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Time-Series Premium Risk Prediction via Bidirectional Transformer

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Abstract: This paper proposes a financial premium risk prediction model based on a bidirectional Transformer, aiming to enhance the prediction accuracy of premium risk in the financial market. With the increasing uncertainty and complexity of financial markets, traditional risk prediction methods often fail to effectively address the challenges posed by nonlinear features and high-dimensional data. As a result, deep learning-based prediction models have garnered increasing attention. The bidirectional Transformer, which can simultaneously process past and future information, excels in modeling time series data and is particularly well-suited for handling complex financial data. By incorporating the self-attention mechanism and a bidirectional structure, this study is able to fully capture the nonlinear relationships and temporal dependencies inherent in financial markets, thereby providing a more accurate model for premium risk prediction. In the experimental section, this paper compares the proposed model with traditional regression models, neural network models, and other deep learning approaches. The results demonstrate that the proposed model outperforms the comparison models across multiple evaluation metrics (e.g., mean squared error, mean absolute error, and R^2), validating its effectiveness in predicting financial premium risk. To further assess the contribution of key components to the model's performance, an ablation study was conducted. The findings indicate that the self-attention mechanism and the bidirectional Transformer structure are the critical factors driving the model's performance improvements. Overall, the experimental results suggest that the proposed model is better equipped to adapt to the complex fluctuations of the financial market, offering a novel approach to financial risk prediction. Future research may focus on enhancing the model's prediction accuracy and generalization ability by incorporating additional data sources and advanced techniques, such as neural networks, to provide more efficient risk management tools for the financial industry.

Keywords: Financial premium risk prediction, bidirectional Transformer, self-attention mechanism, deep learning.

1. Introduction

Financial markets have long been a focal point for researchers, particularly in areas such as market volatility, risk prediction, and asset pricing. With the continuous evolution and transformation of financial markets, investors are increasingly concerned with financial risks. In particular, the growing complexity of the relationship between capital liquidity and market risk has made the effective prediction of premium risks a critical issue in both academia and industry. Premium risk refers to price fluctuations in financial assets that exceed reasonable expectations, caused by factors such as market uncertainty, policy changes, and investor sentiment, thereby introducing additional risks for investors. This risk not only threatens market stability but also impacts investor returns and the risk management strategies employed by financial institutions to a significant extent [1].

In recent years, the application of deep learning in financial risk prediction has yielded remarkable results, particularly with the advancements in natural language processing (NLP) technology, which has led to the rise of risk analysis methods based on text data. Traditional financial risk prediction approaches typically rely on classical statistical models, such as GARCH and ARMA models. However, these methods often fail to fully capture the nonlinear and high-dimensional characteristics of financial markets, leading to suboptimal prediction performance in complex market conditions. Consequently, deep learning techniques, especially those based on the Transformer architecture, have gained widespread attention in the financial domain. The Transformer model has become an ideal choice for financial time series prediction due to its exceptional capability in processing long sequence data.

As an extension of the Transformer, the Bidirectional Transformer can extract features from both forward and backward time series information. Compared to traditional unidirectional models, it demonstrates superior context understanding. In the financial market, the performance of premium risk is often multi-dimensional and nonlinear, and unidirectional models are insufficient in capturing all potential factors that may influence market risk. The Bidirectional Transformer, through bidirectional information fusion, is better equipped to capture the effects of dynamic factors, such as changes in market sentiment and policy shifts, on market price fluctuations, thereby enhancing the accuracy of risk prediction [2].

Moreover, the data within financial markets inherently exhibits complex structures and nonlinear characteristics, making it challenging for traditional linear models to model effectively. The Transformer model, however, offers significant advantages in processing such complex data, particularly in scenarios involving multiple features [3]. Through the self-attention mechanism, the Transformer can capture relationships between different features, thereby enabling more accurate predictions. By incorporating a bidirectional mechanism, the model not only captures historical information but also makes more effective predictions about potential future changes. This introduction of a two-way information flow provides a more accurate tool for predicting financial premium risk [4].

