ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

Research on Hybrid Intelligent Algorithm for Forecasting Bank Wealth Management Product Returns Driven by Financial Technology

Sha Lai[1] *and Xiaoning Zhu*[1,*]

[1] School of Business, Yulin Normal University Yulin 537000, Guangxi, China

SUMMARY: *The returns of wealth management products are influenced by multiple factors such as the international situation, and the prices exhibit high noise and non-linear temporal data characteristics, making forecasting difficult. To optimize the performance of forecasting the returns of bank wealth management products driven by financial technology, this paper proposes a Faster R-CNN-BiLSTM-Transformer wealth management return forecasting model by means of multidimensional features driven by financial technology. Firstly, extract multidimensional femployed text semantic features of financial products and users, and the syntax and semantic information in the names of financial products are captured through convolutional neural networks (CNN); Then, a BiLSTM Transformer by means of gated recurrent units is introduced to optimize the temporal feature extraction mechanism, and a user feature forecasting model is constructed by combining additive attention module and multi head self-attention module; Finally, a forecasting ranking forecasting model for candidate financial products is constructed, which calculates the similarity between users and financial products to find the most suitable financial product for user needs. The results suggest that the multidimensional features Faster R-CNN-BiLSTM-Transformer framework proposed in this paper outperforms the CART regression tree forecasting model and ARMA statistical forecasting model in all evaluation indexes, significantly improving the performance of forecasting the index return rate of financial products.*

KEYWORDS: *Faster R-CNN; BiLSTM; CNN; Transformer; Financial products; Revenue Forecast*

1 Introduction

A wealth management product is a valuable certificate issued by a wealth management company to raise funds and obtain interest and dividends. It can be transferred, bought, sold or mortgaged, and is the main long-term credit tool in the capital market [1]. In 1612, the establishment of the Dutch East India Company marked the emergence of the world's first limited liability company, and wealth management products gradually formed. By 2024, wealth management products had a history of over 400 years. In recent years, the wealth management product index has gradually become well-known to the public. It is an indicator compiled by the wealth management product platform to reflect the overall level and changes of various wealth management products in the entire wealth management product market. The development of China's wealth management product market was relatively late, and it was not until the establishment of the stock exchange in 1991 that the market experienced rapid growth. While wealth management products bring huge profits to people, they also bring certain risks

*rocky_zxn@163.com
https://doi.org/10.65102/is20261130
Published: 10 June, 2026

to investors. In order to avoid high risks, investors want to pursue accurate analysis and forecasting of the wealth management product market. In practice, many complex factors can affect the wealth management product market, such as international conditions, inflation, investor psychology, etc. Meanwhile, the price of financial products is a high noise, non-linear time-series data, which makes it difficult and complex to forecast financial products. In addition, a single wealth management product may have the disadvantage of abnormal fluctuations, while the wealth management product index can better reflect the situation of the wealth management product market. Consequently, most researchers choose the wealth management product index for research. This article also takes the wealth management product index as the research object for the following study.

Nowadays, researchers' research on the financial product market often focuses on the following three aspects [2]: (1) With the growing popularity of the Internet, more and more people begin to express their views on events on various platforms, including some post bars commonly employed by financial product investors. The opinions on the internet can affect the emotions of investors in financial products, which in turn can affect the prices of financial products and have a significant impact on the forecasting of their returns. (2) A single neural network forecasting model may have the disadvantages of imbalanced forecasting results and falling into local optima. Consequently, in order to make the forecasting results more effective and accurate, optimizing the neural network forecasting model is also very important. (3) When forecasting the temporal data of financial products, researchers usually only consider the impact of the same timeline data on future temporal data. However, short-medium-long term timeline data all have an impact on the trend of future temporal data. Consequently, when forecasting the future trend of the financial product market, take into thorough consideration. By means of a rigorous analysis of the above issues, this article proposes a wealth management return forecasting model driven by financial technology and by means of multidimensional features Faster R-CNN-BiLSTM-Transformer, and forecasts the closing price of wealth management product indices.

2 Related Research

2.1 Statistical Forecasting models

It is generally believed that modern temporal data analysis originates from autoregressive forecasting models (AR), among which autoregressive forecasting models, moving average forecasting models, and ARMA forecasting models form the basis of temporal data forecasting analysis. There are also many research results on forecasting the returns of financial products by means of the above forecasting models. For example, Attah et al. [3] forecasting modeled the forecastability of financial product returns using relevant data from Shanghai and Hong Kong, and employed an AR forecasting model to carry out cointegration tests on the main evaluation indexes constructed. They concluded that technical analysis is effective to a certain extent. Khuntaweethep & Koowatatantianchai [4] applied the ARIMA forecasting model to temporal data analysis of the wealth management product market, and againsted the ARIMA forecasting model with several previous forecasting models. The results suggest that the ARIMA forecasting model had smaller forecasting errors for temporal data of wealth management product returns. Khattak et al. [5] concluded through forecasting modeling analysis that the ARIMA forecasting model has good applicability by means of the closing price of financial products. However, the forecasting model accumulates forecasting errors in the forecasting results and has a high dependence on data selection. Ozili [6] employed the generalized autoregressive heteroskedasticity forecasting model (GARCH) to forecast the wealth management product market. When forecasting the returns of wealth management products of Southern and Eastern Airlines, results suggested that the GARCH forecasting model had short-term memory when forecasting the prices of wealth management products. Kureljusic & Karger [7] selected GARCH as the analysis forecasting model for the return rate of financial products by means of temporal data. Through the comparison of empirical results, it suggested that the EGARCH forecasting model has more advantages in forecasting the SSE 300 financial product index. Gallego Losada et al. [8] constructed an ARIMA forecasting model to analyze and forecast the temporal data of financial products. The forecasting results suggested that the forecasting model performed well in forecasting financial product market data.

