networks that cannot effectively model, and significantly improves the model accuracy, robustness and training efficiency of time series prediction and classification tasks.

4. Result

In this experiment, a bidirectional time convolutional network (Bi TCN) was used to optimize the long short-term memory network (BiLSTM) for classification tasks. The specific parameters were set as follows: the input sequence length was fixed at 128 time steps, the Bi TCN layer used two layers, each layer containing 64 filters, the convolution kernel size was 7, the expansion factor was 1/2, and the activation function was ReLU; Its output is connected to a BiLSTM layer containing 128 units; Followed by Dropout layer and fully connected output layer; The model uses Adam optimizer (initial learning rate 0.001), batch size set to 64, and training epochs set to 100. The hardware configuration includes NVIDIA RTX 3090 GPU (24GB video memory), Intel i9-12900K CPU, and 64GB DDR5 memory; The software environment is Matlab R2024a.

Compare the models using KNN, BP neural network, SVM, and logistic regression, and evaluate the parameters using Accuracy, Recall, Precision, F1, and AUC. The output results are shown in Table 2, and the comparison results of the models are shown in Figure 3.

Table 2. The output results

Model	Accuracy	Recall	Precision	F1	AUC
KNN	0.593	0.593	0.5	0.532	0.632
BP neural network	0.706	0.706	0.503	0.587	0.709
SVM	0.519	0.519	0.598	0.533	0.694
logistic regression	0.762	0.762	0.755	0.756	0.844
Our model	0.991	0.991	0.991	0.991	0.998

According to the experimental results, among the comparison models, the logistic regression model has the highest prediction accuracy, reaching 76.2%, followed by the BP neural network model with an accuracy of 70.6%. The prediction accuracy of the other comparison models is less than 70%. The BiTCN LSTM model proposed in this article achieves an accuracy of 99.1% in fraud detection prediction, which is 22.9% higher than the highest 76.2% in the comparison model. Our model also has the best indicators in Recall, Precision, F1, and AUC, achieving accurate classification of fraudulent transactions.

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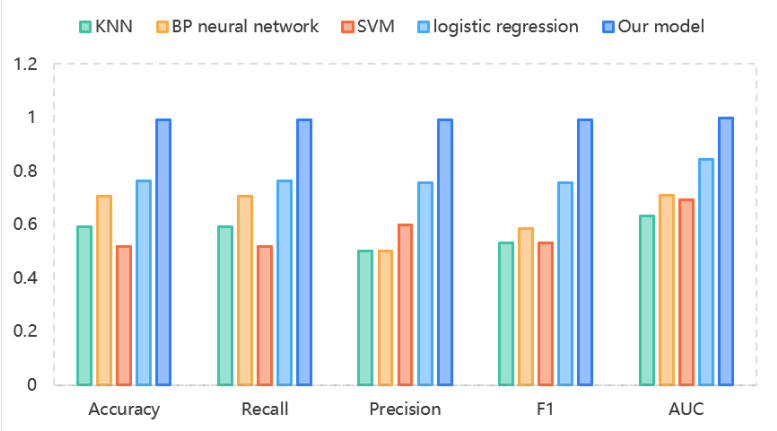

Figure 3. The comparison results of the models

5. Conclusion

This study innovatively proposes a BiTCN LSTM model that combines a bidirectional temporal convolutional network (BiTCN) with a long short-term memory network (LSTM) to meet the critical needs of fraudulent transaction detection in the retail industry. Through systematic comparison with mainstream models such as K Nearest Neighbor (KNN), BP Neural Network, Support Vector Machine (SVM) and Logistic Regression, and comprehensively applying five core evaluation indexes such as accuracy, recall, accuracy, F1 score and area under the curve (AUC) to evaluate the performance, the effectiveness of the proposed model is fully verified. The experimental results show that logistic regression performs best in the comparative model with an accuracy of 76.2%, followed by BP neural network (70.6%), and the accuracy of the other models is below 70%. The BiTCN LSTM model proposed in this paper exhibits significantly superior performance with a fraud detection accuracy of 99.1%, which is 22.9 percentage points higher than the optimal comparison model (logistic regression). More importantly, the model achieves the best results on all other key indicators such as recall, accuracy, F1 score, and AUC, achieving accurate identification and classification of fraudulent transactions with high accuracy and robustness.

The significance of this study is that the BiTCN LSTM model successfully overcomes the limitations of traditional models in dealing with complex, dynamic, and highly unbalanced time series data such as fraudulent transactions, and significantly improves the accuracy and reliability of detection. The outstanding performance of this model, especially its nearly perfect accuracy and comprehensive leading indicators, provides strong technical support for building an efficient and intelligent fraud risk prevention and control system in retail industry. Its application will effectively reduce the economic losses caused by fraudulent transactions, safeguard the common interests of consumers and merchants, and enhance the trust and security of the transaction ecosystem, thus effectively promoting the development of retail industry towards a healthier, more stable and more sustainable direction.

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