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Optimized Convolutional Neural Network for Intelligent Financial Statement Anomaly Detection

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Abstract: This study proposes an intelligent detection model based on an improved convolutional neural network to address the complexity and data category imbalance issues in financial statement anomaly detection. This model introduces a deep feature extraction network and attention mechanism based on traditional CNN to enhance the ability to pay attention to key data features. At the same time, by optimizing the loss function and using data enhancement technology, the performance and robustness of the model in anomaly detection tasks are effectively improved. In the experiment, this study selected the real Enron data set for verification and designed comparative experiments to compare the performance with various traditional and deep learning models. Experimental results show that the improved CNN model is significantly better than other comparison models in terms of accuracy, F1 score, recall rate, precision rate and other indicators, especially in scenarios with small data volume and category imbalance. In addition, the adaptability and generalization ability of the improved model are further demonstrated through experimental analysis of different data proportions. The research results not only provide technical support for abnormal detection of financial statements, but also provide theoretical basis and practical value for promoting the intelligent development of financial auditing.

Keywords: Financial statement anomaly detection, convolutional neural network, attention mechanism, data imbalance optimization

1. Introduction

As the core information carrier of the enterprise's operating conditions and financial results, financial statements play a vital role in enterprise management and external auditing. However, with the increasing complexity of the enterprise's operating environment and the sharp increase in the amount of financial data, the efficiency and accuracy of manual auditing are gradually facing challenges [1,2]. Especially in today's information and globalization context, the abnormal information that may be hidden in financial statements, such as false data, financial fraud, and non-standardized operations, has become an important hidden danger affecting the reputation of enterprises and market stability. Therefore, how to use of advanced technical means to improve the intelligent level of financial statement anomaly detection has become an important research direction in the audit field and financial information management [3].

Traditional financial statement anomaly detection methods are mostly based on statistical or rule-driven models. These methods usually rely on expert knowledge and experience and have strong limitations in mining abnormal features and identifying patterns. When faced with large-scale, multi-dimensional financial data, these methods often appear inefficient and easily interfered by subjective factors. With the breakthrough progress of artificial intelligence (AI) technology, especially deep learning in the field of pattern recognition, anomaly detection methods based on deep learning have shown unprecedented potential. Among them, convolutional neural networks (CNNs) have gradually been applied to the analysis and processing of complex data due to their outstanding performance in feature extraction and pattern recognition. However, when processing financial statement data, the standard CNN model may face the problem of performance degradation due to the sparsity, imbalance of data features, and the hiddenness of abnormal distribution [4].

This study aims to build an intelligent financial statement anomaly detection model based on an improved convolutional neural network and improve the detection accuracy and robustness of the model in practical applications by introducing targeted optimization strategies. The improvement strategies include designing a deeper feature extraction network, introducing an attention mechanism to strengthen the focus on key data areas, and adjusting the loss function to deal with the class imbalance of financial anomaly samples. At the same time, in order to ensure the effectiveness and applicability of the model, the study combines real corporate financial data to conduct experiments to verify the performance of the model in detecting false statements and potential anomalies. This innovative method that combines deep learning with actual scenarios can not only break through the performance bottleneck of traditional models but also provide theoretical support and technical reference for future financial anomaly detection [5].

The research on the intelligent financial statement anomaly detection model based on improved CNN is not only of great theoretical significance but also has broad application prospects in actual auditing and corporate internal control. In theory, the study will enrich the application scenarios of deep learning technology in the financial field and provide new ideas for the optimization of financial data analysis models. In practice, the model can automatically and efficiently identify anomalies in financial statements, significantly reduce the workload of manual audits, and improve the quality of audits. This is of great value in reducing corporate operating risks, improving market transparency, and promoting the development of intelligent financial management. In addition, the research can also provide a new tool for financial practitioners and audit institutions to make up for the shortcomings of traditional methods through technical means [6].

