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RESEARCH ARTICLE

Research on Forecasting and Risk Measurement of Internet Money Fund Returns Based on Error-Corrected 1DCNN-LSTM-SAM and VaR: Evidence From China

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ABSTRACT The rapid development of Internet money funds (IMFs) may become the main development direction of money funds in the future. For the characteristics of IMFs return time series data with solid nonlinearity and poor smoothness, this study uses long and short-term memory (LSTM) neural network to predict IMFs return. By constructing a 1DCNN (one-dimensional convolutional neural network) and a self-attentive mechanism, the LSTM feature extraction capability is optimized, and an XGBOOST model is built after the output layer to construct a prediction error sequence to compensate for the original prediction sequence to achieve a correction effect. Finally, the trained model is applied to rolling forecast the 43-day return data of the actual trading days in the next two months, and the VaR method is applied to realize the IMF risk measure. The results displayed the following: (1) The 1DCNN-LSTM-SAM-XG has a significant improvement in accuracy compared with models such as LSTM neural network and SVR, and the MAPE values are reduced by 1.372% and 2.887%, respectively, indicating that the model established in this study is characterized by high accuracy and robustness. (2) According to the VaR methodology, the FUND series has the highest risk, the BANK series has the second highest risk, and the THIRD series has the lowest risk.

INDEX TERMS Internet money funds, return rate forecasting, 1DCNN-LSTM-SAM-XG, risk assessment, VaR.

I. INTRODUCTION

In recent years, mobile Internet technology has developed rapidly. While the financial system is developing, it is gradually integrating with the Internet, and Internet financial products are rapidly expanding and developing. Unlike traditional money funds, Internet Money Funds (IMFs) rely on the Internet for direct marketing, which reduces the management costs of banks and other channels and improves the yield of the products. With the advancement of the national Internet strategy, Internet money funds will be the main development direction of money funds.

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IMFs are money funds issued by fund companies using the Internet platform, which collect the idle funds of individual investors and then invest by fund companies to obtain income [1]. Among them, Tianhong Yu'E Bao and other products have attracted attention by their high yields and convenient transaction methods. As of March 2023, the scale of the Tianhong Yu'E Bao fund has reached 689.274 billion yuan, and China's Internet money fund has shown explosive growth.

However, the rapid growth of integrating money funds with the Internet, the instability of yield changes, and whether it will pose a risk to the financial market are significant issues facing the industry's development. An analysis of China's Internet Money Funds (IMFs) yields reveals that the current

IMF yields are generally characterized by "high volatility, strong series nonlinearity, sharp peaks and thick tails in the distribution, and seasonal non-stationary series." These characteristics are difficult to analyze and solve, which makes accurate forecasting and risk measurement of IMFs yield a problem that the financial market must face, and also a significant direction for research.

To summarize, the model in this paper must overcome the impact of IMFs yield features and improve the LSTM neural network to make the long-period series prediction more accurate and the model more robust to provide a practical method for Internet money fund yield prediction. In this paper, we first apply the construction of the CNN-LSTM-SAM model to realize the yield prediction, then introduce the XGBOOST module as an error correction layer to further reduce the error and carry out the yield prediction in the next two months, and finally apply the VaR method to realize the risk metrics of IMFs. The innovations and research work of this paper are as follows:

(1) In this study, 22 representative IMFs yield data are obtained, from January 1, 2018, to February 28, 2023, totaling 1519 time series data after preprocessing. The LSTM neural network is optimized by establishing 1DCNN (Convolutional Neural Network) with SAM (Self-Attentive Mechanism) to improve the prediction accuracy. Based on the establishment of the model to predict the yield, and the test set results are compared with the SVR model used by similar researchers, the results show that the model proposed in this paper has a higher prediction accuracy.

(2) The XGBOOST model is established by introducing the XGBOOST algorithm as an error correction layer, taking the LSTM prediction results as input and the actual value of the IMFs returns as output. Based on the difference between the training XGBOOST prediction results and the actual value of yield, the residual sequence is constructed, and then the residual sequence is compensated with the 1DCNN-LSTM-SAM prediction to achieve the correction effect. According to the correction results, it can be seen that the model accuracy is further improved.

(3) The model built above is used to predict the return of the next two months on a rolling basis, excluding non-trading days totaling 43 days. The VaR method is introduced to measure the risk of IMFs, and the risk value of each IMF yield is derived.The remainder of this paper is organized as follows. In Section II, summarize the related literature. in Section III, obtain the return rate data of 22 IMFs and preprocess them for descriptive statistical analysis. In Section IV, we propose the model principles of CNN, LSTM, Self-Attention mechanism, XGBOOST algorithm, VaR method. In Section V, we build a CNN-LSTM-SAM model for predicting IMFs' returns and use XGBOOST for error correction to improve the accuracy, and then roll back to predict two months' returns and apply the VaR method for risk measurement.In Section VI, present the conclusion.

II. LITERATURE REVIEW

The current market share of Internet Money Funds (IMFs) is proliferating. It has become the main development direction of money funds. However, its instability and randomness and whether it will cause risks to the financial market are the industry development problems [1]. At the same time, [2], [3], [4], [5], [6], [7], [8] pointed out that the healthy and upward development of the industry requires reasonable planning and supervision, so this paper will take the idea as a theoretical guide and focus the research direction on the prediction of IMFs yield and risk metrics, in order to determine the future development trend of the IMFs yield and the risk of loss that the development of the industry may cause as a reminder of the development of the industry with a role in supervision.

Accurate prediction of IMFs yield is the basis for risk measurement. Statistical methods, machine learning, and deep learning are the main models to realize the prediction. Statistical methods include the Autoregressive Integrated Moving Average model (ARIMA) [9]. Machine learning and deep learning mainly include Artificial Neural Networks (ANN), Support Vector Machines (SVR), Recurrent Neural Networks (RNN), and Long Short-Term Memory Neural Networks (LSTM) [10], [11], [12], [13].

Although statistical methods can predict time series data, model architectural limitations such as ARIMA only apply to linear time series. The accuracy is poor when facing unstable and nonlinear time series [14]. At the same time, when applying them to the rolling prediction of future data, the error will accumulate with the prediction step, resulting in a significant error in the results [15].