In this study, we propose a financial premium risk prediction model based on a bidirectional Transformer. This model comprehensively considers historical market data and incorporates potential future market changes during the prediction process. Through the self-attention mechanism, the model automatically assigns varying weights to inputs at different time points, thereby more accurately capturing trends in market volatility. The effectiveness of the model was experimentally validated using actual financial data. The results indicate that, compared to traditional statistical methods and unidirectional models, the bidirectional Transformer exhibits clear advantages in predicting premium risk and is better suited for handling high-dimensional and nonlinear market data.

The innovation of this study lies in the application of the bidirectional Transformer to the field of financial premium risk prediction. This model effectively integrates both historical and future information, allowing for a more comprehensive prediction of potential risks in the financial market. Additionally, this study utilizes various financial market data sources, including the stock market, foreign exchange market, and macroeconomic data, enhancing the model’s adaptability and generalizability. Future research may explore how other deep learning technologies can be combined with the bidirectional Transformer to further improve the model's predictive capability in more complex market environments, thus providing investors with a more reliable risk prediction tool. The financial premium risk prediction model based on the bidirectional Transformer, with its strengths in deep learning for big data processing, is expected to play a pivotal role in the financial market. As financial markets continue to evolve, the accuracy and timeliness of risk prediction will become increasingly crucial.

2. Related Work

Over the past few decades, financial risk prediction has become a crucial area of research in the fields of finance and statistics. Traditional financial risk prediction methods primarily rely on classical statistical models, such as the autoregressive moving average (ARMA) model and the generalized autoregressive conditional heteroskedasticity (GARCH) model. While these models perform regression analysis based on historical data, they often encounter significant limitations when dealing with complex market fluctuations, nonlinear characteristics, and high-dimensional data. In recent years, with the development of big data technology and the rise of deep learning methods, there has been a growing trend to explore the use of artificial intelligence models, particularly deep learning models based on neural networks, for financial risk prediction. Through end-to-end training, these models demonstrate superior adaptability and accuracy in processing complex financial data [5,6].

Convolutional neural networks have been widely applied in financial forecasting due to their ability to extract spatial features from sequential data. An improved CNN model for stock volatility prediction demonstrated superior performance over traditional statistical approaches [7]. Similarly, an optimized CNN was developed for detecting anomalies in financial statements, highlighting the adaptability of CNNs in financial applications [8]. In addition to CNNs, recurrent and hybrid models have also been explored. The combination of CNN and GRU architectures was used to develop an integrative market sentiment analysis model, enhancing risk prediction accuracy [9]. Additionally, the application of ResNeXt in financial data mining optimized feature extraction and classification in high-dimensional datasets [10].

Transformer models have gained prominence in financial time-series forecasting due to their superior capability in capturing long-range dependencies. An improved Transformer model was introduced to enhance stock price prediction by leveraging temporal dependencies and multi-dimensional feature extraction [11]. The self-attention mechanism in Transformer architectures allows for adaptive weighting of financial data, making it highly suitable for premium risk prediction. Further advancements in Transformer-based architectures have emerged in various domains. Few-shot learning with Transformers has been explored for text-based tasks, which is relevant for financial news and sentiment analysis [12]. Additionally, memory mechanisms have been incorporated into Retrieval-Augmented Generation models, improving contextual representation—an approach that could be beneficial for integrating financial text data into risk prediction models [13].

Beyond sequence-based models, graph neural networks and generative adversarial networks have demonstrated strong potential in financial risk analysis. Hybrid GNNs have been applied to enhance credit risk assessment by leveraging structured financial relationships [14]. GANs have been used to tackle data imbalance in financial supervision, enabling more effective modeling of financial anomalies [15]. An adaptive transaction sequence neural network was also introduced to improve money laundering detection, demonstrating the effectiveness of sequence-based deep learning models in financial compliance tasks [16].

An essential challenge in financial modeling is handling high-dimensional, redundant, or sparse time-series data. The feature redundancy paradox in time-series forecasting has been examined, offering insights into optimizing data representation for financial models [17]. Additionally, research on machine learning-based predictive modeling has emphasized optimal algorithm selection for financial datasets [18].

