# A PCA-IGRU Model for Stock Price Prediction

*Jingyang Wang, Daoqun Liu, Lukai Jin, Qiuhong Sun, Zhihong Xue**

*Hebei University of Science and Technology, China*
*jingyangw@hebust.edu.cn, 1520822447@qq.com, 1245351277@qq.com, Sunqiuhong@hebust.edu.cn, xzh_hebust@163.com*

## Abstract

Accurate stock price prediction is significant for investors to avoid risks and improve the return on investment. Stock price prediction is a typical nonlinear time-series problem, which many factors affect. Still, too much analysis of influencing factors will lead to input redundancy and a large amount of computation in the model. Although the stock prediction model based on Recurrent Neural Network (RNN) has a good prediction effect, it has the problem of oversaturation. This paper proposes a prediction model of stock closing price based on Principal Component Analysis (PCA) and Improved Gated Recurrent Unit (IGRU), PCA-IGRU. PCA can reduce the redundancy of input information without destroying the correlation of original data, thus reducing the time of model training and prediction. IGRU is an improved Gated Recurrent Unit (GRU) model, which prevents oversaturation by introducing the Anti-oversaturation Conversion Module (ACM) and enhances the sensitivity of model learning. This paper selects the stock trading data of the Shanghai Composite Index (SCI) of China as experimental data. The PCA-IGRU is compared with seven baseline models. The experimental results show that the model has better prediction accuracy and shorter training time.

**Keywords:** PCA, IGRU, Stock closing price prediction, Deep learning

## 1 Introduction

With the financial market development, stock trading has become a common investment method. Stock trading has the characteristics of high risk and high return [1], so stock price prediction has become the key concern and research in the financial field. As the stock market's scale grows, the market environment becomes more and more complex, and its fluctuation trend is complex and nonlinear. Therefore, scientific and efficient research methods for stock prediction are critical [2-3]. Neural networks have been developing and improving, like Memristive Neural Networks (MNN) [4-5] and Discrete-time Recurrent Neural Networks (DRNN) [6]. But stock price prediction is still a complex task, and stock price prediction models still need to be improved [7-8].

This paper proposes a PCA-IGRU-based model to predict the stock closing price. When predicting the stock closing price, a large number of multivariate data sets will provide abundant information for model training. Still, they also increase the workloads of data collecting and processing to a certain extent. Besides, there may be a correlation among many influencing factors, which increases the complexity of problem analysis and information redundancy. If the analysis indicators are reduced blindly, the experiment will lose a lot of helpful information, resulting in wrong conclusions. Therefore, PCA technology is used in this paper to minimize analysis indicators and redundancy under as little as possible sample data loss to analyze the data collected comprehensively. In this paper, ACM is introduced based on GRU, which makes the model more sensitive to the previous learning, thus improving the prediction accuracy of the PCA-IGRU. This paper selects the stock trading data of the SCI of China from January 1, 1992, to March 31, 2022, as the experimental data. The PCA-IGRU is compared with Long Short Term Memory (LSTM), GRU, IGRU, PCA-LSTM, PCA-GRU, CNN-LSTM, and SVR models to verify the prediction effect of the PCA-IGRU. The experimental results show that the PCA-IGRU has better prediction accuracy and shorter training time.

This paper's main contribution is as follows:

(1) PCA technology can reduce the correlation between input data by transforming high-dimensional data into low-dimensional data while ensuring it has as little as possible sample data loss. Therefore, the influence of reduced-dimensional principal component on stock closing price is more significant.

(2) IGRU improves GRU by introducing ACM to prevent oversaturation. The information of the previous moment passes through the Swish activation function after the reset gate, making the model more sensitive to the learning of the previous moment and improving the model's prediction accuracy.

(3) This paper proposes a PCA-IGRU model to predict the stock closing price. LSTM, GRU, IGRU, PCA-LSTM, PCA-GRU, CNN-LSTM, and SVR are used as comparison models. The experimental results show that PCA-IGRU has better prediction accuracy and shorter training time.

## 2 Related Works

The stock prediction has always been a research hotspot in the financial field. In 2014, Xia et al. proposed a method for stock price prediction based on Support Vector Regression (SVR). SVR had good scalability for high-dimensional data

*Corresponding Author: Zhihong Xue; E-mail: xzh_hebust@163.com
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through kernel function, but SVR still had shortcomings in solving multi-classification and large-scale nonlinear regression problems [9]. In 2015, Chen et al. proposed an LSTM based method to predict stock return. They cited the Chinese stock market to analyze the influence of different input characteristics on LSTM prediction results. And they achieved good results, but the analysis of influencing factors of the stock price was not comprehensive enough [10].