Machine learning and deep learning have developed rapidly in recent years, providing the basis for more accurate and convenient methods in classification, control, and prediction [16], [17]. In the area of prediction, Jin et al. [18] realized stock price prediction by building models such as SVR, ANN, ARIMA, etc. The results showed that the accuracy of a single model is relatively low when applied in the field of stock price prediction, but the accuracy of SVR is relatively high. Yan et al. [19] applied LSTM to realize prediction of rapidly fluctuating financial data, compared with the traditional recurrent neural network (RNN), LSTM Compared with traditional recurrent neural network (RNN), LSTM neural network is less likely to suffer from gradient explosion and gradient disappearance when dealing with long-term time series data, and the accuracy is higher than that of RNN. Adhikari and Agrawal [20] applied stochastic wandering (RW) optimized artificial neural network (ANN) for financial time series data prediction. The linear portion of the dataset was processed by applying the RW model. ANN processed The remaining non-linear residuals in parallel to obtain the output results. Su [21] and Wu [22] established ARIMA-SVR model and AdaBoost-LSTM integrated learning model to predict the financial market, respectively, and the results show that the application of fusion methods can make up for the original shortcomings of the model to improve the prediction accuracy, for example, the ARIMA-SVR model has a decrease of 5.0961% in the MSE index compared to SVR. The MSE indicator of the ARIMA-SVR model is decreased by 5.0961% compared to SVR. Meanwhile, the prediction stability is more substantial. And Li and Sun [23] used SVR as the base model, optimized the SVR parameters under multiple kernel functions by optimization algorithms such as network search method, and the experiments showed that the optimization algorithm optimized the parameters, enhanced the applicability of the model, and the prediction index R reached 98.59%, and the MSE was 0.001, which was an excellent prediction result. In summary, artificial intelligence methods are gradually replacing the traditional statistical methods, LSTM compared to the traditional RNN and machine learning models with higher accuracy, will optimize the model parameter selection or combination of prediction models to optimize the data feature extraction, improve the prediction accuracy has become the focus of research. Since the optimization algorithm can only improve the accuracy of the LSTM neural network's full connection layer, it is decided to use LSTM as the basic prediction model, apply an iterative method to debug network parameters, and add network modules to improve the prediction accuracy of the model.

CNN (Convolutional Neural Network) is often used in image recognition due to its strong ability to capture localization [24], [25]. Meanwhile, in the field of natural language processing, Zheng et al. [26] designed a deep fusion matching network including a coding layer, a dependent convolutional layer, and an inference prediction layer. Through the analysis of the network structure, it can be seen that the CNN network directly carries out detailed structural extraction along the linguistic sequences, which improves the interpretability of the data. The experimental verification of the CNN plays a more significant role in this deep network, and the overall correctness of the model reached 89.0%. CNN not only has a robust feature extraction ability in recognition and natural language processing but also has a robust nonlinear feature extraction ability in quantitative data; the fusion of CNN and the time series model perfects the temporal extraction ability that CNN does not have and improves the prediction accuracy of the combined model [27]. Wu et al. [28] added a convolutional neural network (CNN) before the LSTM layer for optimization; through the convolutional neural network (CNN), the LSTM layer is optimized. CNN before the LSTM layer for optimization, extracted the feature vectors in the data through convolutional pooling as inputs into the LSTM, and then optimized the prediction accuracy of the LSTM. The results showed that the prediction accuracy was better than that of the LSTM, RNN, and SVR models. Yang et al. [29] optimized the LSTM by building a three-dimensional CNN without the pooling layer to retain more data information about the vectors inputted to the LSTM, and the experiment showed that the prediction accuracy of the proposed model was higher. Showed that the prediction accuracy of the proposed model is higher. In summary, applying a convolutional neural network (CNN) to extract data feature vectors as LSTM inputs effectively improves the overall prediction accuracy of the model.

It is an essential direction for many researchers and scholars to integrate the attention mechanism with the model to improve the feature extraction ability of the model to optimize the model accuracy [30], [31]. The attention mechanism is often used in fields such as image segmentation [32]. However, it has been proved that combining the attention mechanism with the time series model helps to extract the features that cannot be noticed by the time series model and then optimize the prediction accuracy of the time series model [33]. Gao et al. [34] optimized a multivariate LSTM neural network with a variable attention mechanism by measuring the importance of each variable to the target and then optimizing the network by assigning weights to it, and the results showed that the LSTM optimized by the attention mechanism has higher prediction accuracy. Ren et al. [35] proposed a weight adjustment model similar to the attention mechanism based on the traditional model to balance the short-term trend of the traffic flow with the weights of the observed state, ensuring the model's versatility and sensitivity to the emergence of emergencies. In summary, this paper selects the self-attention mechanism optimization model by learning the overall correlation weights of the input sequences. Further, it enhances the data feature extraction capability by weighting the sequences to optimize the network prediction accuracy.

Because the model feature extraction ability is not enough or the model exists randomness and other factors lead to the error can not be eliminated, the introduction of the predicted value and the actual value of the residuals of this parameter to achieve error correction, optimization of prediction accuracy is an effective method [36], [37], [38], [39]. Li et al. [40] use the SVR model of the prediction results of the residuals of the training by predicting the residuals of the value of the correction of the LSTM prediction value of the temporal order of the accuracy of the optimization. Sun et al. [41] constructed a random forest model to realize the pseudo-range error prediction and correction of the Global Navigation Satellite System (GNSS) and realized the correction of points (PBC) and grids (GBC) through the user's location points and regions, and then realized the accuracy enhancement through the Least Squares Method (LSM). Song et al. [42] established a regression error correction equation after outputting the prediction results, and through the prediction value and the actual values to construct a standard equation, and bring the error correction results into the prediction model to optimize the prediction accuracy. In summary, this paper establishes the XGBOOST model as a residual correction model, which further approximates the actual value by training the predicted value and then constructs the residual series to achieve the optimization purpose.

After obtaining the return of IMFs, it is necessary to calculate the possible risk of IMFs quantitatively, and this

TABLE 1. Information on IMFs.