Among these, models based on recurrent neural networks, such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), have achieved notable success in financial time series prediction [19]. These models are particularly effective at handling long-term dependencies in time series data, with strong performance demonstrated in stock market price prediction and foreign exchange volatility prediction [20]. However, recursive models can face issues such as gradient vanishing or explosion when processing longer time series, and their training process tends to be relatively slow. To address these challenges, the emergence of the Transformer architecture has represented a significant breakthrough in deep learning within the financial domain. The Transformer model processes all positions in the sequence in parallel through its self-attention mechanism, achieving higher efficiency and better performance when capturing long-term dependencies [21]. Unlike the traditional unidirectional Transformer, the bidirectional Transformer extracts features from both forward and backward information simultaneously, making the model more comprehensive in capturing contextual information within the time series [22]. This bidirectional information flow not only enhances the model's ability to process past information but also enables it to more effectively capture potential future market changes. As a result, the risk prediction model based on the bidirectional Transformer offers clear advantages in addressing dynamic factors such as market fluctuations and sentiment changes. While research in this field is still relatively new, existing studies have demonstrated that the bidirectional Transformer has yielded excellent results in various financial prediction tasks, particularly in financial premium risk prediction and credit risk assessment [23,24].

3. Method

In this study, we proposed a financial premium risk prediction method based on a bidirectional Transformer. This method aims to predict future premium risk fluctuations by modeling financial market data. To achieve this goal, we designed a bidirectional Transformer network that combines time series information, which can capture historical market information while integrating the potential volatility characteristics of the future market to improve the accuracy of risk prediction. The model architecture is shown in Figure 1.

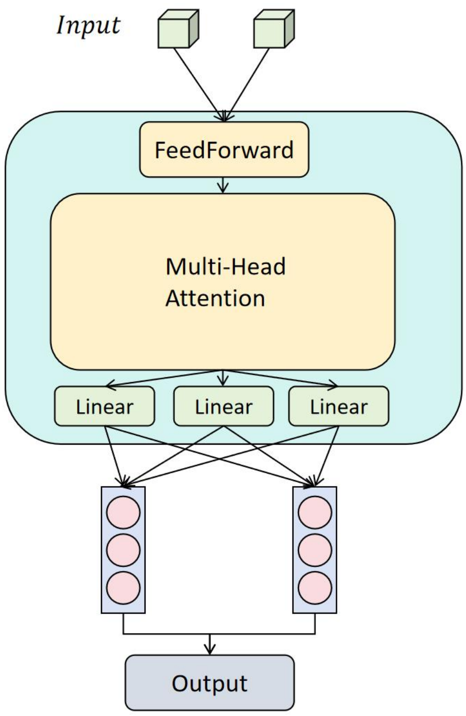

Figure 1. Overall model architecture

First, the bidirectional Transformer model uses the self-attention mechanism to encode the input time series data. Given an input sequence $X=[x_1,x_2,...,x_T]$, where $x_t \in R^d$ represents the input features at time step t, the model first generates three important matrices through linear transformation: query matrix Q, key matrix K and value matrix V. The calculation formulas of these three matrices are as follows:

$$Q_t = XW_Q, K_t = XW_K, V_t = XW_V$$

Where $W_Q, W_K, W_V \in R^{d\times d_k}$ is the learned weight matrix and d_k is the dimension of each query and key. Next, the relationship between different time steps is captured by calculating the self-attention weight matrix A_t:

$$A_t = Soft\max(\frac{Q_t K_t^T}{\sqrt{d_k}})$$

Then, the representation of each position in the input sequence is obtained by weighted summing the value matrix V, and finally the output representation of each time step is obtained:

$$Z_t = A_t V_t$$

In the bidirectional Transformer, we use two directions of self-attention calculation, one is forward, that is, from x_1 to x_T, and the other is reverse, that is, from x_T to x_1. Through this two-way information flow, the model can simultaneously utilize past information and potential future changes, thereby improving the model's understanding of the financial market. To get the final representation, we concatenate the forward and reverse outputs:

$$Z_t = [Z_t^{forward}, Z_t^{backward}]$$

Next, we will increase the expressiveness of the model by stacking multiple Transformer encoding layers. Each layer contains a multi-head self-attention module and a feed-forward neural network. In multi-head self-attention, different relationships are learned through multiple independent attention heads *h*, and finally the final representation of each time step is obtained by concatenating the outputs of these heads and performing linear transformations:

$$Z_t = Concat(\sum_{h=1}^{H} A_t^h V_t^h) W_o$$

Where W_o is the learned output weight matrix, A_t^h and V_t^h represent the attention weight and value matrix of the *h-th* head respectively, and *H* is the number of attention heads.