2.2 Machine Learning Forecasting models

Machine learning research forecasting models include decision trees, support vector machines, etc., which have more advantages in forecasting temporal data againsted to traditional statistical methods. The relevant research on applying machine learning methods to temporal data forecasting in the financial field is already very mature. For example, Bello [9] combined SVM with ARIMA forecasting models for data processing and forecasting modeling, and the final result reflects the linear and nonlinear relationship of temporal data of financial products. Andronie et al. [10] employed SVM to forecast the closing price of financial products, and It can be seen from empirical results that SVM has higher accuracy than traditional methods for forecasting temporal data. Salisbury et al. [11] constructed a temporal data analysis forecasting model for financial products by means of decision tree classification (DTC), and against the forecasting results with classical measurement approaches. Finally, they concluded that the temporal data analysis forecasting model for financial products by means of decision tree classification is more suitable for forecasting financial product market data than classical measurement approaches. Zachariah et al. [12] employed SVM to select multiple feature factors and selected multiple countries' wealth management product markets for forecasting analysis. The results suggested that SVM could successfully identify important feature factors of wealth management products and significantly optimize the forecasting level. Zafar et al. [13] chose decision tree algorithm for research on the financial product market and built a hybrid forecasting model of clustering analysis and decision tree algorithm. Againsted with traditional forecasting models, this hybrid forecasting model made great optimization in the selection of financial product funding. Lazaroiu et al. [14] employed various machine learning methods to forecast the KOSPI wealth management product index in Korea at that time. By comparing the forecasting results, they judged the advantages and disadvantages of different methods. The It can be seen from empirical results that Support Vector Machine (SVM) had more advantages than BP neural network in forecasting temporal data of wealth management products. Boustani et al. [15] successfully constructed an excess return investment portfolio by means of decision tree algorithms.

2.3 Deep Learning Forecasting models

Deep neural networks (DNNs) are a particular category of machine learning forecasting model that often perform better in the analysis and research of big data problems such as financial product temporal data. For example, Dessant et al. [16] introduced neural networks into financial time series data forecasting research, constructed a temporal data by means of IBM's daily market returns, and employed BP neural network forecasting modeling to forecast the daily market returns, providing a new approach for forecasting financial market trends. Pekkaya et al. [17] constructed a neural network forecasting model through layering to forecast the market prices of financial products. It can be seen from empirical results that the stacked neural network forecasting model was greater forecasting accuracy in forecasting temporal data than other approaches. Abbas et al. [18] employed the particle swarm optimization to optimize the conventional CNN, and formulated a forecasting model by means of the price and index of financial products for data forecasting and assessment. The It can be seen from empirical results that the performance of CNN forecasting was optimized after optimization by the particle swarm optimization. Anshika & Singla [19] constructed a temporal data by means of the price index of financial products, employed CNN neural network for forecasting modeling and data forecasting analysis, and then applied cross validation to conclude that CNN neural network has stronger forecasting ability than traditional forecasting methods. Machado & Karray [20] built a hybrid forecasting model by means of HMM, CNN, and particle swarm algorithm. The forecasting results of temporal data in the financial product market show that the hybrid forecasting model has strong forecasting ability. Sriram & Seenu [21] selected the Chemical Reaction Optimization (CRO) algorithm, which could effectively address the issue of local optima, and combined it with artificial neural networks to construct a temporal data using financial product indices. The combined forecasting model was employed to forecast the temporal data, and the results suggested that the proposed combined forecasting model has significant advantages in forecasting financial product temporal data.

2.4 LSTM Forecasting model

Long Short Term Memory (LSTM) forecasting models have better forecasting performance than recurrent neural networks. LSTM forecasting models shows certain superiority in forecasting longer financial market temporal data, and there are also many related research results. For example, Le Quoc [22] constructed a temporal data consisting of investment product index options and investment product index futures contract prices, and employed diverse forecasting models to forecast the trend of temporal data. The forecasting results suggested that LSTM forecasting model was significantly better than existing linear regression forecasting models and ARIMA forecasting models. Mhlanga [23] chose LSTM forecasting model, ARIMA forecasting model, and a hybrid forecasting model of LSTM with ARIMA as comparison forecasting models. In the forecasting experiment of the Shenzhen and Shanghai wealth management product index, the comparative It can be seen from empirical results that the forecasting performance of LSTM forecasting model was better than that of ARIMA forecasting model, but marginally lower than the hybrid forecasting model of the two. De Lima Lemos et al. [24] optimized the LSTM forecasting model using adaptive particle swarm optimization (PSO) algorithm and constructed temporal data of wealth management product data for the Shanghai, Shenzhen, and Hong Kong stock markets. The forecasting results suggested that the proposed forecasting model had higher accuracy in forecasting temporal data. Saleh et al. [25] employed the LSTM-RNN forecasting model to forecast crude oil price sequences and conducted a comparative experiment by means of recurrent neural networks and LSTM forecasting models. The forecasting results suggested that the combined forecasting model was superior to a single forecasting model in the field of crude oil price forecasting. Omowole et al. [26] developed a long short-term memory neural network by means of particle swarm optimization algorithm, using the NASDAQ Wealth Management Product Index as the basic data for forecasting wealth management product indices. The forecasting results suggested that the LSTM forecasting models had significant advantages in forecasting wealth management product indices.

3 Data Selection

3.1 Data Sources

The data selected in this article comes from the Tai'an Financial Database (CSMAR). The real historical temporal data of the Shanghai Stock Exchange Composite Index Wealth Management Product Index, Shanghai Stock Exchange Composite Index a wealth management product index, Shanghai Stock Exchange Composite Index B Wealth Management Product Index, and Shenzhen Composite Wealth Management Product Index were employed as the research samples. A total of raw temporal data related to the return rate of wealth management product indexes were collected from August 2, 2021 to August 2, 2024.

The main purpose of this study is to analyze the factors that affect the index return rate of financial products, and to accurately forecast the future index return rate of financial products using Deep neural networks (DNNs). Consequently, the independent variables selected in this article should be able to effectively reflect the return rate of the financial product index to a certain extent, or have a certain correlation with the return rate of the financial product index. This article will use daily opening financial product index, highest financial product index, lowest financial product index and other evaluation indexes as independent variables to analyze the key factors affecting the return rate of financial product index, and establish a deep learning forecasting model to forecast the return rate of financial product index.

In addition, in order to carry out a more full-scale horizontal comparison of the temporal data, three evaluation indexes were evaluated and incorporated into each individual sample: the rate of change of the investment product index return, the development speed of the investment product index return, and the growth speed of the investment product index return. The definitions and measurements of the variables selected in this article are shown in Table 1.