Category	Fund companies	IMFs	Fund size (billion)	Fund Code
THIRD	Ant Financial	Tianhong Yu'E Bao	689.274	000198
	JD Finance	Jiashi Huoqianbao A	76.728	000581
	Du Xiaoman Finance	Yifangda Yilicai A	201.439	000359
	Tencent Tengan	Huaxia Caifubao A	157.274	000343
	Tencent Tengan	Huitianfu Quan'E Bao A	160.562	000397
	Suning Xingtu Financial	Zhangcheng Shouyi Bao A	49.394	004972
BANK	Bank of Communications of China	Jiaoyin Xianjin Bao A	73.673	000710
	Bank of China	Zhongyin Xinqianbao	69.041	000699
	China Construction Bank	Jianxin Jiaxin Bao A	196.562	000686
	Industrial and Commercial Bank of China	Gongyin Xinjin A	4.561	000528
	Agricultural Bank of China	Nongyin Huili Ririxin A	25.490	004097
	Shanghai Pudong Development Bank	Puyin Ansheng Ririfeng A	0.407	003534
FUND	Noonan Fund	Nuoan Tiantian Bao A	76.262	000559
	Huaan Fund	Huaan Ririxin A	161.424	040038
	Guangfa Fund	Guangfa Tiantianli A	0.565	000475
	China Investment UBS Fund	Guotouruiyin Tianli Bao A	45.679	001094
	Xingzhi Global Fund	Xingquan Tianli Bao	181.625	000575
	Boshi Fund	Boshi Tiantianzengli A	40.396	000734
	Fu Guo Fund	Fuguo Fuqianbao A	167.176	000638
	Efund	Yifangda Zengjin Bao A	46.145	001010
	Changsheng Fund	Zhangsheng Tianli Bao A	16.804	000424
	BOC Fund	Zhongyin Huoqi Bao A	36.251	000539

risk value will effectively prove the riskiness of IMFs [43], [44]. Applying the VaR method to measure the risk is a prescribed use and effective method by researchers and organizations such as investment banks [45]. Shen [46], Jorcano and Novales [47] and Bouri et al. [48] established the VaR method to measure the risk of the financial sector they belong to, which proves the accuracy and effectiveness of the VaR method. For IMFs for the Internet financial industry, this paper should select the VaR method to measure the IMF risk.

In response to the above review, this paper selects CNN (Convolutional Neural Network) and Self-Attentive Mechanism with strong feature extraction ability. It applies these two parts to optimize LSTM neural network to improve the prediction accuracy. At the same time, XGBOOST is introduced to improve the prediction accuracy by correcting the residuals of the prediction results. Finally, the VaR method is applied to the predicted returns of IMFs to realize the risk measure.

III. DATA PROCESSING

A. DATA SELECTION

IMFs are classified into three categories according to the nature of the enterprise to which they belong: IMFs established by third-party enterprises (THIRD), IMFs established by banks (BANK), and IMFs established by foundations (FUND) [1]. In this study, we select the more typical IMF products in each category, a total of 22 IMFs, as shown in Table 1.

As shown in Table 1, there are 22 IMFs in total. To ensure the reasonableness and rigor of the data, the seven-day annualized return and the 10,000-fold fund return from January 1, 2018, to February 28, 2023, are selected for the study. To ensure the accuracy of the subsequent modeling, this study preprocesses the data by excluding the null values according to the nature of the product cycle of IMFs "Sunday does not generate income." Finally, we obtained 1519 items for each IMFs and 33418 items for 22 IMFs.

B. DATA ANALYSIS

Descriptive statistical analysis of the returns was performed to obtain the mean of the returns, the variance indicating stability, the skewness indicating whether the returns are symmetric, and the kurtosis of the data, as shown in Table 2.

Using Table 2, the kurtosis of Gongyin Xinjin A(000528) is less than 0, and the abnormal reason is that the volatility of return is stronger than other IMFs. And the average returns of the selected IMFs are distributed between [2.1590, 2.9016]. By averaging the returns of each type of IMF, we can obtain the average return of THIRD as 2.5453, BANK as 2.5229, and FUND as 2.4092. In summary, the THIRD series has the highest return, the BANK has the second highest average return, and the FUND has the lowest return.

IV. METHODOLOGY

A. DATA STANDARDIZATION

To eliminate data dimensions and accelerate network training process, this study first normalizes the data.

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where, X^* represents the normalized result, X represents the original data, X_{max} represents the column's maximum value, and X_{min} is the minimum value of the column to which it belongs.

B. IMFs FORECAST MODEL FOR RETURN RATES

1) LSTM NEURAL NETWORK MODEL

LSTM neural network is improved from the standard Recurrent Neural Network (RNN), which solves the problem that RNN cannot handle long time series by internal complex gate operation and cellular state so that it can effectively memorize temporal data features [48], [49], [50].

The purpose is to measure the value-at-risk of IMFs with high periodicity, so it is more critical to avoid the error

TABLE 2. Descriptive statistical analysis of IMFs.

Category	Fund Code	Mean Value	Min Value	Max Value	Std.deviation	Skewness	Kurtosis
THIRD	000198	2.2762	1.2920	4.3940	0.7175	1.2243	1.0433
	000581	2.5495	1.0890	5.1530	0.8236	0.9513	0.3662
	000359	2.5244	1.4690	4.6900	0.8105	1.1780	0.4201
	000343	2.5147	1.2720	5.5420	0.8515	1.2075	0.9075
	000397	2.5053	1.3470	4.8060	0.8215	1.1504	0.3553
	004972	2.9016	1.7480	6.9010	0.7963	1.3802	2.3906
BANK	000710	2.3740	1.4400	5.4020	0.6268	1.0205	1.0447
	000699	2.5157	1.1140	4.6760	0.8654	1.0744	0.2680
	000686	2.6632	1.5830	7.6210	0.9013	1.6082	3.8151
	000528	2.5555	1.4210	4.8290	0.8299	0.9054	-0.1693
	004097	2.4903	1.3000	4.7860	0.8544	1.1001	0.3033
	003534	2.5384	1.4330	4.6800	0.6542	0.8230	0.3508
FUND	000559	2.3772	1.3380	4.9090	0.6910	1.5019	1.6438
	040038	2.3712	1.2130	5.3950	0.7596	1.3267	1.4369
	000475	2.3573	1.3700	5.0490	0.7958	1.4203	1.4136
	001094	2.4045	1.3270	6.0670	0.7516	1.3305	1.7827
	000575	2.6071	1.5400	4.7210	0.7724	1.0398	0.3459
	000734	2.1590	1.2390	4.6790	0.5620	1.0433	1.6318
	000638	2.5067	1.2870	4.9960	0.8702	1.1942	0.5958
	001010	2.5671	1.2690	4.9280	0.8149	1.1183	0.2786
	000424	2.2362	1.0500	6.0770	0.7158	1.6655	3.4966
	000539	2.5057	1.1930	4.6340	0.7822	1.1080	0.6215

accumulation of traditional methods and make the prediction results accurate [51]. Therefore, LSTM neural network is chosen for IMFs return forecasting. The structure of the LSTM model is visualized in Figure 1.

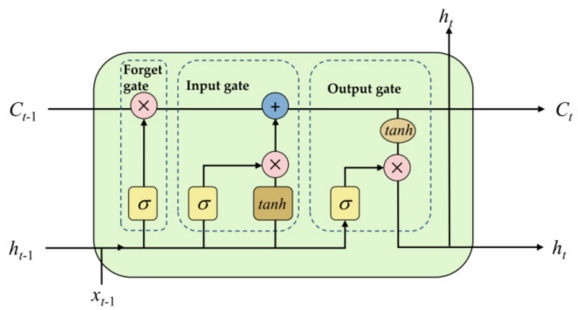


FIGURE 1. Structure of LSTM neural network.