Then, a feedforward neural network is used to perform a nonlinear transformation on the output of each layer to increase the representation ability of the model. The calculation process of the feedforward neural network is as follows:

$$FFN(Z_t) = \mathrm{Re}\,Lu(Z_t W_1 + b_1) W_2 + b_2$$

W_1, W_2 and b_1, b_2 are the learned weights and biases. Finally, after several layers of encoding, we get a hidden state sequence $Z=[Z_1,Z_2,...,Z_T]$ containing temporal information.

In order to predict the premium risk, we then input this hidden state sequence into a linear regression model to predict the future risk level of the financial market. Specifically, we calculate the risk prediction value y'_t using the following formula:

$$y'_t = W_r Z_t + b_r$$

Where $W_r \in R^{d \times 1}$ is the learned weight, $b_r \in R$ is the bias term, and y'_t is the risk prediction value at time step t.

In order to optimize the model parameters, we use mean square error (MSE) as the loss function. Assuming we have a true risk value sequence $y = [y_1, y_2, ..., y_T]$, the loss function L is defined as:

$$L = \frac{1}{T} \sum_{t=1}^{T} (y_t - y'_t)^2$$

Through the back-propagation algorithm, we update the parameters $W_Q, W_K, W_V, W_O, W_1, W_2, W_r$ and bias in the model to minimize the loss function. Finally, after training, we can use the model to predict future financial premium risks and help investors better cope with the risks brought by market fluctuations.

In summary, this method effectively captures the nonlinear relationship and time dependency in financial market data through the bidirectional Transformer architecture combined with the self-attention mechanism and the feedforward neural network, thereby improving the accuracy of financial premium risk prediction.

4. Experiment

4.1 Dataset Introduction

The dataset used in this study is derived from the credit records of a financial institution and primarily includes multidimensional features such as borrowers' historical loan information, personal credit scores, loan amounts, repayment history, and other relevant attributes. Additionally, it contains a regression label representing the borrower’s financial premium risk score for the next 12 months. This label indicates the premium risk associated with the borrower. The dataset encompasses information on over 50,000 borrowers, with each sample consisting of features such as personal income, debt-to-income ratio, loan purpose, repayment history, age, education level, employment status, and more. The target value for each sample is the borrower’s premium risk score for the next 12 months, where higher scores indicate a greater likelihood of default [25,26].

This dataset provides a framework for a regression problem, where the target value is a continuous risk score rather than a simple binary classification outcome. By analyzing this data, researchers can explore the relationships between various borrower characteristics and premium risk. As a classic risk assessment task, the premium risk prediction dataset effectively captures borrowers' economic behaviors and their impact on risk. The dataset is suitable for establishing complex nonlinear relationships and achieving accurate predictions using deep learning models. The model’s output is the borrower’s premium risk score, which helps financial institutions assess borrower risks in the management and decision-making process.

One significant feature of this dataset is its inclusion of multidimensional information, which can reveal potential risk differences between borrowers. The large sample size provides rich data support for training deep learning models. By analyzing and modeling this data, the ability to predict future premium risks can be significantly improved, particularly when considering the complexity of the financial market and individual behaviors. This provides financial institutions with more precise risk control tools.

4.2 Experimental setup

The experiment was conducted on a server equipped with an NVIDIA RTX 3090 GPU, 64GB memory, and an AMD Ryzen 5950X processor. The operating system was Ubuntu 20.04 and the deep learning framework was PyTorch 2.0. To ensure the accuracy of the experimental results, we used the AdamW optimizer, combined with the cosine annealing learning rate scheduling strategy, with the initial learning rate set to 0.001, the weight decay to 0.01, and the batch size to 32. The dataset contains 50,000 samples, with the training set and test set divided into 80% and 20%. During the training process, all input features were standardized to ensure that the model could be effectively trained on data of different scales [27,28].