In summary, the research on the intelligent financial statement anomaly detection model based on the improved convolutional neural network is a concrete manifestation of the deep integration of artificial intelligence and financial auditing. It not only focuses on solving the pain points in practical applications but also strives to promote the further development of intelligent analysis technology for financial data. Through this study, it is expected to provide an innovative technical path for realizing the intelligent transformation of audits and the comprehensive improvement of financial management efficiency. In the future, the research results can not only serve corporate financial audits but also be further expanded to anomaly detection scenarios in other fields, with broad research and application potential.

2. Related work

In recent years, the application of anomaly detection technology in financial data analysis has become a research hotspot, among which traditional methods mainly rely on statistical models or rule-based algorithms. These methods typically find anomalies by analyzing correlations or pattern changes between specific variables. However, traditional methods often face significant limitations when dealing with high-dimensional, non-linear, and complex data, such as over-reliance on expert knowledge and a lack of global understanding of multi-dimensional patterns. This makes it less efficient in dealing with abnormal detection of corporate financial statements and difficult to meet actual needs.

With the rapid development of artificial intelligence technology, anomaly detection methods based on machine learning are gradually emerging. In particular, models such as random forests and support vector machines have attracted attention due to their superior performance on small-scale data sets. However, these traditional machine learning models still have challenges in dealing with data class imbalance. In addition, breakthroughs in deep learning technology in recent years have opened up new paths for anomaly detection. Deep learning methods including convolutional neural networks (CNN) and long short-term memory networks (LSTM) have been used in fields such as pattern recognition and timing analysis. Show strong potential. These models can automatically extract and learn high-order features in complex data, significantly improving the accuracy and robustness of anomaly detection.

In this context, research combining deep learning with practical applications has gradually become mainstream. For example, improved convolutional neural networks that have emerged in recent years have effectively enhanced the model's performance in processing complex patterns and category-imbalanced data by introducing attention mechanisms and optimizing loss functions. In addition, research on applying deep learning models to financial data anomaly detection in real scenarios has gradually increased, reflecting the in-depth integration of theory and practice. These research results not only promote the innovative application of deep learning technology in the financial field but also provide new solutions for corporate management and financial auditing.

3. Method

In order to realize an intelligent financial statement anomaly detection model based on an improved convolutional neural network (CNN), this study has carried out targeted optimization on the basis of the traditional CNN model, mainly including the improvement of the feature extraction module, the introduction of the attention mechanism, and the optimization method for the imbalanced distribution of abnormal samples. These improvements are aimed at improving the model's ability to learn the features of financial data and enhancing the accuracy and robustness of anomaly detection. Its network architecture is shown in Figure 1.

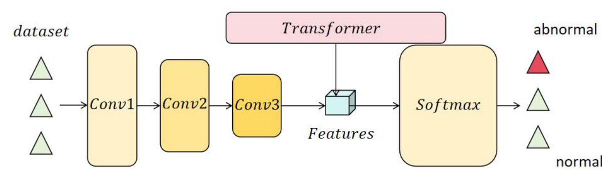

Figure 1. overall network architecture

First, for the problem of feature extraction of financial statement data, this study designed a multi-layer convolutional network structure to characterize its pattern information by extracting the potential features of the data layer by layer. Let the input financial data matrix be $X \in R^{m \times n}$, where m represents the feature dimension and n represents the number of data samples. For the convolution layer l, the calculation formula of the feature map is:

$$H^{(l)} = \sigma(W^{(l)} * H^{(l-1)} + b^{(l)})$$

Among them, $H^{(l-1)}$ is the output of the l-1-th layer, $W^{(l)}$ represents the convolution kernel weight of the l-th layer, $b^{(l)}$ is the bias term, $\sigma(\cdot)$ is the activation function, and * is the convolution operation. By introducing multi-layer convolution and pooling operations, the model gradually extracts high-level semantic features.