Figure 1 shows the interior of the cell structure of the LSTM network, ⊗ for the dot product operation ⊕ for the addition operation, C_{t-1}, h_{t-1} and x_{t-1} represent the input information at moment t-1. Ct, ht and x_t represent the output information at moment t. The LSTM mainly consists of three gating structures controlling memory cells and a cellular state. The gating structure consists of an oblivion gate f_t, an input gate i_t and an output gate o_t.

The forgetting gate serves to decide which information to discard or save. It will be defined as equation (2).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

where, W_f weight matrix, b_f bias vector, h_{t-1} is the input at t-1, xt denotes the input at moment t, and σ sigmoid function.

The role of the input gate is to select the information that needs to be saved at the current moment of control and to decide which cell states to update.

$$\begin{aligned} i_t &= \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \\ \tilde{C}_t &= \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \end{aligned} \tag{3}$$

where, W_i and W_C is the weight matrix, b_i is the bias vector, $\tilde{C}_t$ is the information state through the input gate, and tanh is the hyperbolic tangent function.

The updated cell state equation (4) is as follows:

$$C_t = f_t^* C_{t-1} + i_t^* \tilde{C}_t \tag{4}$$

where, C_{t-1} is the state of the cell at the previous moment, $\tilde{C}_t$ is the state of the information through the input gate.

The function of the output gate is to determine the next state that should output information, and the output part is determined by the sigmoid function. Then the predicted value of the model is obtained by multiplying the information state through the input gate and the output part by tanh.

$$\begin{aligned} O_t &= \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_O\right) \\ h_t &= O_t^* \tanh\left(C_t\right) \end{aligned} \tag{5}$$

where, W_o is the weight matrix, b_O is the bias vector, h_t is the output at the current moment, C_t is the cell state at the current moment.

2) CNN (CONVOLUTIONAL NEURAL NETWORK)

The core of CNN is a weighted summation of data to extract data feature values, which is commonly used in the field of image recognition and later found that the combination of a one-dimensional convolutional neural network (1DCNN) and time series model is optimized for data feature extraction [52], [53]. This study establishes a convolutional neural network (1DCNN) to quickly and efficiently extract feature information from IMFs time-series data.

CNN comprises a convolution layer, a pooling layer, and a full connection layer [54]. The input data is first passed through the convolutional layer to extract the features. Then the pooling layer is used to reduce some of the data features, reduce the dimensionality of the extracted features, reduce the computational effort of the network, and prevent the network from overfitting to some extent. Finally, the global features are obtained through a fully connected layer by accumulating the global features according to the weights given. The Sigmoid function is chosen as the activation function of the convolutional layer, which has the advantages of robustness and low influence by data noise. The expression of the function is (6).

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{6}$$

3) SELF-ATTENTIVE MECHANISM

The core of the attention mechanism is to make the network nodes focus on crucial information at a particular time [28], [55] and suppress irrelevant information to improve prediction accuracy while ensuring that the input and output data dimensions do not change. The Self-attention mechanism is a variant of attention [56], which is good at capturing the internal relevance of the input data. It has been experimentally shown to be effective in improving the accuracy and robustness of the network by adding it to the LSTM network [57], [58].

Introducing the self-attentive mechanism aims to obtain the importance of temporal data at different stages of IMFs. The structure of the self-attentive mechanism is shown in Figure 2.

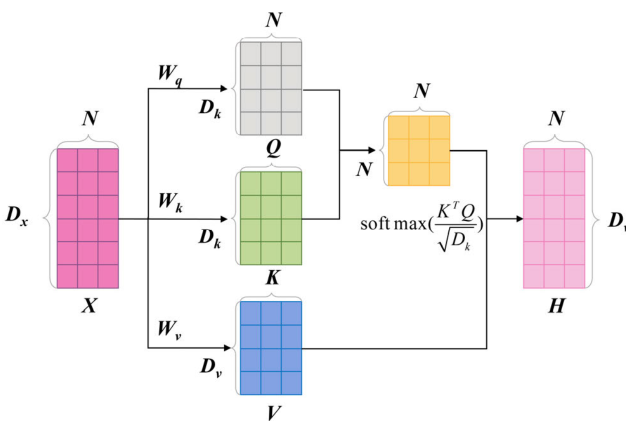


FIGURE 2. Self-attention mechanism structure.

The primary mechanism is to map the input to different spaces to get the query vector (query), key vector (key), and value vector (value). Then the correlation coefficients of the query and key are calculated, and the sequence weights are obtained by softmax. Finally, the sequence weights are weighted and summed with the value vector (value) to obtain the output vector. The calculation procedure is shown in equations (7)-(10).

$$\boldsymbol{Q} = XW^q \tag{7}$$

$$\boldsymbol{K} = XW^k \tag{8}$$

$$\boldsymbol{V} = XW^v \tag{9}$$

$$Attention(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = soft\ \max\left(\frac{QK^T}{\sqrt{D_k}}\right)\boldsymbol{V} \tag{10}$$

where, $\boldsymbol{Q}$, $\boldsymbol{K}$ and $\boldsymbol{V}$ are the query matrix, key matrix and value matrix, respectively, and D_k denotes the matrix dimension.

4) XGBOOST PREDICTION MODEL

The XGBOOST (eXtreme gradient boosting) algorithm is a boosted tree model that performs a second-order Taylor expansion of the loss function based on the GBDT algorithm while explicitly adding a regular term to control the complexity of the model and preventing overfitting while processing the feature selection in parallel, which is faster and interpretable [59], [60], [61]. The purpose of introducing the XGBOOST algorithm in this study is to improve model error correction and improve model accuracy. The objective function of the XGBOOST algorithm is equation (11).

$$L^{(j)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{j-1} + f_j(x_i))l(\cdot)\Omega \tag{11}$$

where, $l(\cdot)$ is the loss function. $\hat{y}_i^{j-1}$ denotes the output of the j-1th tree. $\Omega(f_i)$ is a regular term used to control the complexity of the model.