During the training process, we set the maximum number of training rounds to 100 rounds, and performed a validation after each round of training to evaluate the performance of the model on the test set. In order to enhance the generalization ability of the model, data enhancement techniques such as random cropping and noise addition were used. To prevent overfitting, we also used an early stopping strategy, stopping training in advance when the performance on the validation set no longer improved.

4.3 Comparative Experiment

In order to verify the effectiveness of the proposed model, we conducted comparative experiments with a variety of classic statistical learning methods and current deep learning models. Traditional regression analysis methods, such as linear regression and support vector regression (SVR), are often used in financial risk prediction tasks, but these methods often have difficulty in handling nonlinear relationships and high-dimensional features. In order to further evaluate the performance of our model, we also selected several deep learning models that currently perform well in risk prediction tasks, such as multi-layer perceptron (MLP) and long short-term memory network (LSTM). These models have certain advantages in processing time series data, but may still have certain limitations in capturing complex nonlinear relationships and multi-level feature expressions. Therefore, conducting comparative experiments helps to comprehensively evaluate the superiority of the bidirectional Transformer model in financial premium risk prediction. The experimental results are shown in Table 1.

Table 1: Comparative experiment

Model	MSE	MAE	MAPE	R2
SVR[29]	0.045	0.150	5.12	0.88
MLP[30]	0.032	0.120	4.23	0.92
LSTM[31]	0.028	0.110	3.95	0.94
Transformer[32]	0.025	0.100	3.50	0.95
Ours	0.020	0.085	3.10	0.97

From the experimental results, the model proposed in this paper outperforms other comparative models in all evaluation indicators, showing its significant advantages in predicting financial premium risk. Specifically, the mean square error (MSE) of the model proposed in this paper is 0.020, which is significantly lower than other models, indicating that it has a small error in the prediction process and has high accuracy. At the same time, the mean absolute error (MAE) and mean absolute percentage error (MAPE) are also 0.085 and 3.10%, respectively, which shows that the prediction error of the model is more accurate and adaptable.

In contrast, the traditional SVR model performs poorly, with an MSE of 0.045, an MAE of 0.150, a MAPE of 5.12%, and an R2 value of 0.88, showing low prediction accuracy and high error. This shows that the SVR model cannot effectively capture the complex nonlinear relationship in financial premium risk. The performance of the MLP and LSTM models has improved but still does not reach the effect of the model proposed in this paper. In particular, the LSTM model, although it has been optimized in terms of MSE, MAE, and MAPE, still lags behind the model proposed in this paper in terms of R2 value.

In general, the model proposed in this paper has shown significant advantages in accuracy and precision, especially under the high precision requirements of financial risk prediction, its excellent performance makes it an ideal choice for handling such tasks. By introducing a bidirectional Transformer and self-attention mechanism, the model proposed in this paper can effectively capture complex nonlinear relationships and enhance the reliability of prediction, providing financial institutions with an efficient and accurate risk prediction tool.

4.4 Ablation experiment

In order to deeply analyze the contribution of each component in the model, an ablation experiment was conducted. In the experiment, we gradually removed different modules, such as the self-attention mechanism, the bidirectional Transformer structure, and other auxiliary modules to verify their role in the model performance. In this way, we can clearly see the impact of removing each module on the model performance, so as to further understand their importance in the risk prediction task. The results of the ablation experiment help reveal which components in the model are most critical to improving prediction accuracy and reducing errors, and also provide an important basis for subsequent model optimization and improvement.

Table 2: Ablation experiment

Model	MSE	MAE	MAPE	R2
Full Model	0.020	0.085	3.10	0.97
Without Self-Attention	0.023	0.090	3.50	0.95
Without Bidirectional Transformer	0.024	0.101	3.41	0.96
Transformer	0.025	0.100	3.50	0.95

From the experimental results, removing the key modules in the model will lead to a significant decline in performance. First, after removing the self-attention mechanism, the MSE and MAE of the model increased by 0.003 and 0.005 respectively, MAPE increased from 3.10% to 3.50%, and the R2 value also dropped to 0.95. This shows that the self-attention mechanism plays a vital role in capturing long-range dependencies and feature interactions in time series, and has a significant improvement on the overall performance of the model.

