A Hybrid Deep Learning Approach for Systemic Financial Risk Prediction

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Abstract. Systemic financial risk prediction is a complex nonlinear problem and tied tightly to financial stability since the recent global financial crisis. In this paper, we propose the Systemic Financial Risk Indicator (SFRI) and a hybrid deep learning model based on CNN and BiGRU to predict systemic financial risk. Experiments have been carried out over Chinese economic and financial actual data, and the results demonstrate that the proposed model achieves superior performance in feature learning and outperformance with the baseline methods in both single-step and multi-step systemic financial risk prediction.

Keywords: Financial risk · Deep learning · Time series prediction

1 Introduction

Systemic financial risk is a crucial issue in economic and financial systems. International experience shows that the outbreak of systemic financial risk almost always causes every financial crisis. Since the 1970s, the Bank for International Settlement (BIS) has begun to recognize the importance of systemic financial risk and integrated identification, monitoring and measurement systemic financial risk into the formulation of financial stability policies. The US mortgage crisis triggered the international financial crisis in 2008, which generated panic and chain reactions of the global economy and financial system, and still has a far-reaching impact on many countries and regions even now. Since then, a large amount of academic research has focused on systemic financial risk over the past decade from different research perspectives, including macroeconomics, econometrics, and complex network theory. Nowadays, financial risk and its related researches are established as a scientific field and provide significant contributions in supporting decision-making in theory and practice [1], and how to accurately measure and predict systemic financial risk so as to effectively prevent and defuse risk has become an active research area [27].

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The systemic financial risk includes low liquidity, inability to pay debts or dividends, continual reduction in profitability, and many other aspects of economic and financial information [29]. Traditional systemic financial risk prediction approaches can be mainly divided into three categories: composite indicator methods, risk contagion measurement methods and stress test methods. Composite indicator methods find out the early warning factors affecting systemic financial risk and use econometric, statistical, multivariate analytical methods to constructs financial stress indices to measurement systemic financial risk. For example, Illing et al. [15] developed the Financial Stress Index (FSI) to describe Canadian financial stability and proposed several techniques including generalized autoregressive conditional heteroscedasticity (GARCH) modelling to extract the information about financial risk, which is a groundbreaking piece of research in this strand of literature. Hollo et al. [12] introduced the Composite Indicator of Systemic Stress (CISS) and proposed a threshold vector autoregressive (VAR) model systemic financial risk level of the euro area. Duca et al. [7] developed a macro index for assessing systemic risks and predicting systemic events. Risk contagion measurement methods measure the risk spillover, analyze the transmission effect among financial institutions, and assess the possibility of systemic financial risk [10,14,20]. Stress test methods use sensitivity analysis, scenario analysis and other approaches to evaluate the financial industry's ability to withstand extreme events that may occur [8,17]. In general, systemic financial risk measurement research based on computer simulation and engineering methods is far fewer compared to econometric-based methods or other statistical analysis methods [27].

In recent years, with the rapid development of big data analysis technology and deep learning, computer engineering methods for forecasting financial time series have become a hot concept and a promising research field [18]. Recent studies have shown that financial time series forecasting is a challenging task, due to it exhibits high volatility and non-stationarity [30]. Traditional statistical models, machine learning methods and artificial neural networks have been widely investigated to deal with this problem in the area of financial markets, financial transactions ,and so forth [26,28]. The authors in [16] introduced ANN to predict daily stock price by using the Korea Composite Stock Price Index (KOSPI) as their dataset. [32] presented a framework where wavelet transforms, stacked autoencoders and long-short term memory (LSTM) are combined for stock index forecasting. In [3], a wavelet-neural time series model was used to forecast EUR/RSD exchange rate. The authors of [22] predicted the price of Bitcoin based on Bayesian optimized RNN and LSTM. [13] proposed an integrated system based on artificial bee colony algorithm to forecast stock markets In [23] and [9], LSTM was used to the prediction the movements of the equity price. The authors of [2] introduced stacked LSTM to predict time series data on the Bombay Stock Exchange (BSE). Besides, [4] and [19] proposed predictive methods based on gated recurrent unit (GRU) for financial time series.

However, due to the difficulty in obtaining data, there have been relatively few studies for systemic financial risk. Some scholars attempted to use machine

learning methodologies to study financial risk measurement and early warning. [5] declared that they presented the first systemic risk model based on big data using a Bayesian approach, and the data are selected by two heterogeneous sources: financial markets and financial tweets. [25] briefly introduced some classic intelligent algorithms such as machine learning, network simulation and fuzzy systems for systemic risk. In the study of [21], they applied support vector machine (SVM) to the prediction of banking systemic risk and conducted a case study of the SVM-based prediction model for Chinese banking systemic risk. Nevertheless, these algorithms are mostly belonging to shallow model, which structure is usually no hidden layer nodes or very few hidden layers.