5) OPTIMIZATION OF 1DCNN-LSTM PREDICTION MODEL BASED ON RESIDUAL CORRECTION AND SELF-ATTENTION MECHANISM

Based on CNN-LSTM, this study added SAM(Self-Attention Mechanism) into the designed model to further optimize the prediction accuracy. The model is composed of input layer, convolution layer, maximum pooling layer, full connection layer, Dropout, LSTM layer, attention layer, full connection layer, XGBOOST error correction layer and output layer, each layer has its own weight. Set the convolution kernel of 1DCNN to 64, add the maximum pooling layer, and apply the Sigmoid function as the activation function. Input to the LSTM layer through the fully connected layer sets the number of neurons to 200 and introduces Dropout=0.4 to prevent overfitting. Input continues backward to the attention layer for further optimization and through the full connection layer to the correction layer for output. LSTM selects Adam optimizer for training, which updates step size and automatically adjusts the learning rate.

The overall process is summarized as follows: firstly, the data is input into the model, and the data features are extracted through the convolution, pooling, and full connection layer of 1DCNN and then converted into a one-dimensional matrix to input the LSTM layer. Secondly, the LSTM layer extracts the dependency relationship in the timing data, inputs it into the attention layer to extract the important features of the data, and then enters the error correction layer through the full connection layer. Finally, the residual difference between the real and the predicted value and the predicted value of IMFs were put into the XGBOOST layer to correct the error of the training network. The predicted value of the corrected result was summed with the predicted value of LSTM to get the final predicted sequence. Figure 3 is the model structure diagram.

C. IMFs RISK MEASUREMENT MODEL FOR RETURN RATES

1) VAR(VALUE AT RISK) MODEL

Value at Risk, abbreviated as the VaR model, is commonly used to quantify the value at risk that may arise in the financial sector, which represents the maximum possible loss of IMFs return at a certain time in the future at a certain confidence interval [1]. In this study, the VaR method was used to calculate the risk of the 43-day backward forecast of IMFs' returns. VaR can be expressed as (12).

$$Prob(\Delta P < VaR) = \alpha \tag{12}$$

where, ΔP is expressed as the loss of IMFs return during the holding period, and VaR is expressed as the value of loss at the α confidence level, α is expressed as the confidence level.

In this study, we assume that IMFs return volatility is only market related [62], while defining IMFs return volatility as value at risk, σ_i as in equation (13).

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{N} (x_{it} - \mu_i)^2}{N - 1}} \tag{13}$$

where, x_{it} denoted as the current IMF return, μ_i is the average return, and N is the number of days.

The VaR value is (14).

$$VaR_i = P_0 \cdot \left(z_c \cdot \sigma_i \cdot \sqrt{\Delta t}\right) \tag{14}$$

The confidence level is set to 95%, corresponding to $z_c = 1.96$. P0is the initial value. Because the selected IMFs are daily returns, set $\Delta t = 1$.

D. PERFORMANCE INDEX

In this study, we use MAE, RMSE, MAPE, and R2 to measure the accuracy of IMFs' return forecasts. The above indicators are defined in equations (15)-(18).

$$MAE = \frac{1}{n} \sum_{s=1}^{n} |y_s - \widehat{y}_s| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{s=1}^{n} (y_s - \hat{y}_s)^2} \tag{16}$$

$$MAPE = \frac{1}{n} \sum_{s=1}^{n} \left| \frac{y_s - \hat{y}_s}{y_s} \right| \tag{17}$$

$$R^2 = 1 - \frac{\sum_{s=1}^{n} (y_s - \hat{y}_s)^2}{\sum_{s=1}^{n} (y_s - \bar{y}_s)^2} \tag{18}$$

where, $\hat{y}_s$ is the predicted value of IMFs return, y_s is the actual value of IMFs return, and $\bar{y}_s$ is the mean of the actual value of IMFs return.

V. FORECASTING AND RISK MEASUREMENT FOR IMFs

The obtained returns of IMFs are predicted according to the CNN-LSTM-SAM prediction model. The return's of IMFs are predicted based on the trained network rolling backward for 43 trading days in the next two months, while the risk measure of IMFs' returns is performed according to the VaR method to obtain the possible risk index of each IMF.

A. FORECASTING IMFs RETURNS

1) CNN-LSTM-SAM ESTABLISHMENT

In this study, the Keras framework was used to build the model. Regarding parameter setting, the traditional LSTM was first used to predict the rate of return. The experiment showed that the number of LSTM neurons was 200, and the prediction accuracy and stability were the best. Secondly, the data extracted by convolutional pooling is used as LSTM input, then set the number of convolutional cores is 64, and the convolutional step is 3, activate the function to select the Sigmoid function, and then add Self-Attentive Mechanism for attention allocation. The weight of attention and the weighted output sum enter into the full connection layer and become a one-dimensional vector for output. Finally, the residual difference between prediction and true value is predicted and optimized by the XGBOOST algorithm to realize the forecast output.

For model training, the first 80% of the training set is selected to train the network model, and the last 20% is the test set to verify the feasibility of the model. The training step of the LSTM network is 6, the batch size is 64, the training times are set to 100, the initial learning rate is 0.001, the optimizer is Adam optimizer, and the Dropout mechanism is introduced to prevent overfitting, and the parameter is set to 0.4. LSTM neural network model parameters are shown in Table 3.

TABLE 3. LSTM parameter Settings.

Parameter	Parameter Value
batch size	64
learning rate	0.001
Training step	6
Dropout	0.4
optimizer	Adam
LSTM neurons	200

In this study, we optimize the prediction accuracy of the LSTM neural network through 1DCNN and self-attention mechanism and construct the residual sequence to further approximate the true value through the XGBOOST algorithm. 1DCNN specific feature extraction is performed by, sliding the convolution kernel in the return's data, calculating elemental multiplications, learning various local relationships in the sequence, and aggregating the results to

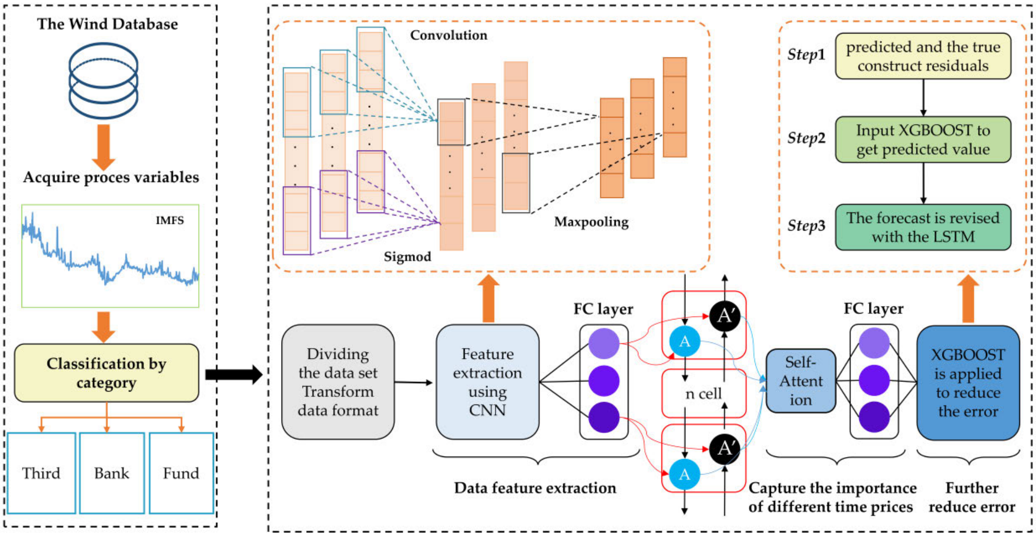


FIGURE 3. Structure of CNN-LSTM-SAM-XG forecast model.