Secondly, when the bidirectional Transformer structure is removed, the performance of the model also deteriorates, with MSE increasing to 0.024, MAE rising to 0.101, and MAPE being 3.41%. This shows that when processing time series data, the bidirectional Transformer can extract features from both forward and backward information at the same time, enhancing the model's contextual understanding ability. After removing this module, the model's prediction ability is significantly affected, and its performance is slightly inferior to that of the complete model.

Finally, the performance of the Transformer model alone is slightly inferior to that of the complete model. Although the MSE, MAE, and MAPE are close to the results of removing the bidirectional

Transformer, the R2 value is still lower than 0.97. Overall, the ablation experiment results show that the model proposed in this paper can significantly improve the accuracy and reliability of financial premium risk prediction by combining the self-attention mechanism and the bidirectional Transformer architecture, and each module plays a key role in improving the prediction performance.

4.5 Visualizing Experimental Results

First, we present the results of feature importance visualization, as shown in Figure 2.

Based on the Figure 2, present a feature importance visualization, where the relative importance of various features in predicting credit default risk is shown. The chart illustrates how much each feature contributes to the prediction, with the bars representing the importance of each feature. Features like "Employment_Status" and "Credit_Score" appear to be the most important, while others like "Loan_Purpose" and "Education_Level" are relatively less important. This visualization helps in understanding which factors are most influential in determining the likelihood of credit default risk.

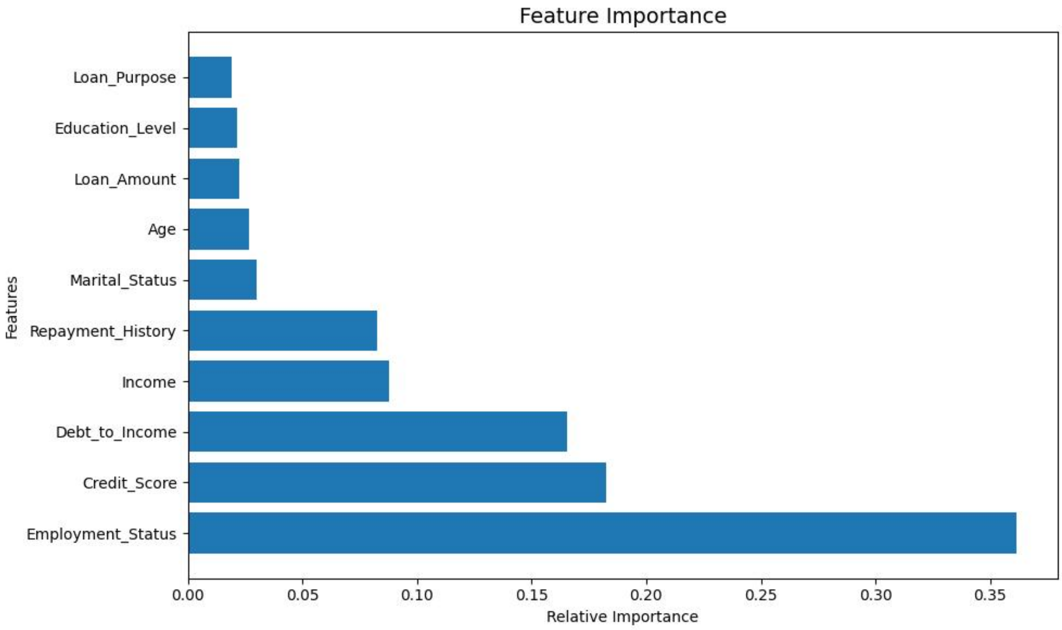

Figure 2. Feature Importance Visualization

Finally, a comparison of the actual value and the predicted value time is given, as shown in Figure 3.