Summing up, systemic risk is frequently interrelated to various economic and financial factors closely, then predict it essentially is a multivariate time series prediction problem. Because of the dynamic instability and long-term dependence of the time series of systemic financial risk, in this paper, we attempt to develop a predictive approach based on convolutional neural network and bidirectional gated recurrent unit (CNN-BiGRU) to mine, form a model of relevant economic and financial time series data, and predict systemic financial risk trends. At first, we construct a new indicator of systemic financial risk related to macro-economic and financial market. Then, the time series data are fed into CNN-BiGRU networks to further mine information characteristics provided by different data sources in financial data, and establish the nonlinear relationship between the time series of multivariate and systemic financial risk. In order to verify the effectiveness of the proposed method, we compared the prediction performance of several popular learning methods in financial risk problem.

2 Methodologies

2.1 Systemic Financial Risk Measurement Method Base on Composite Indicator

The characteristics of risks are complicated, multifaceted, and concealment in a real-world financial system. Only focus on the risks taken by banks and other financial markets individually was not sufficient to prevent financial crises. According to standard definitions of systemic financial risk, we construct the Systemic Financial Risk Indicator (SFRI) based on the statistical design method, which is a reflection of contemporaneous stress in the financial system and considers the interrelationships between different risk sources. SFRI is inspired by FSI [15] which pays close attention to the financial system risk management. In contrast, we aimed to indicate overall macroeconomic activity and financial risk changes through SFRI, so we attempted to extend the abilities of FSI. In this process, we assume financial risk manifests if and when the indicators move together, and the simultaneous linkage degree of these indicators reflects systemic financial stress.

First of all, let us define a data set of a raw indicator x_t as $x = (x_1, x_2, \cdots, x_n)$, which has n total number of observations in the sample. x_t possesses a variety of distributions that leads to developing a compatible aggregation

scheme with each indicator difficultly. Consequently, it is necessary to transform all indicators to guarantee compatibility before aggregation. We propose a transformation of raw systemic financial risk indicators based on their empirical cumulative distribution function (CDF). The CDF transformation changes the mean to achieve a common measure of central tendency and modifies the range and variance to achieve a common measure of dispersion. Specifically, we calculated this transform by involving the order statistics of each observation. We denote the ordered sample of x_t is x_t is $(x_{[1]}, x_{[2]}, \cdots, x_{[n]})$ where $x_{[1]}$ is the smallest and $x_{[n]}$ is the largest. In other word, we calculated the CDF transform as the rank of each observations divided by the cardinality of x_t similar to [24]. Then, x_t transformed into y_t based on the following empirical distribution function 1:

$$y_t = CDF_n(x_t) = \begin{cases} \dfrac{r}{n}, x_{[r]} \leq x_t \leq x_{r+1}, r = 1, 2, \cdots, n-1 \\ 1, x_t \geq x_{[n]} \end{cases} \tag{1}$$

$CDF_n(\chi)$ measures the total number of observations x_t not exceeding a particular value χ compared to total number of observations in the data set. If a value x of observation occurs more than once, the ranking numbers are set as the average rankings that would have been assigned to each of the observations.

Next, all indicators were grouped into different categories including financial markets and economic spheres. In the absence of any evidence that one submarket contributes more to systemic financial risk than another, we roughly calculated average arithmetic value of indicators for each sub-market (fields) and get the $SFRI$ for each sub-market, the formula is as follows:

$$s_{i,t} = \frac{1}{m} \sum_{j=1}^{m} y_{i,j,t} \tag{2}$$

where $s_{i,t}$ is the ith sub-market $SFRI$ at time t, $(i = 1, 2, \ldots, n)$; m is the number of feature in ith sub-market. This means that each indicator is given equivalent weight in the specific sub-market.