Table 1: Definition and measurement of variables

variable type	variable	Measurement method	symbol
dependent variable	Index return rate of financial products	Rate of return calculation	Retindex
independent variable	Transaction Date	Represented by YYY-MM-DD	Trddt
	week	1=Monday, 2=Week 2. 0=Sunday	Daywk
	Opening Wealth Management Product Index	The first wealth management product index in daily trading	Opnindex
	Highest Wealth Management Product Index	The highest financial product index in daily trading	Hindex
	Minimum Wealth Management Product Index	The last financial product index in daily trading	Loindex
	Closing Wealth Management Product Index	The last financial product index in daily trading	Clsindex
	Growth in return rate of financial product index	Yi-Yi-1	Regro
	Development speed of return rate of financial product index	Yi/Yi-1	Resp
	Growth rate of return on investment product index	(Yi-Yi-1) / Yi-1	Regros
	volume of business	Total number of shares traded in the daily market	TraVo
	Transaction volume	Total daily market transaction amount	AMO

3.2 Data preparation

The data preparation section mainly involves reviewing, filtering, and utilizing sorting methods to identify the inherent features of the data [27, 28]. This article selects the real historical data of the Shanghai Stock Exchange Composite Index Wealth Management Product Index, Shanghai Stock Exchange Composite Index A Wealth Management Product Index, Shanghai Stock Exchange Composite Index B Wealth Management Product Index, and Shenzhen Composite Wealth Management Product Index from August 2, 2021 to August 2, 2024. Taking into account the opening and closing of real wealth management products, each sample has 758 valid data points. With regard to data preparation, the data should be initially analyzed, that is to say, preliminary investigation and identification of various factors should be used to eliminate influencing factors of error, For the purpose of ensuring the data of satisfactory quality. Secondly, data that meets the criteria should be selected for subsequent research and analysis. Finally, the inherent features of the data itself should be excavated. The detailed procedures of this section are the handling of missing value imputation and data normalization [29, 30].

(1) Fill in missing nearest neighbor values. For the purpose of ensuring the authenticity and accuracy of the data, it is essential to review the primary data, which includes integrity and accuracy checks. Integrity review should check whether there are any omissions in the primary data of the samples to be investigated and whether the evaluation indexes to be investigated are over. Consequently, before investigating each variable, it is essential to conduct a preliminary check the completeness of the data, analyze the missing data, and handle the missing values in the data.

In the independent variables of the primary data in this article, the two evaluation indexes of trading date and week are discrete variables, while the other evaluation indexes such as opening wealth management product index, highest wealth management product index, lowest wealth management product index, and closing wealth management product index are continuous variables. At the same time, the dependent variable of the primary data employed in this article. Continuous variables can be imputed with missing values in a linear manner, that is, linear or second-order and third-order spline curves can be employed to interpolate missing values, which can greater forecasting performance fit the real situation.

The nearest neighbor method refers to the calculation results by means of Euclidean Distance, determining the K nearest samples to missing data samples, and estimating the missing data of the samples through weighted averaging of these K values. The calculation formula for Euclidean distance is as follows:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

where, d represents the distance of the sample, (x_1, y_1) and (x_2, y_2) are two samples respectively.

(2) Standardized processing. One of the principals aims of standardizing data is to eliminate dimensional relationships, making the data more suitable for comparison. The aim of standardization processing is to carry out data standardization according to a certain ratio, so as to the data can fall into a smaller specific interval after processing. Where, the most typical method of standardization is data normalization, which means that the normalized data can be mapped one by one to the interval of [0,1].

At present, the commonly employed methods for data standardization include min max standardization, log function conversion, atan function conversion, and z-score standardization. Different standardization methods have different effects on the results of the forecasting model. At the same time, in data standardization, the selection of methods also needs to be by means of the situation of the data and the forecasting model.

The most important benefits of standardized processing are twofold: firstly, it can effectively optimize the convergence speed of the forecasting model; Secondly, it can optimize the performance of the forecasting model. For the purpose of ensuring the reliability of the results, it is usually necessary to standardize the original indicator data. Due to the strong sensitivity of the deep learning forecasting model framework built in this article to input data, it is essential to standardize the data. Consequently, this article readjusts the primary data to the range of 0 to 1 through standardization processing. In this article, the goal of normalizing experimental data is twofold: firstly, to map the raw data to decimals in the [0,1] interval, which facilitates data processing; Secondly, convert dimensional expressions into dimensionless expressions.

Logistic transformation is the process of converting data using the logistic function. The logistic function is shown below.

$$y_i = \frac{1}{\left(1+e^{-x_i}\right)} \tag{2}$$

The main reasons for normalizing the continuous characteristic attributes such as the opening wealth management product index, the highest wealth management product index, the lowest wealth management product index, and the closing wealth management product index in the data preparation operation of this article are twofold: firstly, the indicator that this article intends to study and forecast is the return rate of the wealth management product index, and its data fluctuates within the range of [-1,1] over time, with a small fluctuation range. However, the continuous characteristic attributes such as the opening wealth management product index, the highest wealth management product index, the lowest wealth management product index, and the closing wealth management product index in this article have a large fluctuation range againsted to the return rate of the wealth management product index. Consequently, for the purpose of ensuring the performance of analysis and forecasting, it is essential to normalize the data of these continuous evaluation indexes; Secondly, the deep learning forecasting model framework constructed in this article is greatly affected by data, and for the purpose of ensuring the performance of its forecasting, it is essential to normalize the data.

4 Construction of Multi-dimensional Feature Faster R-CNN-BiLSTM-Transformer Wealth Management Income Forecasting model

4.1 Forecasting model Framework

On the basis of the candidate set obtained through label matching, the purpose of multi-dimensional feature fusion recommendation is to extract and fuse the features of candidate financial products in more detail, comprehensively consider multiple factors, accurately evaluate the matching degree between each financial product and the user, and provide the most relevant and valuable recommendation results for the user. The pursuit is the accuracy and precision of financial product recommendation.

This chapter is by means of the concept of multi-dimensional feature fusion and combines machine learning technology to construct a financial wealth management product recommendation system. The system adopts a convolutional neural network (CNN) forecasting model by means of additive attention module to extract the features of financial investment products browsed by users and the features of candidate financial investment products. Figure 1 shows the architecture of the multi-dimensional feature financial investment product fusion recommendation algorithm forecasting model constructed in this chapter.