In 2017, Hua et al. proposed a PCA-ARIMA-BP model for stock price prediction and compared it with BP, PCA-BP, and other neural network models. The results showed that the PCA-ARIMA-BP had better prediction accuracy, but the effect of ARIMA in analyzing nonlinear problems needed to be improved. And BP neural network had the shortcomings of long training time and insufficient generalization ability [11]. In 2018, Lv et al. proposed an LSTM based on Particle Swarm Optimization (PSO-LSTM) to predict the closing price of the stock and introduced PSO to optimize the weight of LSTM to reduce the prediction error. The improved LSTM had better prediction accuracy [12]. In 2019, Hu et al. proposed a prediction method of oil well production based on PCA-GRU. PCA could reduce the dimension of input data. GRU could alleviate the gradient explosion and gradient disappearance of the RNN. The results showed that PCA-GRU had a good performance [13]. In 2020, Lu et al. proposed a composite model of Convolutional Neural Networks (CNN) and LSTM, CNN-LSTM, taking the historical transaction data of the SCI as experimental data and comparing CNN-LSTM with baseline models. The results showed that CNN-LSTM had better prediction accuracy. However, this experiment only considered the stock trading indicators as the influencing factor of the closing price, so the analysis was not comprehensive enough [14]. In 2021, Prajitno et al. used GRU to predict McDonald's stock price. The results showed that GRU had a good effect on stock price prediction, but the prediction accuracy of a single model needed to be improved [15]. In 2022, Sheng et al. combined PCA and LSTM to predict stock price. The experimental results showed that the prediction accuracy of the PCA-LSTM was better than other baseline models. However, compared with LSTM, GRU has a better effect on stock forecasting due to its simpler structure [16].

## 3 Models

### 3.1 PCA

Researchers may introduce as many factors as possible into the study when analyzing the multiple influencing factors, leading to information redundancy and computation increase. The PCA is a statistical method of dimensionality reduction, which can transform multiple indicators into several comprehensive indicators under little information loss. Each principal component is a linear combination of original variables, and each one is unrelated, so the original variables can be expressed with lower-dimensional data on the premise of losing little information [17-18]. The PCA is used to reduce the dimension of feature data affecting stock price in this paper.

### 3.2 IGRU

RNN has a good learning ability and is widely used in time-series prediction problems [19]. Hochreiter et al. improve RNN and put forward the LSTM model [20]. LSTM adds the cell state that can maintain the long-term state and gated technologies such as forget gate, input gate and output gate so that LSTM can memorize and learn the input information for a long time [21-22].

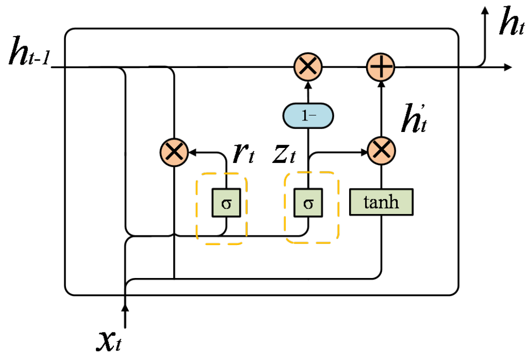


**Figure 1.** GRU structure

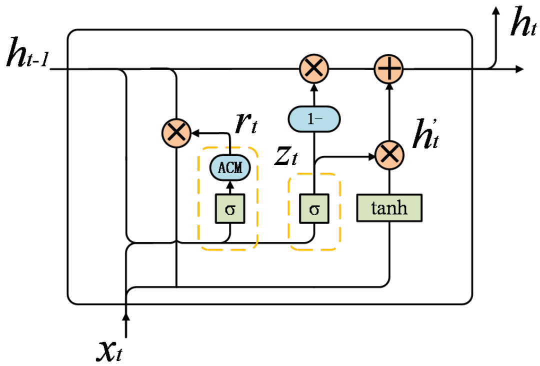


**Figure 2.** IGRU structure

As shown in Figure 1, GRU simplifies the internal structure based on LSTM [23-24]. The GRU has two gates, an update gate and a reset gate. The update gate controls the retention degree of information at the current and previous moment. The reset gate is used to control the retention degree of the previous moment information in the current candidate set $h_t'$. GRU removes the memory cell of linear self-updating and directly uses gating to carry out linear self-updating in hidden cells [25-27].

As shown in Figure 2, IGRU introduces ACM into GRU, and the computation processes are as follows:

(1) The update gate mainly controls the retention degree of information at the current and previous moment. In the time step t, formula (1) is used to calculate the update gate $z_t$.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]). \tag{1}$$

In formula (1), $x_t$ is the input vector at the current moment. $h_{t-1}$ is the hidden state of the previous moment. $x_t$ and $h_{t-1}$ are separately weighted summed, where $W_z$ is the weight matrix of the update gate. Then the summation is processed by the Sigmoid activation function, the output $z_t$ of the update gate is obtained, and the range of $z_t$ is between 0 and 1.