The SFRI is now calculated according to formula 3, and it is continuous, unit-free and bounded by the half-open interval $(0, 1]$.

$$SFRI = (w \odot s_t) C_t (w \odot s_t)' \tag{3}$$

where $w = (w_1, w_2, \cdots, w_n)$ is the vector of weights, and $s_t = (s_{1,t}, s_{2,t}, \cdots, s_{n,t})$ is the vector of indicators at time t. C_t is the matrix of time-varying cross-correlation coefficients $\rho_{ij,t}$ between indicators i and j:

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{2n,t} \\ \vdots & \vdots & 1 & \vdots \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & 1 \end{pmatrix} \tag{4}$$

where $\rho_{ij,t}$ can calculated by exponentially-weighted moving averages (EWMA) method. The formula of EWMA is shown as 5:

$$\begin{aligned} \sigma_{ij,t} &= \lambda\sigma_{ij,t-1} + (1-\lambda)\widetilde{s}_{i,t}\widetilde{s}_{j,t} \\ \sigma^2_{i,t} &= \lambda\sigma^2_{i,t-1} + (1-\lambda)\widetilde{s}^2_{i,t} \\ \rho_{ij,t} &= \sigma_{ij,t}/\sigma_{i,t}\sigma_{j,t} \end{aligned} \tag{5}$$

where $i = 1, 2, \cdots, n$; $j = 1, 2, \cdots, n$; $i \neq j$; $t = 1, 2, \cdots, T$. λ is the smoothing parameter (or decay factor), which is held constant through time.

In this paper, considering the economic and financial situation of developing countries, especially China, we selected prediction indicators of SFRI. Dynamics of financial risk are usually influenced by miscellaneous factors and different sources, such as macro economy, commercial bank, stock market, bond market, and so forth. We selected 36 features (from X_1 to X_{36}) of systemic financial risk characterization grouped into 8 sub-markets categories by synthetically considering the national development situation, degree of importance system, and data availability. The list of prediction indicators is specified in Table 1.

2.2 Convolutional Neural Network for Systemic Financial Risk Feature Extraction

With the help of input preprocessing, the quality of the financial data can be significantly improved. The convolutional neural network (CNN) is a hierarchical feedforward deep neural network model, which usually contains the convolutional layer and pooling layer. The convolutional layer consists of the convolution operation, which is utilized to extract local features for further processing by subsequent layers. The discrete convolution is defined in formula 6:

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \tag{6}$$

where s denotes output which sometimes referred to as the feature map, t denotes time, w denotes kernel, a denotes variable. The pooling operation replaces the output of the net at a specific location with a summary statistic of the nearby outputs. CNN mainly includes three critical characteristics: sparse interactions, parameter sharing, and equivariant representations [11]. Hence, CNN architecture is not only excellent in image or vision processing (such as image classification, image segmentation, and object detection), but also proper for time series analysis [31]. In order to extract features of economic and financial data quickly and predict systemic financial risk trend accurately, we put forward to use 1-D convolutional neural network as a local feature extractor in this paper.

2.3 Bidirectional Gated Recurrent Unit for Systemic Financial Risk Time Series Prediction

Recurrent Neural Networks (RNNs) are one of the attention-attracting technologies of deep learning domain in recent years. RNNs are a family of neural

Table 1. List of prediction indicators of Chinese systemic financial risk

Fields	Indicators
Macro economy ($S1$)	Year-on-year growth of GDP (X_1)
	Year-on-year growth of CPI (X_2)
	Year-on-year growth of CGPI (X_3)
	Year-on-year growth of PPI (X_4)
	Year-on-year growth of in fixed assets total investment(X_5)
	Year-on-year growth of industrial added value (X_6)
	Difference between year-on-year growth of finance rev. and exp. (X_7)
	Registered urban unemployment rate (X_8)
Commercial bank ($S2$)	Deposit-to-loan (X_9)
	Ratio of medium and long term loans to total (X_{10})
	Liquidity ratio (X_{11})
	Capital adequacy ratio (X_{12})
	Non-performing loan ratio (X_{13})
	Year-on-year growth of M2 (X_{14})
	Ratio of Year-on-year growth of M2 to M1 (X_{15})
Stock market ($S3$)	P-E Ratios (X_{16})
	Year-on-year growth of listed companies circulation market value (X_{17})
	Year-on-year growth of total market value of listed companies (X_{18})
	Year-on-year growth of transaction amount of stock (X_{19})
Bond market ($S4$)	Difference between maturity rate of 5-year and 3-month bonds (X_{20})
	ChinaBond new composite index (X_{21})
	Yield gap with 6-month corporate bond to central bank bill (X_{22})
	Year-on-year growth in bond issuance (X_{23})
Monetary market ($S5$)	Fixing Repo Rate (FR007) (X_{24})
	Difference between 1-year and 1-week SHIBOR (X_{25})
	Difference of 1-week SHIBOR and 1-week LIBOR (X_{26})
Insurance market ($S6$)	Year-on-year growth of insurance payout) (X_{27})
	Year-on-year growth of premium income (X_{28})
Foreign exchange market ($S7$)	Real effective exchange rate index (X_{29})
	Year-on-year growth of foreign exchange reserves (X_{30})
	Year-on-year growth of total import and export volume (X_{31})
	Year-on-year growth of actual utilized FDI value (X_{32})
Real estate market ($S8$)	Year-on-year growth of real estate investment (X_{33})
	Residential housing price index (X_{34})
	Year-on-year growth of average price of commercial housing (X_{35})
	Year-on-year growth of total amount of commercial housing (X_{36})