generate a feature map. Meanwhile, the linear activation function Sigmoid is applied after the convolution operation to map the output of the convolution operation into a nonlinear space so that the model better captures the complex and nonlinear relationships in the input data and extracts nonlinear features. The self-attention mechanism optimizes the feature extraction capability by capturing the dependencies between any pair of positions in a sequence. Enabling the model to focus on important elements and better understand the relationships between them, specifically according to the mechanism to weigh the importance of different elements in the sequence based on their correlations, thus generating attention weights. In turn, each sequence element's query, key, and value are calculated and the attention weights are computed by performing similarity calculations between the query and the key vectors. The softmax function is then applied to obtain the normalized weights. The weights are multiplied with the values to generate a weighted sum indicating the attention between the query and the input sequences to represent the extracted feature relationships to help optimize the accuracy of the model.

2) TEST SET PREDICTION ACCURACY VALIDATION

According to the current situation of domestic and foreign research, it can be known that a support vector machine (SVR) is often applied to economic prediction [18]. LSTM, CNN-LSTM, CNN-LSTM-SAM, and SVR are established in this study respectively. Results are based on the THIRD series Tianhong Yu'E Bao (000198), BANK series Jiaoyin Xianjin Bao A (000710), and FUND series Fuguo Fuqianbao A (000638) as examples.

Table 4 shows the performance indexes of each model established, and Figure 4 shows the visualization of each model with actual values.

The analysis of Figure 4 shows that the accuracy of the proposed IMFs return prediction model is higher than that of the traditional model and more advanced approaches, and the local feature extraction capability is more robust, which is higher for the prediction accuracy improvement. The following analysis results can be obtained by evaluating the indexes.

MAE(Mean Absolute Error) represents the closeness between predicted and actual data. The smaller the value, the better the fitting effect. In the THIRD series, the CNN-LSTM-SAM value is the lowest, which is reduced by 1.144% compared with traditional LSTM and 2.369% compared with similar research models. Compared with traditional LSTM and similar research models, CNN-LSTM-SAM in the BANK series decreased by 1.446% and 3.278%, respectively. Compared with traditional LSTM and similar research models, the model proposed by the FUND series is reduced by 1.984% and 6.595%, respectively. From the above analysis, it can be seen that the model proposed in this paper has the highest approximation to the true value under the three IMFs categories and the greatest improvement in the FUND series.

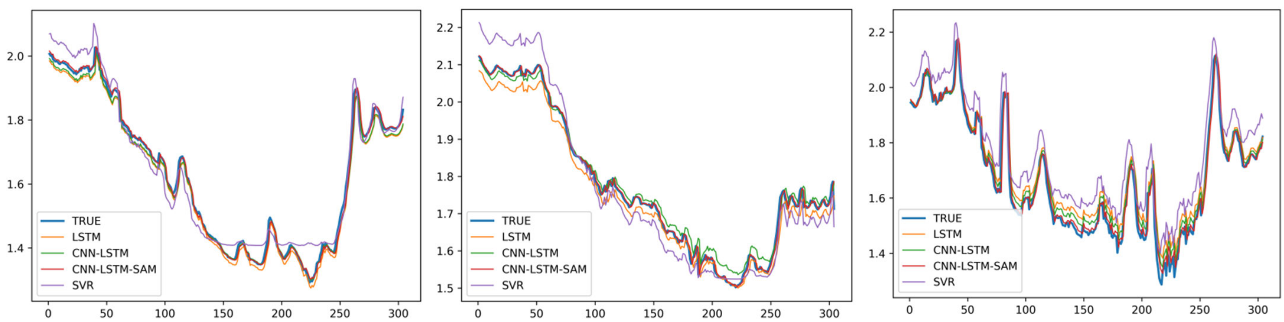
MSE (Mean squared error) represents the degree of data variation, and the smaller the value, the closer it is to the true value. The CNN-LSTM-SAM has the lowest value in all IMFs series and the result is the closest to the true value.

RMSE (Root Mean Square Error) represents the deviation between the predicted and observed. The CNN-LSTM-SAM has the lowest value among the three IMFs, with 0.967%, 1.440%, and 1.861% improvement compared with the traditional LSTM, and 2.537%, 3.554%, and 5.477% improvement compared with the similar research model (SVR), respectively.

MAPE (Mean Absolute Percentage Error) represents the percentage difference between the actual value and the observed value, and the lower the value, the better the fitting effect. The CNN-LSTM-SAM has the lowest values in all three IMFs categories, which are 0.00636, 0.00637, and 0.0152.

TABLE 4. Modeling performance comparison.

Category	Fund Code	Model	MAE	MSE	RMSE	MAPE	R^2
THIRD	000198	LSTM	0.02183	0.00065	0.02549	0.01333	0.98713
		CNN-LSTM	0.01495	0.00040	0.02005	0.00883	0.99204
		CNN-LSTM-SAM	0.01039	0.00025	0.01582	0.00636	0.99504
		SVR	0.03408	0.00170	0.04119	0.02129	0.96619
BANK	000710	LSTM	0.02554	0.00084	0.02897	0.01393	0.97642
		CNN-LSTM	0.01553	0.00037	0.01917	0.00919	0.98969
		CNN-LSTM-SAM	0.01108	0.00021	0.01457	0.00637	0.99404
		SVR	0.04386	0.00251	0.05011	0.02397	0.92875
FUND	000638	LSTM	0.04497	0.00310	0.05571	0.02854	0.92865
		CNN-LSTM	0.03345	0.00193	0.04388	0.02087	0.95574
		CNN-LSTM-SAM	0.02513	0.00138	0.03710	0.01520	0.96836
		SVR	0.09108	0.00844	0.09187	0.05598	0.80515



(a) (b) (c)

FIGURE 4. Structure of CNN-LSTM-SAM-XG forecast model.(a) Comparison of the predicted and true values of the four models(000198). (b) Comparison of the predicted and true values of the four models(000710). (c) Comparison of the predicted and true values of the four models(000638).