The forecasting model first uses the FinBERT forecasting model to extract semantic features from multidimensional employed text descriptions of financial investment products and users. Through convolutional neural networks, the forecasting model can effectively capture the syntax and semantic information in the names of financial products, and convert them into deep semantic feature vectors. By leveraging local perception and feature extraction capabilities, CNN can process the structural information of phrases and phrases, and identify semantic relationships that depend on long-distance dependencies in text descriptions, thereby enhancing the forecasting model's understanding of text data. Then, a temporal feature extraction mechanism by means of gate-controlled loop units is introduced to achieve feature extraction of browsing financial investment product lists, and a user feature forecasting model is constructed by combining additive attention module and multi head self-attention module to obtain user features. Finally, a forecasting ranking forecasting model for candidate financial products is constructed to calculate the similarity between the generated product word vectors and the user browsing history word vector matrix, in order to evaluate the correlation between the user and each recommended financial product. The data in the user browsing history includes the user's past click history, purchase history, search preferences, etc., which reflect the user's interests and needs. By calculating the similarity between users and financial products, the forecasting model can identify the most suitable financial product for users' needs and recommend the most relevant financial product for them.

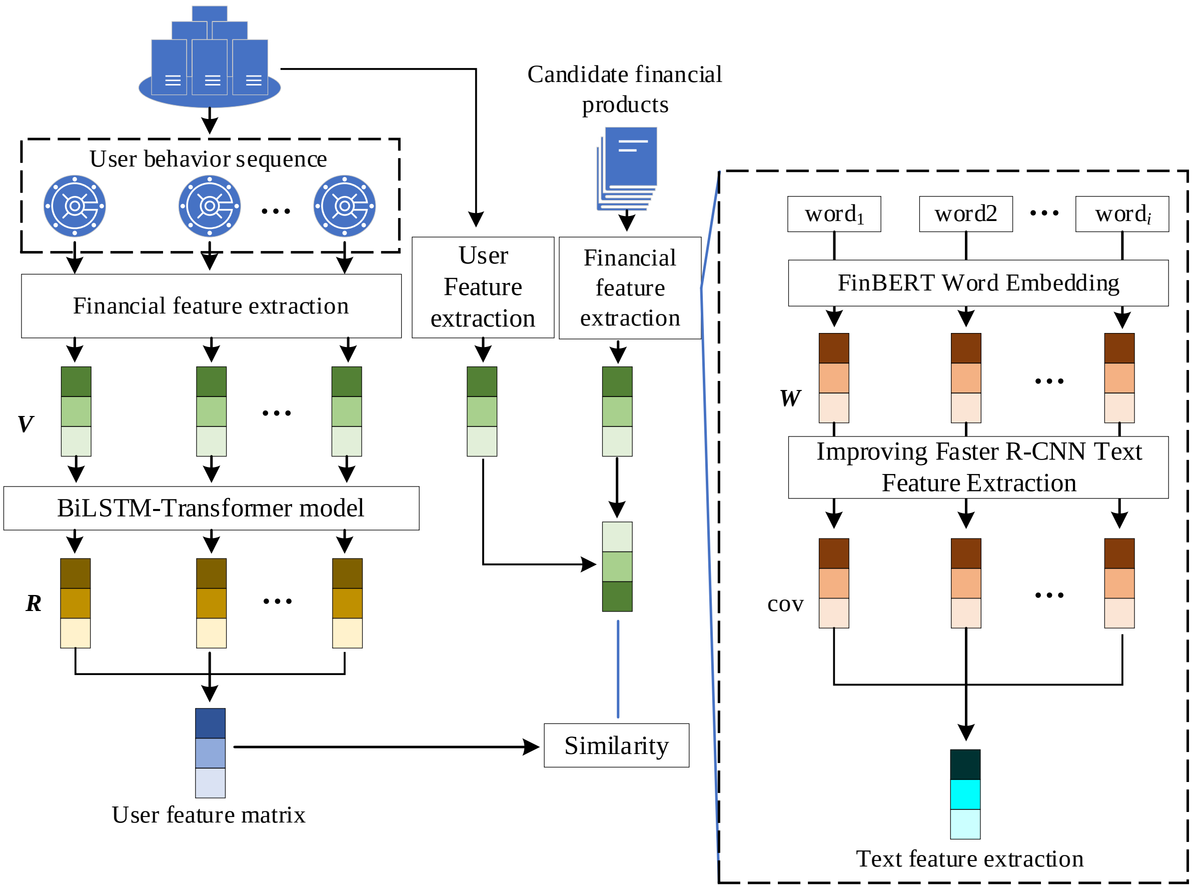

Figure 1: Multi-dimensional feature Faster R-CNN-BiLSTM-Transformer financial income forecasting model

The multi-dimensional feature fusion mechanism first concatenates the static dimensions composed of user attributes and financial product attributes in the data preparation stage; And dynamic behavior fusion that combines long short-term memory networks to forecasting model user historical behavior; At the same time, FinBERT is employed to extract semantic features of financial product text, and convolutional neural networks and attention modules are integrated to achieve fine-grained semantic expression of text semantic fusion. Finally, the system utilizes a weighted feature concatenation and semantic matching scoring mechanism to comprehensively utilize multidimensional data in recommendation decisions, achieving comprehensive and accurate financial investment product recommendations.

4.2 Improving Faster R-CNN Text Feature Extraction

In response to the problems of low forecasting performance and poor robustness of existing algorithms for financial investment products, this paper optimizes the Faster R-CNN algorithm from the following aspects: using a hot restart cosine annealing strategy to update the learning rate and optimize the convergence speed of the forecasting model during training. The structure diagram of the optimized Faster R-CNN is shown in Figure 2.

In order to optimize the convergence speed of forecasting model training and save computational resources, this paper adopts the hot restart cosine annealing strategy to update the learning rate in Faster R-CNN, which can help the forecasting model avoid falling into local minima and find global minima. The hot restart cosine annealing strategy includes two parts: cosine annealing and hot restart. Cosine annealing is the process of slowly cooling the system from a high-energy state and gradually stabilizing it to the lowest energy state. In the adjustment of the learning rate, cosine annealing periodically reduces the learning rate according to the cosine function, and its learning rate formula is as follows:

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min}) \times \left[1 + \cos\left(\frac{T_{\mathrm{cur}}}{T_{\max}}\pi\right)\right] \tag{3}$$

where, η_t represents the current learning rate; $\eta_{\max}$ and $\eta_{\min}$ represent the maximum and minimum learning rates; T_{cur} represents the number of iterations in the current cycle; $T_{\max}$ represents the number of iterations per cycle.