networks for processing a sequence of value $x_1, \cdots, x_\tau$, which maintain a memory cell to store the history information and enables the model to predict the current output based on long-distance features [11]. However, there are some defects of simple RNNs, including vanishing and exploding gradient problems, which means it might take a very long time to learn long-term dependencies tasks. In order to mitigate the shortcomings of the former RNNs, some variants of RNN, like GRU, is proposed.

GRU is a kind of gate-based recurrent unit which has smaller architecture and comparable performance to the LSTM [6]. GRU has two gates(update gate and reset gate), this is the main difference with the LSTM, which is a single gating unit simultaneously controls the forgetting factor and the decision to update the

state unit. Inside a GRU, the update gate $z(t)$ specifics which information can be retained to the next state, and the reset get $r(t)$ specific how the previous state information is combined with the new input information. The formula for the next output and state value in the GRU unit is as follow:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{7}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_f) \tag{8}$$

$$\widetilde{h}_t = tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{9}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h}_t \tag{10}$$

where σ is the activation function which generally uses *sigmoid* function; $x(t)$ denote the input; $h(t-1)$ denote the previous output; b_i, b_f, b_o, b_c, U_z, U_r, U, h, and W_z, W_r, W_h respectively denote the biases, input weights, and recurrent weights into the GRU cell. Due to GRU has fewer parameters, it is faster to train and requires fewer samples.

The GRU model only has a forward pass, and each node will only be affected by the previous one. Nevertheless, for the financial time series prediction task, the features of the rear node will also be useful to the front node. Based on the GRU model, we employ a BiGRU networks which compose by two ordinary GRU, which processes the input sequence from two directions of time series (both chronological and anti-chronological), then merge their representations. The method of the bidirectional training model can provide more useful information in modeling. By viewing systemic financial risk data from two directions enables the model to get richer representations and capture patterns that may be ignored when using one-direction GRU, thereby improving the performance of ordinary GRU.

2.4 CNN-BiGRU Model for Systemic Financial Risk Prediction

From what has been discussed above, the complete methodology and overall framework of CNN-BiGRU model for systemic financial risk are shown in Fig. 1. The whole model is divided into four major parts.

1. SFRI is calculated and educed by original economic and financial data.
2. 1-D CNN used to acquire local features and dimensionality reduction on systemic financial risk indicators. The input sequences are processing by 1-D CNN through convolution and pooling operation, and the features of time series are selected.
3. the feature sequences are fed into the BiGRU networks, so that it can learn the time dependence relationship between the information extracted from 1-D CNN. By processing a sequence both way, BiGRU networks can catch patterns that may have been overlooked by one-direction GRU.
4. At the end of the framework, the fully connected layers are stacked.