R2 (Coefficient Of Determination) represents the model goodness of fit. The IMFs return prediction model proposed in this study is the closest to 1 in all three series because the value of the selected IMFs return in the FUND series has a higher intensity of variation, and the value is lower than the THIRD and BANK series.

3) XGBOOST ERROR CORRECTION MODEL FOR IMFS RETURN' S FORECASTING

In order to further reduce the error and improve the accuracy of the model, this paper introduces XGBOOST model as the error correction layer to optimize the prediction results of 1DCNN-LSTM-SAM, and further approximate the real value on the basis of the prediction. At this time, the predicted value of 1DCNN-LSTM-SAM output is used as the XGBOOST input, and the real value of IMFs return is used as the output to build the XGBOOST model. The residual sequence is constructed according to the difference between the predicted results of training XGBOOST and the real value of the return rate, and then the residual sequence is compensated with the predicted value of 1DCNN-LSTM-SAM to achieve the correction effect.

Set the first 80% of data in the XGBOOST model to the training set and the remaining 20% to the test set to build the model. The XGBOOST model parameters are shown in the Table 5.

TABLE 5. XGBOOST parameter Settings.

Parameter	Parameter Value
Base learner	gbtree
Number of base learners	100
Learning rate	0.1
L1 regular term	0
L2 regular term	1
Maximum depth of tree	10

According to the XGBOOST prediction results can be found that most of the values are closer to the true yield. The 1DCNN-LSTM-SAM predicted value and the real value of the return rate make a difference, and the XGBOOST predicted value and the real value make a difference to obtain the residual sequence, at this time, the XGBOOST residual sequence is the compensation residual sequence. Comparison of the two residual series can be learned after the XGBOOST model approximation of the true value of the compensated residual series is reduced by a larger magnitude, that is, the application of this method to compensate for the model will effectively improve the model prediction accuracy. Table 6 compares predicted IMFs return indicators before and after the introduction of residual correction, and Figure 5 shows the visualization of residuals before and after residual correction. To summarize, the error of each node is reduced more obviously compared with the original data, i.e., the residual

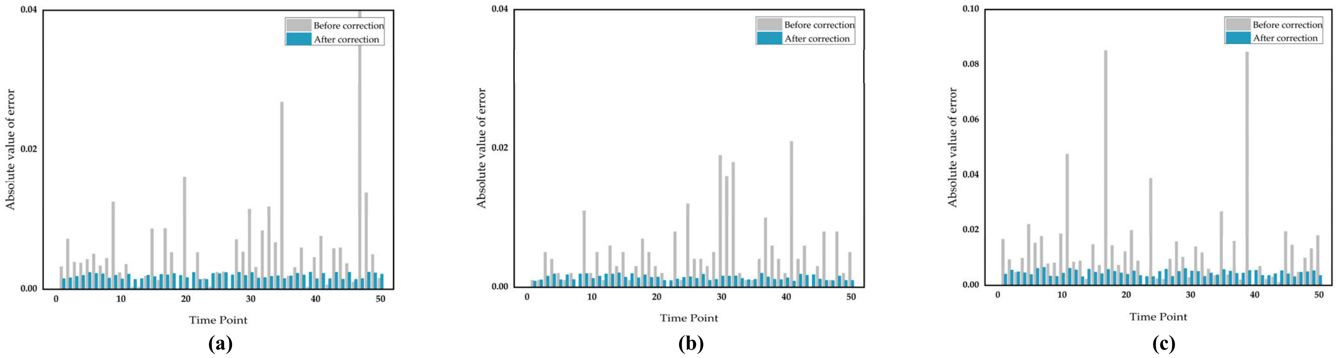


FIGURE 5. (a) Comparison of absolute values of errors before and after residual correction(000198). (b) Comparison of absolute values of errors before and after residual correction(000710). (c) Comparison of absolute values of errors before and after residual correction(000638).

TABLE 6. Comparison of evaluation indicators after introducing residual correction.

Category	Fund Code	Model	MAE	MSE	RMSE	MAPE	R2
THIRD	000198	CNN-LSTM-SAM	0.01039	0.00025	0.01582	0.00636	0.99504
		CNN-LSTM-SAM-XG	0.00556	0.00008	0.00921	0.00355	0.99832
BANK	000710	CNN-LSTM-SAM	0.01108	0.00021	0.01457	0.00637	0.99404
		CNN-LSTM-SAM-XG	0.00492	0.00006	0.00779	0.00286	0.99828
FUND	000638	CNN-LSTM-SAM	0.02513	0.00138	0.03710	0.0152	0.96836
		CNN-LSTM-SAM-XG	0.01365	0.00047	0.0216	0.00823	0.98928

TABLE 7. Seven-day annualized return forecast results for 22 IMFs.

Category	Fund Code	1 March 2023	2 March 2023	3 March 2023	5 March 2023	27 April 2023	28 April 2023
THIRD	000198	1.81658	1.82224	1.82640	1.82968	1.87762	1.87826
	000581	1.67245	1.67409	1.67569	1.67724	1.68371	1.68368
	000359	1.99333	1.99648	2.00123	2.00672	2.10080	2.10097
	000343	1.93964	1.94043	1.93780	1.93782	1.85461	1.85467
	000397	1.85340	1.85501	1.85623	1.85724	1.88549	1.88614
	004972	2.33794	2.32634	2.31747	2.30413	2.29417	2.29437
BANK	000710	1.76636	1.77116	1.77362	1.77510	1.82026	1.82133
	000699	1.93998	1.92990	1.92634	1.92597	2.00032	2.00124
	000686	2.05468	2.01886	1.99628	1.99510	1.95399	1.95263
	000528	1.87166	1.87189	1.87310	1.87476	1.89620	1.89626
	004097	1.66651	1.66884	1.67871	1.70492	1.81133	1.81940
	003534	1.90065	1.90901	1.91607	1.92162	2.00831	2.00969
FUND	000559	2.00919	2.01165	2.01411	2.01656	2.09259	2.09412
	040038	1.72090	1.71915	1.71766	1.71630	1.65960	1.65782
	000475	1.81721	1.79377	1.76848	1.76735	1.64518	1.63139
	001094	1.77514	1.77400	1.77159	1.76858	1.64942	1.64708
	000575	1.92724	1.92948	1.93115	1.93249	1.95121	1.95148
	000734	1.73943	1.73576	1.73212	1.72854	1.68060	1.67777
	000638	1.81457	1.81536	1.80914	1.80792	1.90721	1.91340
	001010	2.06597	2.06323	2.06097	2.05935	1.99407	1.99463
	000424	1.84037	1.82409	1.81751	1.79468	1.85047	1.84963
	000539	1.75909	1.75351	1.74898	1.74596	1.83457	1.83195

correction helps to improve the model prediction accuracy. At the same time, the correction effect of the THIRD series of IMFs (000198) and the BANK series of IMFs (000710) is better than that of the FUND series (000638).