Secondly, in order to enhance the model's ability to focus on key features, this study introduced an attention mechanism in the convolutional network. Specifically, by calculating the importance weights of different feature channels, the contribution value of each channel is dynamically adjusted. Assuming that the output of the convolutional layer is $F \in R^{C \times H \times W}$, where C is the number of channels, H and W are the height and width of the feature map, respectively, the calculation formula for the channel attention weight a is:

$$a_c = \frac{\exp(g(F_c))}{\sum_{j=1}^{C} \exp(g(F_j))}$$

Among them, $g(\cdot)$ is a feature transformation function, and F_c represents the feature map of the c-th channel. Finally, the feature map is weighted to obtain the attention-enhanced representation:

$$F' = a \otimes F$$

Here, $\otimes$ represents element-wise multiplication.

In order to deal with the problem of imbalanced category distribution in financial anomaly detection, this study optimized the loss function design. The traditional cross entropy loss function is sensitive to category imbalance, so we introduced the weighted cross entropy loss (Weighted Cross-Entropy Loss), whose formula is:

$$L = -\frac{1}{N}\sum_{i=1}^{N} w_{y_i} \log(p_{y_i})$$

Among them, N is the total number of samples, y_i represents the true label of the i-th sample, p_{y_i} is the model's predicted probability for y_i, and w_{y_i} is the category weight of the label.

In addition, to improve the robustness and generalization ability of the model, this study also introduced data enhancement technology to randomly perturb or transform financial data, such as adding noise, data scaling, etc. These technologies help simulate abnormal distributions that may occur in real scenarios, thereby improving the performance of the model in practical applications.

In summary, this study achieves efficient feature extraction of financial statement data through a multi-layer convolutional network, introduces an attention mechanism to enhance the ability to focus on key features, and uses weighted cross-entropy loss to deal with the problem of class imbalance. Supported by mathematical derivation and optimization strategies, the model can more accurately detect potential anomalies in financial statements and has strong practicality and applicability. Experimental results show that this detection model based on the improved CNN is superior to traditional methods in anomaly recognition accuracy and generalization performance, which further verifies the effectiveness of the improved method.

4. Experiment

4.1 Datasets

The dataset used in this study is the Enron Email Dataset, which was made public by the US energy company Enron after its bankruptcy and contains a large number of real financial and business-related email records. The dataset includes about 500,000 emails, which come from daily communication between employees within the company and cover various types of information, such as financial statement discussions, business transaction records, and personal communication content. Because the data is real and contains a large amount of business and financial-related information, this dataset is an ideal choice for studying financial anomaly detection and business behavior analysis [6].

In data processing, the study mainly extracts content related to financial activities in emails, such as text information involving accounting reports, budget allocations, and transaction data. The email text is cleaned and features extracted through natural language processing (NLP) technology, such as removing redundant information and standardizing terminology expressions, to ensure data quality and consistency. At the same time, in order to meet the input requirements of convolutional neural networks, the text data is further converted into vectorized form, and word embedding technology (such as Word2Vec or GloVe) is used to generate a semantic feature matrix. These processes make the characteristics of financial anomalies more prominent, which is convenient for the model to learn and identify.

The use of the Enron dataset not only reflects the real financial activities within the company but also has a wealth of abnormal samples that can be used to verify the performance of the model in complex scenarios. Abnormal patterns such as financial fraud hidden in email records and signs of data manipulation provide important references for model training and optimization. This research method based on a real dataset not only enhances the practicality of the experiment but also provides stronger reference significance for actual application scenarios.