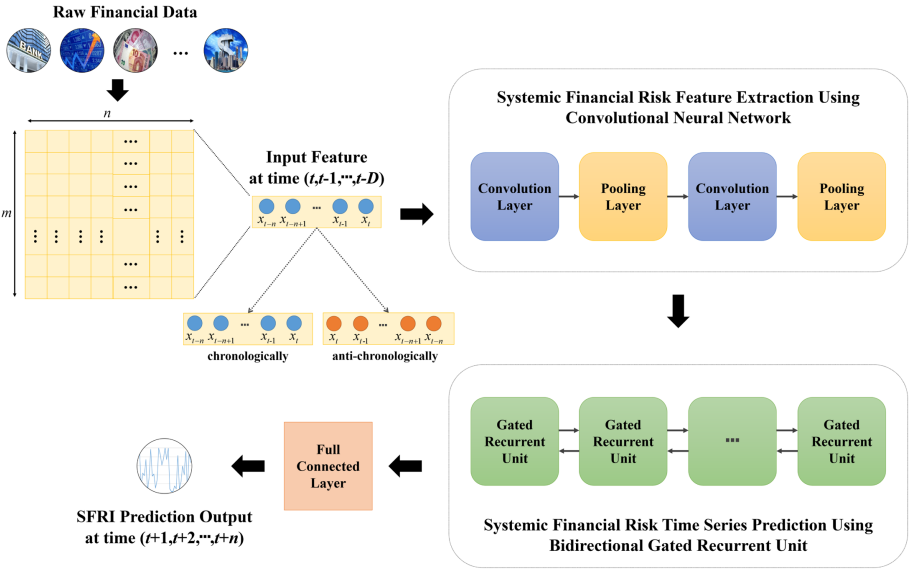

Fig. 1. The overall framework of convolutional neural network and bidirectional gated recurrent unit for systemic financial risk prediction.

3 Experiments and Results

In this section, the detailed steps of our experimental implementation and the analysis of the results are described. We choose the Chinese financial system as an example to evaluate the proposed prediction model for systemic financial risk and conduct empirical analysis based on the existing Chinese economic and financial data set.

3.1 Dataset and Data Preprocessing

The experimental dataset used for this paper is the financial time series data of China from the first trading day of 2016 to the end of March 2019. which contained 4837 independent observation points (daily). All data samples are from relevant departments of the Chinese government, including People's Bank of China (PBC), National Bureau of Statistics of China (NBS), National Development and Reform Commission (NDRC), China Bank and Insurance Regulatory Commission (CBIRC), and China Securities Regulatory Commission (CSRC). Because the sampling frequency of some variables is different, we converted data from one frequency to another by Denton method. which uses statistical interpolation minimizing the proportional first difference between the interpolated and high frequency target series. For example, data of year-on-year growth of GDP (X_1) in Table 1 moved from monthly to daily. Data normalization can avoid attribute over-branch of large-valued intervals with features of small-valued intervals and reduce computational complexity in the calculation process. According

1 and 2, we computed each sub-market $SFRI$. Then, we calculated sub-market weight based on the sub-market $SFRI$ by PCA (Principal Components Analysis) algorithm. According to the algorithm 3 mentioned above, the vector of weights $w = (w_1, w_2, \cdots, w_n)$ is w =(0.1633, 0.1257, 0.0915, 0.1276, 0.0776, 0.1292, 0.1521, 0.133), and then we composite SFRI.

3.2 Performance Evaluation Metrics

In this paper, the loss function is defined by Mean Absolute Error (MAE). MAE is an excellent way to reflect the actual situation of the prediction error, which is defined as follow 11:

$$MAE_{(y',y)} = \frac{1}{n}\sum_{i=1}^{n}|y'_i - y_i| \tag{11}$$

Meanwhile, Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE) and R squared(R^2) is selected to evaluate the performance of the deep learning network, the calculation formula is as shown in formula 12, 13, 14, and 15.

$$RMSE_{(y',y)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y'_i - y_i)^2} \tag{12}$$

$$MAPE_{(y',y)} = \frac{1}{n}\sum_{i=1}^{n}|\frac{y'_i - y_i}{y_i}| \tag{13}$$

$$SMAPE_{(y',y)} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y'_i - y_i|}{(y'_i + y_i)/2} \tag{14}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y'_i - y_i)^2}{\sum_{i=1}^{n}(y'_i - \overline{y})^2} \tag{15}$$

which n is the total number of samples, y and y' denote the observation value and its forecast value respectively.

3.3 Experimental Configuration

The proposed CNN-BiGRU model for systemic financial risk prediction was trained on Keras framework with TensorFlow backend, while comparative machine learning methods are implemented by the scikit-learn library. At first, we set up the hyperparameters for the proposed models. The training implemented in mini-batches with a batch size of 120, and all the models trained for 100 epochs. In order to avoid the overfitting problem, a dropout factor used between layers with a probability of 0.2. If the loss of past epoch is higher than the current epoch, weight matrices are stored. The adam optimization algorithm

was employed with learning rate of 0.001 The ReLU selected as the activation function, which has a significant impact on the convergence of random financial risk samples. Furthermore, all models used an early stopping condition during the training, which stops the training if the validation loss on the validation data does not change within ten training epochs. The training set used to train model while the test set used independently to validate the model accuracy and assess the performance of the model. We use a spilled ratio of 70% for training and 30% for testing in the experiments.

Table 2. Effect of the number of neurons in bidirectional GRU model.

