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Abnormal Stock Price Fluctuation Recognition Based on Convolutional Neural Networks and Its Application in Financial Risk Monitoring

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Abstract: This paper studies the abnormal stock price fluctuation recognition algorithm based on convolutional neural network (CNN). Through comparative experiments with models such as support vector machine (SVM), long short-term memory network (LSTM), and bidirectional long short-term memory network (BiLSTM), the superior performance of CNN in the task of identifying abnormal stock price fluctuations is verified. The experimental results show that CNN is superior to other models in terms of accuracy and F1 score, and can more effectively capture the local fluctuation characteristics of stock prices. This study provides technical support for abnormal fluctuation monitoring and risk warning in the financial market, and lays the foundation for further application of deep learning in financial analysis.

Keywords: abnormal stock price fluctuations, convolutional neural network, deep learning, risk monitoring

1. Introduction

In recent years, with the rapid development of financial markets, abnormal stock price fluctuations have brought huge risks to investors and financial institutions. Abnormal stock price fluctuations are often accompanied by major economic events or policy changes. Such fluctuations may lead to increased market uncertainty and trigger chain reactions. Traditional financial analysis methods are difficult to accurately capture these abnormal fluctuations in a short period of time. Therefore, it is of great practical significance to build an efficient algorithm for identifying abnormal stock price fluctuations[1,2,3].

At present, deep learning has become an important tool for data analysis in the financial field. Among them, convolutional neural networks (CNNs) have received widespread attention due to their excellent performance in image and sequence data processing. CNN can automatically extract features through convolution operations, avoiding the complex feature engineering process in traditional methods. Applying CNN to the identification of abnormal stock price fluctuations can effectively capture subtle changes in stock price trends, thereby improving the accuracy and timeliness of abnormal fluctuation identification[4,5].

In the identification of abnormal stock price fluctuations, the diversity and complexity of data put forward higher requirements for the model[6,7]. Stock market data has time series characteristics and contains the combined influence of multiple factors, such as market sentiment, company fundamentals, and the external economic environment. CNN can identify potential abnormal patterns in stock price time series through multi-layer convolution operations, making this method highly adaptable and robust in complex financial data[8,9].

In addition, the abnormal fluctuation recognition algorithm based on CNN can achieve fast calculation in large-scale data, which provides the possibility of real-time detection of abnormal stock price fluctuations. Compared with traditional statistical analysis methods, CNN models are more efficient in processing massive data and more suitable for the dynamic change environment of financial markets. With the improvement of computing power and the enrichment of data acquisition methods, CNN-based algorithms have broad application prospects in real-time monitoring and risk warning of the stock market[10,11,12].

This study aims to use the CNN model to identify abnormal stock price fluctuations, extract stock price fluctuation features through the convolution layer, and combine the time series analysis method to improve the detection accuracy of abnormal fluctuations. By designing an effective model structure and optimization strategy, we hope to verify the application value of CNN in stock price fluctuation recognition and provide technical support for risk control in the financial market.

In summary, the abnormal stock price fluctuation recognition algorithm based on CNN not only provides investors with new technical means, but also provides effective tools for risk management and market forecasting of financial institutions. The innovation of this method lies in combining deep learning technology with financial market data, which improves the efficiency and accuracy of identifying abnormal fluctuations and provides strong technical support for intelligent financial analysis.

2. Method

In this method, we designed an abnormal stock price fluctuation identification algorithm based on a convolutional neural network (CNN) to improve the detection accuracy of abnormal fluctuations in financial markets. The method includes steps such as data preprocessing, feature extraction, model structure design and optimization. Its overall architecture is shown in Figure 1.

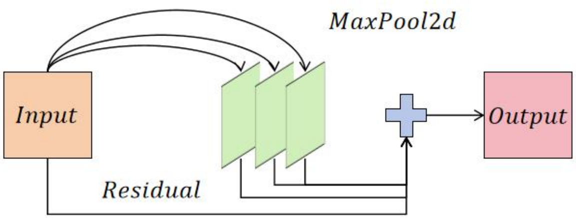

Figure 1. Convolutional Neural Network Architecture

First, in the data preprocessing stage, we normalize the historical stock price data to reduce the impact of the amplitude difference of data fluctuations. Stock price data usually contains information such as opening price, closing price, highest price, and lowest price. In order to better extract the fluctuation characteristics of stock prices, we use normalization method to map these data to a relatively small numerical range, so that the model is not affected by different price ranges during the learning process. Let the normalized value of each data point be x_{norm}, and its calculation formula is:

$$x_{norm} = \frac{x - \min(X)}{\max(X) - \min(X)}$$

Among them, x is the original data, X is the set of all data in the time series, and min(X) and max(X) represent the minimum and maximum values of the sequence respectively. Through normalization, we get the processed stock price data so that the subsequent model can extract features more effectively.