TABLE 8. IMFs VaR values.

Category	Fund Code	IMFs	VaR	Average VaR
THIRD	000198	Tianhong Yu'E Bao	0.03267	0.03576
	000581	Jiashi Huoqianbao A	0.00665	
	000359	Yifangda Yilicai A	0.06625	
	000343	Huaxia Caifubao A	0.05874	
	000397	Huitianfu Quan'E Bao A	0.01858	
	004972	Zhangcheng Shouyi Bao A	0.03165	
BANK	000710	Jiaoyin Xianjin Bao A	0.03021	0.04973
	000699	Zhongyin Xinqianbao	0.04883	
	000686	Jianxin Jiaxin Bao A	0.04223	
	000528	Gongyin Xinjin A	0.01469	
	004097	Nongyin Huili Ririxin A	0.10264	
	003534	Puyin Ansheng Ririfeng A	0.05598	
FUND	000559	Nuoan Tiantian Bao A	0.04996	0.05413
	040038	Huaan Ririxin A	0.03650	
	000475	Guangfa Tiantianli A	0.09017	
	001094	Guotouruiyin Tianli Bao A	0.07815	
	000575	Xingquan Tianli Bao	0.01269	
	000734	Boshi Tiantianzengli A	0.02645	
	000638	Fuguo Fuqianbao A	0.06585	
	001010	Yifangda Zengjin Bao A	0.05264	
	000424	Zhangsheng Tianli Bao A	0.04305	
	000539	Zhongyin Huoqi Bao A	0.08582	

In conclusion, this study builds a CNN-LSTM-SAM-XG model to forecast the IMF's return rate in the next two months.

4) FORECAST RESULTS

Using the CNN-LSTM-SAM-XG model to forecast the returns of 22 IMFs, we obtain seven-day annualized returns from March 1 to April 30, 2023, for 43 days due to the exclusion of weekends. IMFs' return forecasts are shown in Table 7.

B. APPLYING VaR METHODS TO IMPLEMENT RISK METRICS FOR IMFs

The model achieves a total of 43 days, IMFs return forecast, and the risk measure is achieved by applying the VaR model, and the quantitative results of the risk measure for 22 IMFs are shown in Table 8.

IMFs return VaR value represents the risk of the fund, the more significant the VaR value, the higher the risk.

From Table 8, among the 22 IMFs selected in this study, the THIRD series VaR value is 0.03576, the BANK series VaR value is 0.04973, and the FUND series VaR value is 0.05413. It shows that the risk value of investing in the THIRD series is lower than that of the BANK and FUND.

Among the THIRD series, Tianhong Yu'E Bao (000198), Jiashi Huoqianbao A (000581), and Huitianfu Quan'E Bao A (000397) have relatively small VaR values with low risk. Other IMFs have relatively larger VaR values and higher riskiness.

Among the BANK series, Jiaoyin Xianjin Bao A (000710) and Gongyin Xinjin A (000528) have low risky VaR values. The VaR values of the returns of other IMFs are relatively large and risky.

Among the FUND series, Xingquan Tianli Bao (000575) and Boshi Tiantianzengli A (000734) have low VaR risk. The VaR values of the other IMF returns are relatively large and risky.

In summary, the THIRD series IMFs have the lowest risk, the BANK has medium risk, and the FUND has the highest risk. The main reasons as follows: THIRD series transaction mode is "T+0"; the buyer can redeem or use it the same day of purchase consumption, which is very convenient; the BANK series is usually "T+1" mode, which can not do the same day purchase the same day of redemption, the investment funds can only be received the next day. The FUND series is set up by various funding companies, usually for bond funds, and is considered to have high-risk characteristics.

VI. CONCLUSION

In this study, we establish a 1DCNN-LSTM-SAM-XG model to predict the return of IMFs more accurately and predict the actual 43 trading days return data in the next 60 days based on the model. The VaR method is also applied to measure the risk of the prediction results and obtain the more suitable types of IMFs for investment. A summary of the above leads to the following conclusions.

(1) Firstly, the LSTM neural network is optimized according to the 1DCNN and Self-Attention module, which has a solid ability to obtain time-series data features, improving the LSTM network accuracy. The IMFs data are brought in for training, and the CNN-LSTM-SAM is compared with the traditional LSTM and SVR models to learn that the model established in this study has higher prediction accuracy and is suitable for long-period IMFs return prediction.

(2) Secondly, based on the original model, XGBOOST model is introduced as the residual correction layer to further optimize the prediction accuracy. According to the difference between the training XGBOOST prediction result and the actual return rate, the residual sequence is constructed, the residual sequence is compensated with the 1DCNN-LSTM-SAM prediction to achieve the correction effect.

(3) Finally, the CNN-LSTM-SAM-XG model is applied for the future prediction of returns of 22 IMFs with a prediction period of 60 days and actual trading days of 43 days. The risk measure of different IMF returns by introducing the VaR method. According to the VaR value, we can know that among the three IMFs series, the THIRD series is less risky, the BANK series is higher, and the FUND series is the riskiest. And the most suitable IMFs for future investment are Tianhong Yu'E Bao, Jiashi Huoqianbao A, Huitianfu Quan'E Bao A, Jiaoyin Xianjin Bao A, Gongyin Xinjin A, Xingquan Tianli Bao, Boshi Tiantianzengli A, and other IMFs products.

In this study, the CNN-LSTM-SAM-XG model and VaR method are used to predict the return of IMFs and measure the risk of future IMFs' return, but the current study still needs to be improved. First, the number of selected data is limited, the number of products under the three categories of IMFs is significant, and only 22 IMFs return data are selected in this study, which cannot support the conclusion of risk assessment well, so future research needs to expand the sample of more IMFs to make the conclusion more meaningful guidance. Secondly, the attention mechanism and time series forecasting models are still developing, and expert experience also has a guiding role for IMFs return forecasting, so combining more advanced and accurate models with expert experience in the future is essential. Finally, this paper selects the VaR method to realize the risk measure of IMFs' future yield, which is a more direct method in the field of financial risk measurement, in order to carry out a more accurate risk measure of IMFs yield, the VaR method can be improved in the future by combining with the risk characteristics of the yield.

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