Neurons	MAE	RMSE	MAPE	SMAPE	R^2
20	0.00859	0.01167	0.36039	0.27364	0.83431
40	0.00776	0.01131	0.22373	0.19852	0.852
60	0.00567	0.0087	0.16849	0.16765	0.91243
80	0.00553	0.00964	0.13683	0.14316	0.89263
100	0.00772	0.01196	0.21477	0.19577	0.89467
120	0.00732	0.01055	0.18523	0.19709	0.8712

In the CNN part, it contains two convolutional layers with activation functions of ReLU, and each layer have 120 convolution kernel (filter) as feature extractor, the length of the filter window size is 5. In the BiGRU part, the number of deep learning neurons set to an equivalent value chosen from a candidate set. Several experiments were performed, and the corresponding errors recorded in Table 2. The results show that with the increase of neurons of the hidden layer, the forecasting performance first improves significantly and then begins to deteriorate. Under the same configuration, over-fitting problems arise when neurons exceed 60. Hence, we set the number of neurons to 60 in the successive experiments. The training algorithm description is shown in Algorithm 1.

3.4 Experimental Results and Discussion

Preliminary Verification. After model training to convergence, we obtained the optimal model weights of the CNN-BiGRU systemic financial risk prediction. Figure 2 provides the calculated and single-step predicted values of SFRI from the proposed CNN-BiGRU model. The results of the multi-step prediction will be soon in a later section. From Fig. 2, it is observed that the green curve is satisfactory fitting the blue curve. It illustrates that the CNN-BiGRU model produced outstanding results that can follow the fluctuations of raw values during the testing set successfully. Hence, it proved that CNN-BiGRU architecture is adequate for predicting systemic financial risk. Further, in order to find the optimal CNN-BiGRU model, different convolutional layers were generated, and the experimental results are shown in Table 3, from which we can see that as the

Algorithm 1. The CNN-BiGRU model training algorithm

Input: The Original economic and financial data train_X/Y, valid_X/Y, test_X/Y at time $(t, t-1, \ldots, t-D)$.