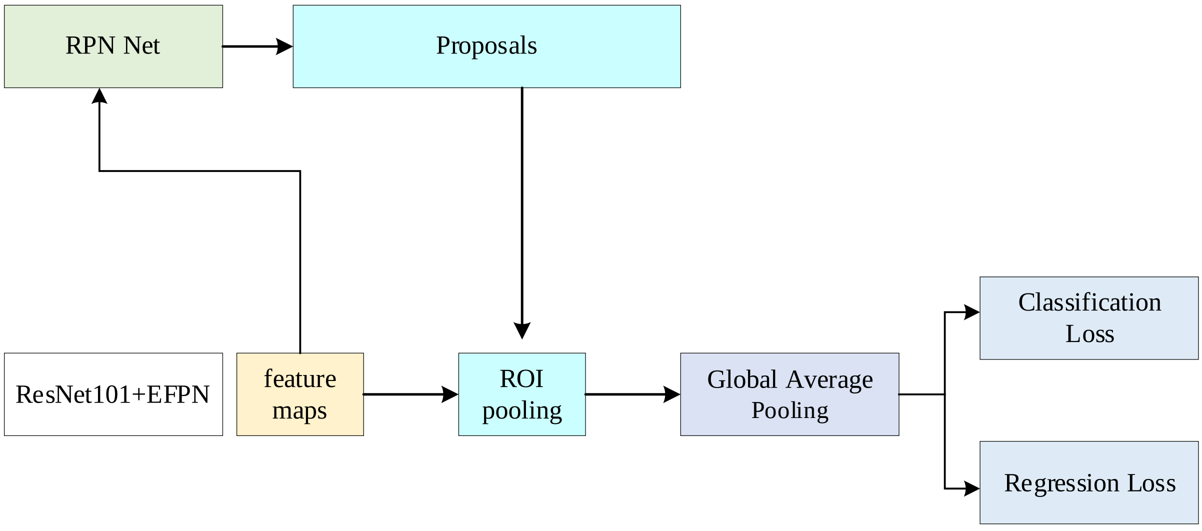

Figure 2: Optimized Faster R-CNN Structure Diagram

Hot restart refers to resetting the learning rate to a higher value after each annealing cycle and gradually annealing again. This type of hot restart can help the forecasting model escape from local optima and find new parameter spaces. After each hot restart, the cycle length $T_{\max}$ usually increases.

4.3 BiLSTM-Transformer forecasting model

Long Short Term Memory (LSTM) networks can effectively solve the gradient vanishing problem that ordinary RNNs are prone to when forecasting modeling long sequences by introducing forget gates, input gates, and output gates into the traditional RNN structure, and can better capture the long-term dependencies of input data. This study uses bidirectional LSTM to fuse forward and backward sequence information, providing a more comprehensive temporal feature representation for subsequent forecasting models. Its structure is shown in Figure 3.

As shown in Figure 3, the bidirectional long short-term memory network is an extension and optimization of the traditional LSTM network. By introducing both forward and backward LSTM layers in the network, the time forward and backward features of the sequence are forecasting modeled separately, thereby achieving comprehensive capture of global contextual information of time-series data. This can effectively optimize the forecasting modeling ability of the forecasting model for long-distance dependencies and demonstrate higher accuracy in processing complex time-series feature recognition and classification tasks.

The Transformer forecasting model is a revolutionary network architecture that adopts the classic encoder decoder structure, consisting of key components such as position encoding, multi head attention layers, and feedforward networks. It not only achieves efficient parallel computing, but also fundamentally solves the forecasting modeling problem of long-distance dependencies, capturing global correlations in sequences. The input of the self attention module includes the query matrix $\boldsymbol{Q}$, key matrix $\boldsymbol{K}$, and value matrix $\boldsymbol{V}$, and the calculation formula is:

$$\text{Attention}\ (\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = \text{Softmax}\left(\boldsymbol{Q}\boldsymbol{K}^{\mathrm{T}} \big/ \sqrt{d_k}\right)\boldsymbol{V} \tag{4}$$

$$h_i = \text{Attention}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V})_i \tag{5}$$

$$\text{MultiHead}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = \text{Concat}\left(\sum_{i=1}^{m} h_i\right) \tag{6}$$

$$\boldsymbol{Q} = \boldsymbol{X}_f\boldsymbol{W}^Q, \boldsymbol{K} = \boldsymbol{X}_f\boldsymbol{W}^K, \boldsymbol{V} = \boldsymbol{X}_f\boldsymbol{W}^V \tag{7}$$

where, m is the number of attention heads; d_k is the dimension of $\boldsymbol{Q}$, $\boldsymbol{K}$, and $\boldsymbol{V}$; $\boldsymbol{W}^Q$, $\boldsymbol{W}^K$, $\boldsymbol{W}^V$ are trainable matrices; h_i is the calculation result of the i-th attention head; $\boldsymbol{X}_f$ is the input sequence matrix; $\text{Concat}(\cdot)$ is the calculation result of concatenating various attention heads.

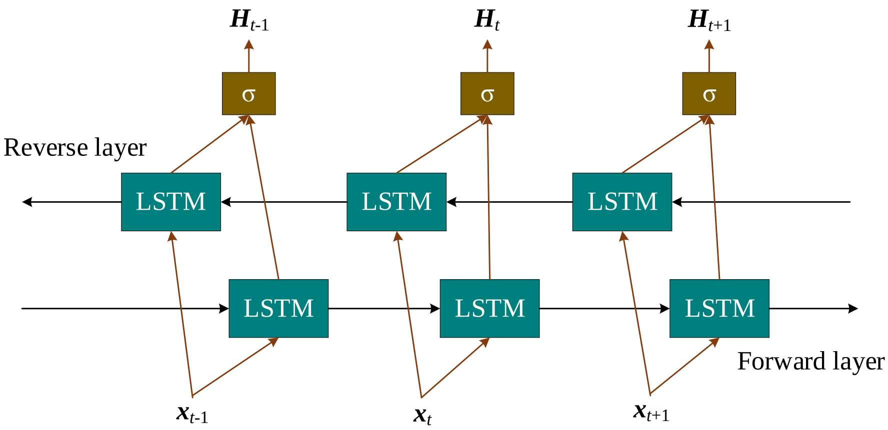

Figure 3: BiLSTM Network Structure

The forecasting model structure of this article combines the temporal recursive forecasting modeling capability of BiLSTM, the locally efficient attention module of ASSA, and the global context forecasting modeling advantage of Transformer, with stronger sequence understanding ability. BLSTM is employed to extract the forward and backward dependency structures of raw features, ASSA focuses on key moment signals to enhance local responsiveness, and Transformer supplements the forecasting modeling of long-distance dependency relationships. The forecasting model ultimately achieves classification output through a multi-layer fully connected neural network, and introduces Dropout to suppress overfitting during the training process, further enhancing the forecasting model's generalization ability.