Next is the feature extraction stage, using CNN to automatically extract the implicit features in the time series. The convolution kernel commonly used in image processing by convolutional neural networks is applied to one-dimensional stock price data, which can effectively extract the fluctuation pattern in different time windows. The basic form of convolution operation is the inner product of the convolution kernel and the input data, and different feature maps are calculated layer by layer by moving the window. In the task of identifying abnormal stock price fluctuations, this one-dimensional convolution operation can capture the sharp fluctuations of stock prices in a short period of time and identify the fluctuation characteristics hidden in the data. Assuming that the convolution kernel is E, the result of the convolution operation is:

$$y_i = \sum_{k=0}^{n-1} w_k \cdot x_{i+k}$$

Among them, y_i represents the value of the i-th output position, n is the size of the convolution kernel, and x_{i+k} is the position of the input data in the current window. Through the convolution layer, the model can extract the local features of stock price fluctuations layer by layer, providing support for subsequent classification and recognition.

In terms of model structure design, we designed a multi-layer convolutional network architecture to enhance the model's ability to extract features at different levels. Each convolutional layer is followed by a pooling layer to reduce the dimension of the data, retain the most important features and suppress noise interference. The pooling layer reduces data complexity and improves computational efficiency by taking the maximum or average value within the window. Assuming that maximum pooling is used, the output result is:

$$z_i = \max(y_{i:j})$$

Among them, z_i represents the data after pooling, and $y_{i:j}$ is the feature value in the pooling window. The pooling operation can not only reduce the amount of calculation, but also improve the robustness of the model to a certain extent, making the model more stable when dealing with data fluctuations.

Finally, in the model optimization process, we introduced the cross entropy loss function as the objective function to measure the difference between the predicted value and the true label. By minimizing the loss function, the model can continuously adjust the parameters to improve the accuracy of abnormal fluctuation identification. The cross entropy loss function is defined as:

$$L = -\sum_i (y_i \log(y'_i) + (1 - y_i)\log(1 - y'_i))$$

Among them, y_i is the true label and y'_i is the model prediction probability. Through the gradient descent algorithm, we update the model parameters in each iteration so that the loss function gradually tends to the minimum value, thereby optimizing the model. To avoid overfitting, we also use regularization technology in model training and set early stopping conditions to ensure that the model has good generalization performance on the test set.

In summary, the CNN-based stock price abnormal fluctuation recognition algorithm extracts features from time series through convolution operations, and combines pooling layers and optimization strategies to effectively identify abnormal stock price fluctuation patterns. This method improves recognition accuracy while reducing artificial feature engineering and has good applicability.

3. Experiment

3.1. Datasets

The dataset used in this study is real stock market data provided by Yahoo Finance, including historical price records of multiple stocks. The dataset contains information such as the opening price, closing price, highest price, lowest price, and trading volume of each stock, covering daily trading data from the past few years to the most recent. These data can more comprehensively reflect the market volatility and provide rich training samples for the model to identify abnormal fluctuations. Due to the dynamic and complex nature of stock market data, these multi-dimensional features can help the model more accurately identify potential abnormal fluctuations.

In the data preprocessing stage, we normalized and normalized the data to reduce the impact of differences in price ranges between different stocks on the model. Specifically, the normalization process can map prices to a relatively consistent range, so that the model can process data in the case of multiple stocks without being disturbed by different price levels. In addition, we divide the data into training and test sets in chronological order to ensure that the training and test data of the model come from different time periods to more realistically simulate the prediction effect of the model in the actual financial market.

In order to improve the representativeness of the data, we also expanded the training dataset through data enhancement technology. In stock price time series data, abnormal fluctuations often have characteristics that are difficult to capture, so we generate more samples by adjusting the window size, sampling frequency, and other methods to enrich the model's training data. In addition, in order to verify the generalization ability of the model, we added stock data in different market environments to the data set, covering different scenarios such as bull markets, bear markets, and volatile markets, so that the model can maintain good recognition effects under various market conditions. Through this diverse processing method, we expect the model to be able to more accurately identify abnormal fluctuations in stock prices and provide more reliable prediction results.

3.2. Experimental setup

In the experimental setting, we first preprocessed the dataset, including normalization, outlier removal, and missing value filling, to ensure the quality and consistency of the data. After that, we divided the data into training and test sets in chronological order, of which 80% was used for model training and 20% was used for model testing. This division method can simulate the real market situation and ensure that the model has better generalization ability in predicting future abnormal stock price fluctuations.

Then, we input the preprocessed data into a convolutional neural network (CNN)-based model for training. In order to improve the performance of the model, we optimized the hyperparameters, including the convolution kernel size, number of layers, learning rate, etc., to ensure the best effect of the model in identifying abnormal stock price fluctuations. During the training process, we adopted the early stopping mechanism to prevent overfitting, and set multiple evaluation indicators, such as accuracy (ACC) and F1 score, to comprehensively evaluate the performance of the model in the abnormal fluctuation identification task.

3.3. Experimental Results

In the experimental results, we selected four models for comparison, namely the traditional support vector machine (SVM), long short-term memory network (LSTM), bidirectional long short-term memory network (BiLSTM) and convolutional neural network (CNN). As a traditional machine learning algorithm, the support vector machine performs stably on small-scale data, but its performance is often limited when faced with complex time series data. LSTM can capture the changing trend of stock prices because of its ability to remember long-term series dependencies. BiLSTM further enhances the effect of LSTM and improves the ability to understand time series data by considering both forward and reverse information. CNN, with its excellent feature extraction capabilities, is able to identify local features in stock price fluctuations, thereby showing stronger performance in identifying abnormal fluctuations. The experimental results are shown in Table 1.