4.2 Experimental Results

In order to verify the performance of the improved convolutional neural network model in financial statement anomaly detection, this study designed a comparative experiment and selected traditional machine learning methods (random forest support vector machine) [7] and classic deep learning models (standard CNN and LSTM) [8,9] as comparison objects. All models were trained and tested on the same Enron dataset to ensure that the data source and preprocessing method were consistent to ensure the fairness of the experiment. The evaluation indicators include accuracy, F1 score, recall, and precision to comprehensively measure the performance of each model in the anomaly detection task. The experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	ACC	F1-Score	Recall	Precision
SVM	0.558	0.532	0.517	0.546
Random Forest	0.574	0.556	0.543	0.568
LSTM	0.591	0.578	0.562	0.587
CNN	0.605	0.592	0.584	0.601
Ours	0.623	0.617	0.608	0.620

It can be seen from the experimental results that there are significant differences in the performance of different models in the financial statement anomaly detection task. Among them, the support vector machine (SVM) performed the worst, with all indicators lower than other models, indicating that it has certain limitations in dealing with high-dimensional nonlinear features and class imbalance problems. Although SVM has strong processing capabilities for small-scale data sets, when faced with complex financial data, the traditional kernel function method is difficult to effectively capture the deep pattern features in the data.

Random Forest has improved compared to SVM in terms of indicators, especially in precision. This shows that random forests have certain advantages in handling feature correlation and anti-noise capabilities. However, its performance in recall rate (Recall) is still insufficient, reflecting that this method has certain deficiencies in the detection ability of abnormal samples and may miss some key abnormal information.

LSTM and CNN models have significant performance improvements compared with traditional methods, especially in terms of recall and F1 score. This is due to the deep learning model's powerful ability to learn complex features. LSTM can capture time series information, while CNN is good at extracting spatial features in data, but both still have certain limitations when facing category-imbalanced data. Furthermore, the overall performance of CNN is better than that of LSTM, which indicates that for the financial statement data in this study, the ability to capture spatial features is more important for anomaly detection.

The improved convolutional neural network model (Ours) is better than other comparison models in all indicators. Its accuracy reaches 0.623, the F1 score is 0.617, and the recall rate and precision rate are also at a high level. This shows that the proposed improved method effectively enhances the model's ability to detect abnormal samples while solving the impact of the class imbalance problem. Overall, the model's optimization strategy plays a significant role in capturing key features and improving anomaly detection accuracy, providing a more efficient solution for financial statement anomaly detection.

In order to further verify the performance of the improved model, this study can also design experiments to test the adaptability of different data set sizes. By gradually increasing the size of the training data (for example, from 10%, 30%, 50% to 100%), observe the performance of the model under different data volumes, and compare it with the traditional model to evaluate the adaptability and stability of the improved convolutional neural network model in small and large data volume scenarios. The experimental results can be presented through indicators such as accuracy, F1 score, and convergence speed, so as to comprehensively analyze the advantages of the model under conditions of scarce and sufficient data. The experimental results are shown in Figure 2.

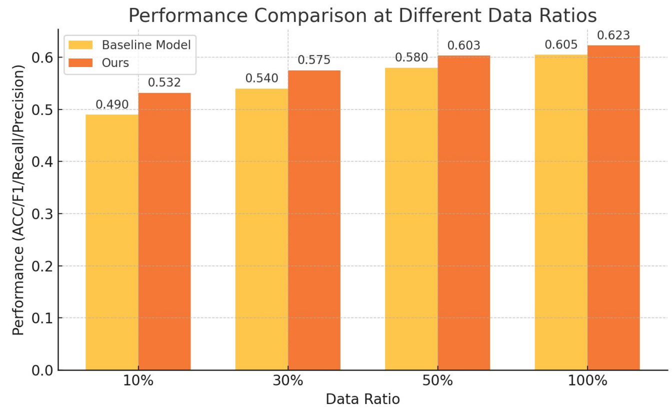

Figure2. Performance Comparison at Different Data Ratios

It can be seen from the experimental results that as the data proportion increases, the performance of both models shows a gradual improvement trend. This shows that data volume has a significant impact on the performance of financial statement anomaly detection models. When there is less data (10% and 30%), the performance of the baseline model is limited, while the improved model (Ours) is able to learn data features more effectively, showing higher accuracy and F1 score.