5 Experimental Analysis

In order to further verify the optimizement of the forecasting performance of the framework for the sample index return rate of various wealth management products, this paper uses the following baseline forecasting models for comparative verification: (1) machine learning forecasting model. The machine learning forecasting model employed for comparison in this article is a decision tree forecasting model, which includes a root node, several internal nodes, and several leaf nodes. The leaf nodes correspond to decision results, while each other node corresponds to an attribute test. The path from the root node to the leaf node corresponds to a judgment test sequence. Common decision tree forecasting models include ID3, CART, etc. The CART forecasting model in decision tree forecasting models includes classification trees and regression trees, among which the CART regression tree adopts the minimum average error criterion and has good performance in regression forecasting problems. (2) Statistical forecasting models. The statistical forecasting model chosen for comparison in this article is the ARMA forecasting model, and a large number of scholars have conducted ARMA forecasting model forecastings on temporal data, proving the effectiveness of ARMA forecasting models in temporal data forecasting. The order of the AR and MA forecasting models is (1,1). The empirical results of this article are shown in Table 2.

Table 2: Results of Forecasting model Forecasting Evaluation Evaluation indexes

Sample Wealth Management Product Index	Method	Evaluation metric			
		MSE	RMSE	MAE	MAPE
Shanghai Stock Exchange Composite Index A Wealth Management Product Index	Proposed method	1.13×10^{-4}	1.03×10^{-2}	8.48×10^{-3}	2.26×10^{-1}
	CART	1.32×10^{-4}	1.17×10^{-2}	8.59×10^{-3}	2.38×10^{-1}
	ARMA	1.27×10^{-4}	1.12×10^{-2}	8.73×10^{-3}	2.57×10^{-1}
Shanghai Stock Exchange Composite Index B Wealth Management Product Index	Proposed method	6.82×10^{-5}	8.17×10^{-3}	6.06×10^{-3}	4.18×10^{-1}
	CART	8.85×10^{-5}	9.34×10^{-3}	6.48×10^{-3}	2.28×10^{0}
	ARMA	7.90×10^{-5}	8.86×10^{-3}	7.15×10^{-3}	2.19×10^{0}
Shanghai Stock Exchange Composite Index Wealth Management Product Index	Proposed method	1.06×10^{-4}	0.97×10^{-2}	5.24×10^{-2}	1.87×10^{-1}
	CART	1.29×10^{-4}	1.08×10^{-2}	6.79×10^{-2}	3.56×10^{0}
	ARMA	1.25×10^{-4}	1.05×10^{-2}	8.25×10^{-2}	1.90×10^{0}
Shenzhen Composite Wealth Management Product Index	Proposed method	1.85×10^{-4}	1.27×10^{-2}	1.06×10^{-2}	6.73×10^{-2}
	CART	2.76×10^{-4}	1.56×10^{-2}	1.47×10^{-2}	3.18×10^{0}
	ARMA	2.09×10^{-4}	1.49×10^{-2}	1.59×10^{-2}	1.28×10^{0}

According to the data in Table 2, by comparing the forecasting evaluation evaluation indexes of different forecasting models on various sample financial product indices, it can be clearly seen that the framework proposed in this article has advantages. (1) For the Shanghai Stock Exchange Composite Index A Wealth Management Product Index, the framework MSE value proposed in this paper is 1.13×10^{-4}, the CART forecasting model is 1.32×10^{-4}, and the ARMA forecasting model is 1.27×10^{-4}. The framework MSE value in this paper is the smallest, and the RMSE, MAE, and MAPE values are also lower than the other two forecasting models, indicating smaller forecasting errors and higher accuracy. (2) In the Shanghai Stock Exchange Composite Index B Wealth Management Product Index, the MSE of this framework is 6.82×10^{-5}, CART is 8.85×10^{-5}, and ARMA is 7.90×10^{-5}. The advantages of this framework are obvious, and it also shows better forecasting performance in RMSE, MAE, and MAPE evaluation indexes. (3) The Shanghai Stock Exchange Composite Index Wealth Management Product Index and the Shenzhen Composite Wealth Management Product Index are the same, and this framework outperforms the CART and ARMA forecasting models in all evaluation indexes. For example, the Shenzhen Composite Wealth Management Product Index has a framework MSE of 1.85×10^{-4}, CART of 2.76×10^{-4}, and ARMA of 2.09×10^{-4}. Overall, the multidimensional feature Faster R-CNN-BiLSTM-Transformer financial return forecasting model constructed in this article has significantly optimized forecasting performance against to common CART regression tree forecasting models and ARMA statistical forecasting models in forecasting index returns of various sample financial products.

From this result: (1) With regard to overall performance, the multi-dimensional feature Faster R-CNN-BiLSTM-Transformer financial income forecasting model constructed in this paper has significantly better forecasting performance than the decision tree forecasting model and ARMA forecasting model in the comparative forecasting models. (2) From the perspective of comparative forecasting models, among all comparative forecasting models, the decision tree forecasting model has slightly better forecasting performance than the ARMA forecasting model; It can be seen that in the study of the index return rate of financial products for the sample, the performance of machine learning forecasting models is slightly better than traditional statistical forecasting models; And the forecasting performance of ARMA forecasting model is poor. (3) From the perspective of samples, it is found that there are significant differences in the performance of forecasting between different samples. For example, the Shanghai Stock Exchange Composite Index A Wealth Management Product Index and the Shanghai Stock Exchange Composite Index B Wealth Management Product Index have better forecasting effects on the return rate of wealth management product indices, while the Shenzhen Composite Wealth Management Product Index has poorer forecasting effects.