Table 1. Experimental Results

Model	ACC	Recall	F1-Score
SVM	0.68	0.62	0.64
LSTM	0.72	0.66	0.68
BILSTM	0.75	0.69	0.71
CNN	0.82	0.78	0.80

Judging from the experimental results, there are significant differences in the performance of each model on the task of identifying abnormal stock price fluctuations. First, the overall performance of the support vector machine (SVM) is relatively low, with an accuracy (ACC) of 0.68, a recall (Recall) of 0.62, and an F1 score of 0.64. This shows that SVM has certain limitations in processing financial time series data. Although SVM performs relatively stably in classification tasks, when faced with complex stock price fluctuation data, it is difficult to identify subtle features in abnormal stock price fluctuations due to the lack of modeling capabilities for time series dependence. Especially in tasks where time series information is rich and data dependencies need to be captured, the characteristics of SVM cannot be effectively adapted, which also reflects its limitations in this task.

In contrast, LSTM has shown better results in identifying abnormal stock price fluctuations, with an accuracy rate of 0.72, a recall rate of 0.66, and an F1 score of 0.68. LSTM has the advantage of capturing the long-term dependence of time series, allowing it to better identify trends and fluctuations in stock prices. Through its unique memory gate structure, LSTM can retain and utilize historical information to a certain extent, which makes it highly adaptable in financial market data. However, due to its high computational complexity, the LSTM model training takes a long time, and when facing high-frequency financial data, the performance of LSTM may still be limited by the sequence length. Therefore, although LSTM has made certain progress compared to SVM, there is still some room for improvement when processing complex financial time series data.

On the basis of LSTM, BiLSTM further improved the effect of identifying abnormal stock price fluctuations, reaching an accuracy of 0.75, a recall of 0.69, and an F1 score of 0.71. BiLSTM captures data characteristics in both the forward and reverse directions of the time series through bidirectional information flow, allowing the model to more comprehensively understand changes in sequence data. This structure makes BiLSTM more advantageous than one-way LSTM in identifying abnormal stock price fluctuations, especially showing strong robustness in complex financial data. By integrating the two-way information of the sequence, BiLSTM can more accurately capture the features in the data, and has a stronger ability to identify the trends and characteristics of stock price fluctuations, thus showing higher accuracy and stability when identifying abnormal fluctuations.

Finally, among all models, the CNN-based model achieved the best recognition effect, with an accuracy of 0.82, a recall of 0.78, and an F1 score of 0.80. This shows that CNN has strong advantages in processing financial data, especially in capturing the local characteristics of stock price fluctuations. The convolutional structure of CNN enables it to automatically extract patterns in time series data without relying on manual feature selection, and it is able to capture data changes within short time windows. Due to the feature extraction capabilities of the convolutional layer, CNN exhibits higher accuracy and reliability than other models in identifying abnormal stock price fluctuations. This advantage is especially obvious in high-frequency data in financial markets, because CNN can quickly capture the subtle characteristics of stock price fluctuations, thus having significant advantages in real-time prediction and anomaly detection.

In summary, by comparing the experimental results of the four models, it can be seen that SVM does not perform satisfactorily when processing complex financial data, while LSTM and BiLSTM perform well in identifying abnormal stock price fluctuations by capturing sequence dependencies, especially BiLSTM. Bidirectional information flow improves recognition results. The CNN-based model showed strong adaptability and recognition ability to stock price fluctuation patterns through the convolutional feature extraction method, and finally achieved the best performance in accuracy and F1 score. This result verifies the advantages of CNN in identifying abnormal stock price fluctuations, illustrates its irreplaceable role in capturing complex patterns and local features, and provides reliable technical support for risk monitoring and abnormal fluctuation detection in financial markets.

4. Conclusion

Through the experiments and comparative analysis in this article, it can be concluded that in the task of identifying abnormal stock price fluctuations, the overall performance of deep learning-based models is better than traditional machine learning methods. In particular, the convolutional neural network (CNN), with its powerful feature extraction capabilities, has shown significant advantages in identifying local fluctuation patterns of stock prices, achieving the highest accuracy and F1 score. In contrast, support vector machine (SVM) performs worse than deep learning models on complex financial data due to its lack of modeling capabilities for time series characteristics, while LSTM and BiLSTM perform better through memory and bidirectional capture of time series. Compared with SVM, it is still slightly inferior to CNN in recognition accuracy.

In short, the experimental results of this article show that the CNN model has high accuracy and robustness in identifying abnormal stock price fluctuations, and is suitable for high-frequency data processing and real-time monitoring of financial markets. Future research can further optimize the model structure based on CNN and combine more market variables to improve the prediction ability and generalization of abnormal stock price fluctuations and provide more effective technical support for financial risk management.

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