Output: The SFRI prediction at time $(t+1, t+2, \ldots, t+n)$.

```
Initialization of time series data and model parameters.
define model
    add Convolution Layer (Conv1D)
    add Pooling Layer(MaxPooling)
    add Convolution Layer(Conv1D)
    add Pooling Layer(MaxPooling)
    add Bidirectional GRU
    add Full Connected Layer
repeat
  Forward propagate model with train_X
  Backward propagate model with train_Y
  Update model parameters
  train_MSE, train_MAE = model(train_X, train_Y)
  valid_MSE, valid_MAE = model(valid_X, valid_Y)
until train_MSE, valid_MSE remains the same in the previous iteration or reach
  certain threshold
test_MSE, test_MAE = model(test_X, test_Y)
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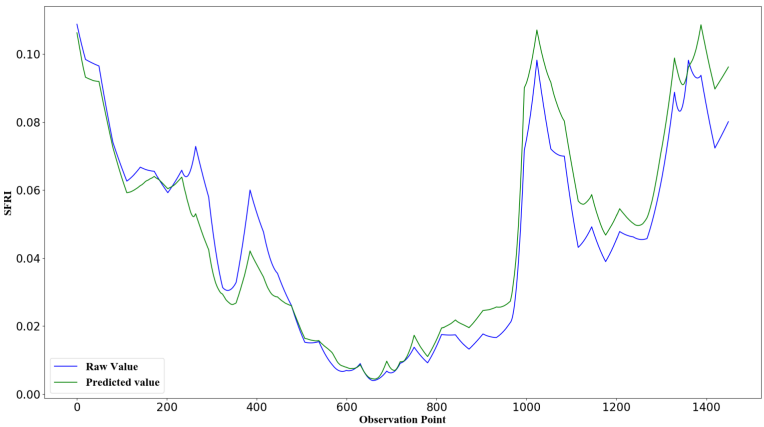


Fig. 2. Systemic financial risk prediction result of proposed model.

number of convolutional layers increases, the computation time of each epoch also increases but the performance of SFRI prediction is reduced. In terms of R^2, CNN-BiGRU model with two convolutional layers is 0.11 higher than CNN-BiGRU model with five convolutional layers, at the same time, computation time per epoch reduce by 42.7%. The reason for this may be that too many

convolution layers may lead to overfitting. When the convolutional layers are two, the prediction accuracy of SFRI is the highest, which indicates that it may achieve the best effects. Therefore, we choose the CNN-BiGRU model with two convolutional layers.

Table 3. Performance comparison of the proposed model with different convolutional layers.

Layers	MAE	RMSE	MAPE	SMAPE	R^2	Time
1	0.0122	0.0194	0.3081	0.267	0.5409	15.6 s
2	0.0057	0.0087	0.1685	0.1677	0.9124	37.4 s
3	0.0064	0.0101	0.1324	0.1377	0.8762	42.5 s
4	0.0106	0.015	0.2202	0.2548	0.726	52.2 s
5	0.0085	0.0128	0.2009	0.2067	0.8012	65.3 s

Comparative Analysis. From the view of the existing literature, the studies of financial time series forecasting are focused on predicting the next price movement of the underlying asset, for instance, stock price prediction, bond price forecasting, commodity (such as oil, gold) price prediction, and so on [26]. However, there are few studies about financial risk trend prediction, and most of them focus on financial risks in a single field (bank bankruptcy risk) rather than systemic financial risks. To show the performance advantage of CNN-BiGRU architecture, we built several well-known deep learning methods for financial time series forecasting to evaluate the performance of the proposed model in comparative experiments. For fairness, all reference deep learning models in this experiment used the same hidden layers and the number of neurons, Besides, the input to other models was using the chronological data sample except the proposed model and BiGRU model.

- **RNN** [13,22]: Simple RNN network is a commonly used model for time-sequential data processing such as stock price forecasting, index prediction, and cryptocurrency price prediction.
- **LSTM** [9,23]: Standard LSTM model is a specialized version of RNN, which can remember both short term and long term values. LSTM network is the preferred choice of many researchers and developers in financial time series forecasting.
- **Stacked LSTM** [2]: Stacked LSTM is a model with multiple hidden LSTM layers, which can predict multiple future time steps of the financial market based on the historical data. Two LSTM layers are used in our experiments.
- **BiGRU** [4,19]: The GRU architecture is similar to the LSTM model and has some applications in processing financial time series data. The BiGRU network is selected to verify the influence of two-way inputs.

Figure 3 shows the single-step predicted values of SFRI from the compared models. Generally, these results summarize that the proposed CNN-BiGRU