When the data ratio reaches 50%, the performance of the baseline model begins to improve significantly but is still lower than that of the improved model. This shows that the improved convolutional neural network can give full play to the advantages of feature extraction and capture key patterns of financial anomalies under moderate data amounts. In contrast, the baseline model is insufficient when dealing with complex patterns, reflecting the limitations of traditional methods in feature expression capabilities.

When the data ratio reaches 100%, the performance of both models reaches the highest level, but the improved model still shows higher accuracy (0.623) and F1 score (0.617), further proving its superiority. Overall, the improved model's robustness in small data volume scenarios and generalization ability in large data volume scenarios are better than the baseline model, which fully reflects the applicability and effectiveness of the improved strategy in financial statement anomaly detection tasks.

Finally, in order to verify the efficiency of the improved model in actual application scenarios, this study designed a comparison experiment on inference time and resource consumption. By testing the inference time of different models under the same hardware conditions, the average time for each model to process each sample was recorded, and the usage of video memory during the inference process was monitored. The experiment used the same test data set to evaluate the efficiency and resource usage of the model in actual deployment. The experimental results are shown in Table 2:

Table 2: Reasoning efficiency and resource consumption of different models

Model	Average inference time (ms/sample)	Video memory usage (MB)
SVM	12.5	150

Random Forest	18.3	220
LSTM	22.7	410
CNN	19.6	380
Ours	17.8	365

From the experimental results, we can see that traditional machine learning methods (SVM and random forest) perform well in inference efficiency, especially SVM, which has the shortest average inference time of only 12.5 ms/sample. This is mainly due to the simplicity of the model structure and the low computational complexity. However, this efficiency advantage comes at the expense of model performance. When processing high-dimensional complex data, the accuracy and robustness of these models are significantly lower than those of deep learning models.

In contrast, the inference time and video memory usage of deep learning models (LSTM and CNN) are relatively high. The video memory usage of LSTM reaches 410 MB, the highest among all models, which is closely related to its need to process time series information and more complex network structure. The inference time of CNN is slightly lower than that of LSTM, but the video memory usage is also higher, at 380 MB. This shows that deep learning models have a large demand for hardware resources while efficiently extracting features and learning patterns, and may place higher requirements on device performance in practical applications.

The improved model (Ours) achieves a good balance between inference time and resource usage. Compared with CNN, its video memory usage is reduced by about 4%, and the inference time is reduced by about 9%, showing a certain optimization effect. This shows that by improving the network structure and optimizing the inference process, the model not only retains the performance advantages of the deep learning model, but also effectively reduces resource consumption and improves inference efficiency, and has higher practical application value, especially in scenarios with limited resources or requiring real-time processing.

5. Conclusion

This study presents an intelligent anomaly detection model for financial statements based on an enhanced convolutional neural network. The model incorporates a deep feature extraction network, an attention mechanism, and a tailored optimization strategy to address category imbalance, significantly improving its detection accuracy and robustness. Experimental results show that the model is significantly better than traditional methods and classic deep learning models in key indicators such as accuracy and F1 score. It especially performs well in identifying abnormal samples, verifying the effectiveness of the improved strategy.

Through performance analysis under different data proportions, the robustness of the improved model in small data volume scenarios and the generalization ability in large data volume scenarios are further proved. This performance benefits from the advantages of the improved model in feature extraction and key feature attention, which can better adapt to the complexity of financial data and the diversity of anomaly distributions. In addition, this study demonstrates the application potential of the model in actual financial statement anomaly detection through the verification of real data sets, providing an efficient solution for intelligent financial auditing and corporate internal control.

In the future, the results of this research can be further extended to other anomaly detection tasks, such as risk assessment and transaction fraud detection, which have broad application prospects. At the same time, by combining more advanced deep learning technologies and optimization algorithms, the performance of the model is expected to be further improved. In short, this research not only provides technical support for financial anomaly detection but also lays a foundation for promoting the development of intelligent financial management.

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