In order to verify the effectiveness and accuracy of the recommendation algorithm, this paper conducted more comparative experiments and against the proposed multidimensional feature Faster R-CNN-BiLSTM-Transformer financial income forecasting model with various recommendation methods. (1) HieRec, This method adopts a hierarchical structure to forecasting model user interests, learning interest representations at sub topic level, topic level, and overall user level respectively, in order to more comprehensively capture users' multi-level preferences. The evaluation evaluation indexes selected for this experiment are AUC, MRR nDCG@5 All three evaluation indexes indicate that the larger the result, the better. (2)FIM, This method aims to capture fine-grained interest matching relationships between users and candidate content, and achieve greater forecasting accuracy recommendation results by forecasting modeling fine-grained features in user historical behavior. (3)LSTUR, This method believes that user interests consist of both long-term and short-term interests, with long-term interests being more stable. LSTUR forecasting models users' long-term interests through gated loop units, thereby capturing user preferences more comprehensively. (4)NPA, This is a neural network-based content recommendation method that uses personalized attention module to weight and forecasting model content and user representations, improving the accuracy and personalization of recommendations. (5)DKN, This forecasting model inputs word embedding vectors into a convolutional neural network to extract local semantic features and introduces attention modules to capture users' interest preferences. The relevant results are presented in Table 3, and the visualization results are shown in Figure 4.

Table 3: Comparison results of evaluation indexes for different recommendation algorithms

Forecasting model	AUC	nDCG@5	MRR
DKN	0.6401	0.3286	0.3032
NPA	0.6680	0.3569	0.3318
LSTUR	0.6813	0.3603	0.3326
FIM	0.7002	0.3715	0.3419
HieRec	0.7013	0.3801	0.3475
Proposed method	0.7679	0.4386	0.3982

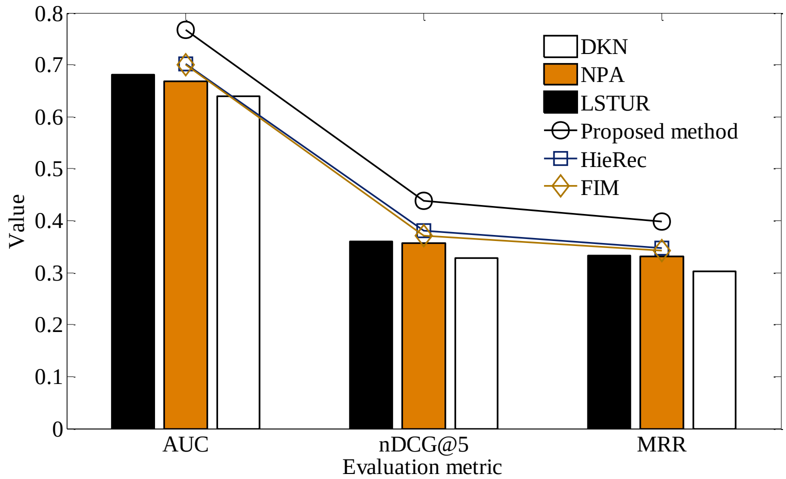

Figure 4: Visualization results of evaluation indexes for different recommendation algorithms

According to the data in Table 3 and Figure 4, the empirical results are analyzed as follows: (1) With regard to AUC index, DKN is 0.6401, NPA is increased to 0.6680, LSTUR further reaches 0.6813, FIM is 0.7002, HieERec is 0.7013, while the forecasting model proposed in this paper reaches as high as 0.7679, significantly higher than other approaches, indicating that this forecasting model has stronger ability to distinguish positive and negative samples. (2) In nDCG@5 With regard to evaluation indexes, the values of each forecasting model are 0.3286, 0.3569, 0.3603, 0.3715, and 0.3801, respectively. The forecasting model in this paper has a value of 0.4386, indicating a significant advantage and better ranking quality of its recommended results. (3) With regard to MRR evaluation indexes, other approaches have values between 0.3032-0.3475, while our forecasting model reaches 0.3982, reflecting that this forecasting model performs better in locating the correct recommended item positions. Taking into account the three evaluation indexes, the recommendation algorithm proposed in this article has demonstrated excellent performance in all aspects, verifying its effectiveness and accuracy.

6 Conclusion

This article proposes a Faster R-CNN-BiLSTM-Transformer hybrid intelligent algorithm by means of multidimensional features for forecasting the returns of bank wealth management products driven by financial technology. By integrating text semantic features, temporal features, and global contextual information, it effectively solves the problems of low accuracy and poor robustness faced by traditional forecasting models in forecasting the returns of high noise and nonlinear wealth management products. The empirical results show that the forecasting model proposed in this paper is significantly better than the CART regression tree forecasting model and ARMA statistical forecasting model in various forecasting evaluation evaluation indexes, verifying its effectiveness and superiority.

Next research steps: (1) Attempt to introduce more advanced deep learning techniques, such as graph neural networks, reinforcement learning, etc., to further optimize the forecasting performance and generalization ability of the forecasting model; (2) Consider incorporating more macroeconomic evaluation indexes, market sentiment data, and other external factors to more comprehensively reflect the factors influencing the returns of wealth management products; (3) By introducing attention module visualization, feature importance analysis and other methods, the interpretability and transparency of the forecasting model are optimized, providing investors with more intuitive decision support.

Funding

This work was supported by the Scientific Research Basic Ability Improvement Project for Young and Middle-aged Teachers in Guangxi Universities (Grant No. 2023KY0591, No. 2024KY0578).

Author's Profile

Sha Lai was born in Yulin, Guangxi, P.R. China, in 1989. She obtained a master's degree from Guangxi University in China. She is currently working at the School of Business, Yulin Normal University. Her research interests include the areas of Fintech and Digital Economy. m15677100408@163.com

Xiaoning Zhu was born in Liuzhou, Guangxi, P.R. China, in 1988. He obtained a doctor's degree from SEGI University in Malaysia. He is currently working at the School of Business, Yulin Normal University. His research interests include the areas of green finance, digital economy and insurance. rocky_zxn@163.com

References

[1] Amaliah I, Ali Q, Sudrajad O Y, et al. Does digital financial inclusion forecast sustainable economic growth? Evidence from an emerging economy[J]. Journal of Open Innovation: Technology, Market, and Complexity, 2024, 10(2): 100262.