model achieves obvious superiority in terms of its performance compared with the baseline models. For example, the SMAPE value of the proposed method is 0.02, 0.08, 0.17 higher than those of stacked LSTM, LSTM, BiGRU, respectively. The performances of two-way training models are improved obviously compared with other traditional models. Also interesting is all comparison methods except the CNN-BiGUR model fails at the tail of SFRI time series. From the above analysis, it can be found that the CNN-BiGRU model is more sensitive to long-term dependencies features, which mainly attributed to the existence of bidirectional GRU architecture. Besides, we further focus on the comparison between CNN-BiGRU and BiGRU, which can be viewed as ablation studies that remove CNN parts from the proposed model. From Table 4, we observe that BiGRU performs significantly worse when used alone than the fusion architecture of CNN and BiGRU. Take MAPE for example, the value of the proposed method is 35% higher than that of BiGRU. This confirms that the implementations of CNN in the model proposed in this paper can capture richer local trend information systemic financial risk. To sum up, it demonstrated that the CNN-BiGRU model could learn intricate patterns from economic and financial data batter than others, which indicates that using the fusion scheme of CNN and BiGRU is the proper approach.

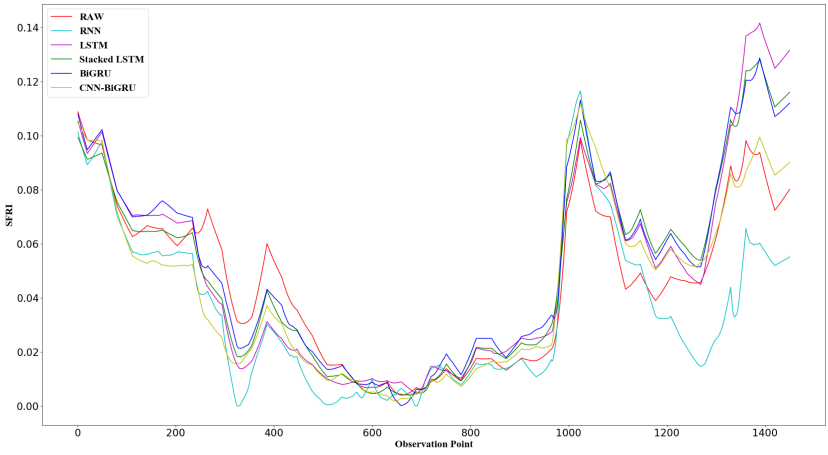


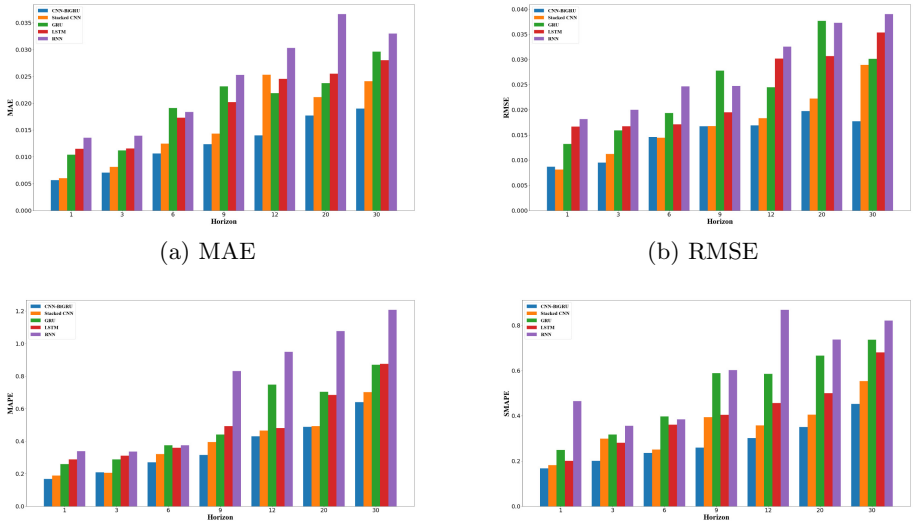
Fig. 3. The prediction results of compared models.

Multi-step Prediction Results. To investigate the capacity for multi-step prediction performance of different models, we considered seven horizon values. In Fig. 4, we can see that the prediction errors of all methods grow as the horizon increases. It indicates that the proposed CNN-BiGRU model is superior to others at all time horizons and achieves relatively a quality of higher precision with numerical stability for long-term prediction. Meanwhile, we can see that in the case of single-step prediction, the performance of stacked LSTM and the

Table 4. Performance comparison of different models for systemic financial risk prediction.

Method	MAE	RMSE	MAPE	SMAPE	R^2
RNN	0.01358	0.01814	0.33895	0.46517	0.59965
LSTM	0.0115	0.01667	0.2876	0.28151	0.66194
Stacked LSTM	0.00603	0.00814	0.18906	0.18057	0.90946
BiGRU	0.0104	0.01321	0.25978	0.24938	0.78755
CNN-BiGRU	0.00567	0.0087	0.16849	0.16765	0.91243

proposed model at nearly the same level. However, with the number of prediction steps increases, the CNN-BiGRU model performs much better than stacked LSTM. This implies that our proposed model with the fusion mechanism of convolutional layers and bidirectional gated recurrent units is significantly effective, which can extract features from historical data and accurate predicting trends in a long time. For instance, in terms of the 30-step prediction, the SMAPE value of the proposed method is improved 22.2% compared with stacked LSTM.



(a) MAE (b) RMSE

(c) MAPE (d) SMAPE

Fig. 4. The multi-step prediction performance of the compared models.

4 Conclusions and Future Work

Systemic financial risk prediction is a complex nonlinear problem and linked closely to financial stability. Dynamics of financial risk are usually influenced by miscellaneous factors and different sources. According to the complex nonlinear

characteristics of financial risk, in this paper, we employ data-driven design method to construct SFRI, which can reflect the overall financial risk level of the entire financial system due to uncertainty and loss of forecasting changes. On this foundation, we proposed a model based on CNN-BiGRU to accurately predict degree and future trends of systemic financial risk.

To verify the performance of the method proposed in the paper, experiments have been carried out over Chinese economic and financial actual data collected from relevant departments of the Chinese government. Thirty-six features of Chinese systemic financial risk characterization from eight sub-markets by synthetically considering the national development situation, degree of importance system, and data availability, including macro economy, commercial bank, stock market, bond market, monetary market, insurance market, foreign exchange market, real estate market. The example verification results show that the CNN-BiGRU model can achieve better performance of systemic financial risk prediction than other baseline methods. It is probably because the CNN-BiGRU architecture processes the financial risk time series chronologically and antichronologically, which captures feature patterns that may be ignored by unidirectional deep learning models. At the same time, we discuss the multi-step prediction performance of the CNN-BiGRU model, and the results show that it could lead to more accurate prediction results than other baseline models. In the future, we will aim at verifying CNN-BiGRU model in systemic financial risk prediction of different countries and regions.

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