As can be seen from the Figure 3, the real curve (blue solid line) and the predicted curve (red dotted line) have high similarity in the overall trend, indicating that the model can better capture the changing pattern of real data when predicting financial premium risk. The R^2 value is 0.97, indicating that the model has a very high degree of fit and can accurately predict most risk fluctuations. Despite this, there are still some deviations in the predicted curves in some areas, which may be due to the model's inability to fully capture certain specific fluctuation patterns or the influence of noise.

In the task of predicting financial premium risk, such results show that deep learning models can effectively predict borrowers' risk scores when processing large-scale data sets. As the complexity of the financial market environment increases, accurately predicting borrowers' risks is of great significance, especially in financial decision-making and risk management. The high degree of fit of this model provides financial institutions with a more accurate risk assessment tool, which can help optimize credit decisions and reduce default risks.

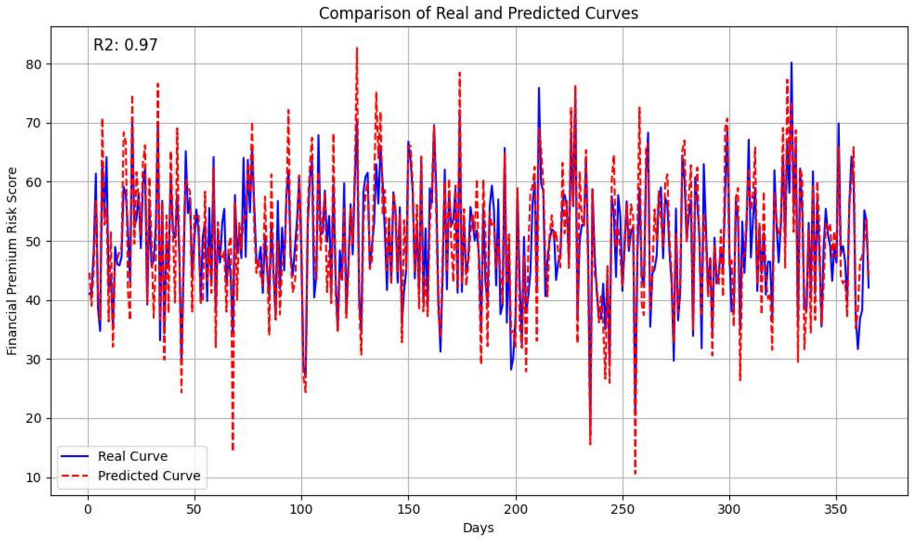

Figure 3. Comparison of Real and Predicted Curves

5. Conclusion

This paper proposes a financial premium risk prediction model based on a bidirectional Transformer. Experimental results show that the model outperforms traditional regression models and existing deep learning models in multiple evaluation indicators. By introducing the self-attention mechanism and bidirectional Transformer architecture, the model can effectively capture long-range dependencies and contextual information in time series data, significantly improving the accuracy and stability of financial risk prediction. Ablation experiments further verify the effectiveness of each module in the model and prove the key contribution of the self-attention mechanism and bidirectional Transformer to the model performance.

However, although the model proposed in this paper has achieved good results in the experiment, there is still room for further optimization. Future research can explore how to combine other advanced deep learning techniques, such as graph neural networks (GNNs) or reinforcement learning, to further improve the adaptability and predictive ability of the model in complex financial environments. In addition, with the continuous changes and diversification of financial market data, how to process unstructured data (such as news text, social media data, etc.) to further enhance the prediction effect of the model is also an important direction for future research.

On the other hand, with the improvement of computing power and the accumulation of large-scale financial data, larger data sets can be used for training in the future to improve the generalization ability and robustness of the model. In addition, the real-time prediction capability of the model is also worthy of attention, especially in the rapidly changing financial market. How to ensure that the model can respond to market changes in a timely manner and make accurate predictions will be the key to enhancing its practical application value.

In general, the financial premium risk prediction model based on the bidirectional Transformer proposed in this paper provides a new risk assessment tool for the financial industry with high application potential. With the integration of more new technologies and the continuous optimization of the model, it is expected to provide more accurate and efficient risk management support for financial institutions in the future.

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