[2] Okeke N I, Bakare O A, Achumie G O. Forecasting financial stability in SMEs: A rigorous analysis of strategic budgeting and revenue management[J]. Open Access Research Journal of Multidisciplinary Studies, 2024, 8(1): 139-149.

[3] Attah R U, Garba B M P, Gil-Ozoudeh I, et al. Advanced financial forecasting modeling and innovative financial products for urban development: Strategies for economic growth[J]. Int J Eng Res Dev, 2024, 20(11): 1362-73.

[4] Khuntaweethep W, Koowattanatianchai N. Comparison of the performance of macroeconomic finance forecasting models for financial planning (MFM-FP) and ARIMA-common size in forecasting roe of real estate developers in the stock exchange of Thailand[J]. ABAC Journal, 2022, 42(4): 14.

[5] Khattak B H A, Shafi I, Khan A S, et al. A systematic survey of AI forecasting models in financial market forecasting for profitability analysis[J]. IEEE Access, 2023, 11: 125359-125380.

[6] Ozili P K. Digital finance research and developments around the world: A literature review[J]. International Journal of Business Forecasting and Marketing Intelligence, 2023, 8(1): 35-51.

[7] Kureljusic M, Karger E. Forecasting in financial accounting with artificial intelligence–A systematic literature review and future research agenda[J]. Journal of Applied Accounting Research, 2024, 25(1): 81-104.

[8] Gallego-Losada M J, Montero-Navarro A, García-Abajo E, et al. Digital financial inclusion. Visualizing the academic literature[J]. Research in International Business and Finance, 2023, 64: 101862.

[9] Bello O A. The role of data analytics in enhancing financial inclusion in emerging economies[J]. International Journal of Developing and Emerging Economies, 2024, 11(3): 90-112.

[10] Andronie M, Iatagan M, Uță C, et al. Big data management algorithms in artificial Internet of Things-based fintech[J]. Oeconomia Copernicana, 2023, 14(3): 769-793.

[11] Salisbury L C, Nenkov G Y, Blanchard S J, et al. Beyond income: Dynamic consumer financial vulnerability[J]. Journal of Marketing, 2023, 87(5): 657-678.

[12] Zachariah R A, Sharma S, Kumar V. Systematic review of passenger demand forecasting

in aviation industry[J]. Multimedia tools and applications, 2023, 82(30): 46483-46519.

[13] Zafar M W, Zaidi S A H, Mansoor S, et al. ICT and education as determinants of environmental quality: The role of financial development in selected Asian countries[J]. Technological Forecasting and Social Change, 2022, 177: 121547.

[14] Lazaroiu G, Gedeon T, Rogalska E, et al. Digital twin-based cyber-physical manufacturing systems, extended reality metaverse enterprise and production management algorithms, and Internet of Things financial and labor market technologies in generative artificial intelligence economics[J]. Oeconomia Copernicana, 2024, 15(3): 837-870.

[15] Boustani N, Emrouznejad A, Gholami R, et al. Improving the forecasting performance of the cross-selling of consumer loans using deep learning networks[J]. Annals of Operations Research, 2024, 339(1): 613-630.

[16] Dessaint O, Foucault T, Frésard L. Does alternative data optimize financial forecasting? The horizon effect[J]. The Journal of Finance, 2024, 79(3): 2237-2287.

[17] Pekkaya M, Uysal Z, Altan A, et al. Artificial intelligence-based evaluation of the factors affecting the sales of an iron and steel company[J]. Turkish Journal of Electrical Engineering and Computer Sciences, 2024, 32(1): 51-67.

[18] Abbas A, Triani N, Syahrir S N. Forecasting the Prospect of the Future Business Growth and Detecting Distorted Earnings in Public Insurance Industry: The Voice from Indonesia[J]. Asia Pacific Fraud Journal, 2023, 8(1): 123-136.

[19] Anshika, Singla A. Financial literacy of entrepreneurs: a systematic review[J]. Managerial Finance, 2022, 48(9-10): 1352-1371.

[20] Machado M R, Karray S. Applying hybrid machine learning algorithms to assess customer risk-adjusted revenue in the financial industry[J]. Electronic Commerce Research and Applications, 2022, 56: 101202.

[21] Sriram H K, Seenu A. Generative ai-driven automation in integrated payment solutions: Transforming financial transactions with neural network-enabled insights[J]. International Journal of Finance (IJFIN), 2023, 36(6): 70-95.

[22] Le Quoc D. The impact of digital financial inclusion on income inequality amid economic complexity: a GMM and Bayesian regression approach[J]. Social Responsibility Journal, 2025, 21(7): 1383-1400.

[23] Mhlanga D. The role of big data in financial technology toward financial inclusion[J]. Frontiers in big Data, 2024, 7: 1184444.

[24] de Lima Lemos R A, Silva T C, Tabak B M. Propension to customer churn in a financial institution: A machine learning approach[J]. Neural Computing and Applications, 2022, 34(14): 11751-11768.

[25] Saleh I, Marei Y, Ayoush M, et al. Big data analytics and financial reporting quality: qualitative evidence from Canada[J]. Journal of Financial Reporting and Accounting,

2023, 21(1): 83-104.

[26] Omowole B M, Urefe O, Mokogwu C, et al. Strategic approaches to enhancing credit risk management in microfinance institutions[J]. International Journal of Frontline Research in Multidisciplinary Studies, 2024, 4(1): 053-062.

[27] Udeagha M C, Muchapondwa E. Green finance, fintech, and environmental sustainability: fresh policy insights from the BRICS nations[J]. International Journal of Sustainable Development & World Ecology, 2023, 30(6): 633-649.

[28] Adewale T T, Olorunyomi T D, Odonkor T N. Big data-driven financial analysis: A new paradigm for strategic insights and decision-making[J]. Journal of Financial Innovation and Analytics, 2023, 1(1): 1-15.

[29] Agu E E, Chiekezie N R, Abhulimen A O, et al. Building sustainable business forecasting models with forecasting analytics: Case studies from various industries[J]. International Journal of Advanced Economics, 2024, 6(8): 394-406.

[30] Meher B K, Singh M, Birau R, et al. Forecasting stock prices of fintech companies of India using random forest with high-frequency data[J]. Journal of Open Innovation: Technology, Market, and Complexity, 2024, 10(1): 100180.