(2) The reset gate controls the retention degree of hidden state information at the previous moment. The computation method is shown in formula (2). In the same way as the data processing of the update gate, the information of the previous moment $h_{t-1}$ and the current moment $x_t$ of the reset gate are linearly transformed respectively. The two parts of the linear transformation are combined and then processed by the Sigmoid activation function.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]). \tag{2}$$

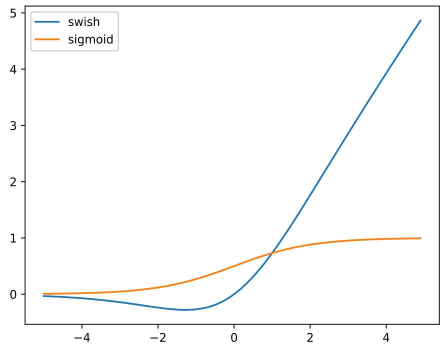


**Figure 3.** Swish, Sigmoid function

The Sigmoid activation function values are between 0 and 1, and the closer it is to 0 or 1, the lower the sensitivity of model learning is. The ACM can improve the learning sensibility of the model to the input data. As shown in formula (3) and formula (4), when the data pass through the reset gate, it is transformed by ACM, that is, by the Swish function. As shown in Figure 3, Swish is a smooth function between the linear function and Relu function, and β is an adjustable constant. The Swish function is smooth and monotonous within intervals of (0, 1). Therefore, the reset gate value obtained after the Swish transformation will be more significant.

$$\mathrm{Swish}(x) = x \cdot Sigmoid(\beta x). \tag{3}$$

$$\mathrm{ACM} = \mathrm{Swish}(r_t). \tag{4}$$

(3) First, $h_{t-1}$ and $x_t$ are multiplied by weight matrices and to perform the linear transformation, respectively. Then the Hadamard product of ACM and $U \cdot h_{t-1}$ is calculated, which will determine the historical information to be retained and forgotten. Finally, the two parts are summed, and then the summed data are processed by the Tanh activation function, as shown in formula (5).

$$h_t^{'} = \tanh(W \cdot x_t + \mathrm{ACM} * U \cdot h_{t-1}). \tag{5}$$

(4) $z_t * h_{t-1}$ represents the extent to which the information in the hidden state of the previous moment is retained at the current moment. $(1 - z_t) * h_t^{'}$ represents the retention degree of information in the candidate hidden set of the current time. The combination of these two parts of retained information is the hidden state of the current moment $h_t$, as shown in formula (6).

$$h_t = z_t * h_{t-1} + (1 - z_t) * h_t^{'}. \tag{6}$$

### 3.3 PCA-IGRU

The whole structure of PCA-IGRU is shown in Figure 4, consisting of the input layer, PCA layer, IGRU layer, and output layer. Firstly, the historical trading indicators data of the SCI and other important market index closing price are used as the input data. The principal component of stock influencing factors is selected after PCA dimensionality reduction. Then, time-series data are constructed and input into the IGRU model. Through the training of the model, the appropriate parameters and weight matrix can be learned, and SCI's closing price on the next trading day is output as the forecast result.

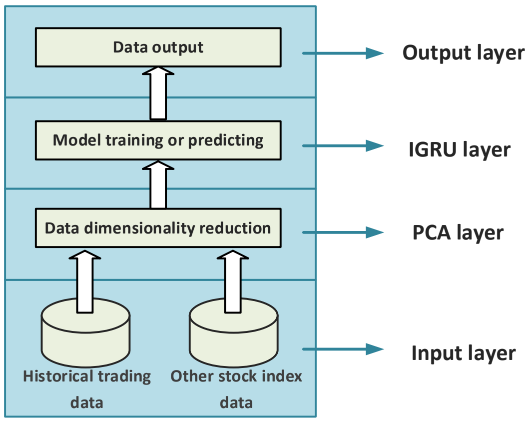


**Figure 4.** Model framework

## 4 Experiment

### 4.1 Experimental Environment

The experimental environment of this paper is shown in Table 1.

**Table 1.** Experimental environment

| Item | Type |
|---|---|
| Operation system | Windows 10 |
| CPU | Core i5-10300H |
| Memory | 8.00GB |
| GPU | NVIDIA GTX1650Ti |
| Development tool | PyCharm 2020.1.3 x64 |
| Programing language | Python3.7.0 |
| Learning framework | keras2.1.0, TensorFlow1.14.0 |

### 4.2 Experimental Data

This paper selects the trading indicators data of the SCI, the closing price of the NASDAQ Composite Index (NASDAQ), the closing price of the Dow Jones Industrial Average Index (DJIA), the closing price of the Hang

Seng Index (HSI), and the closing price of the Shenzhen Component Index (SZ) as the experimental data. These data are generated from January 1, 1992, to March 31, 2022. To some extent, the SCI reflects the status of China's market economy. The trading indicators data of the SCI are shown in Table 2. The closing price of the SCI is also affected by the closing price of some important international stock indexes under the trend of economic globalization, as shown in Table 3.

In Table 2, Pre is the previous closing price of the SCI, Opening is the opening price, Highest is the highest price, Lowest is the lowest price, Closing is the closing price, Volume is the trading volume, Turnover is the trading amount, Rise & Fall is the rising & falling volume, and Rate is the rising & falling rate. In Table 3, HSI, NASDAQ, DJIA, and SZ respectively refer to the closing price of the HSI, NASDAQ, DJIA, and SZ.

**Table 2.** The trading indicators data of the SCI

| Date | Pre | Opening | Highest | Lowest | Closing | Volume | Turnover | Rise & Fall | Rate |
|---|---|---|---|---|---|---|---|---|---|
| 2021/9/13 | 3703.1103 | 3699.2534 | 3716.8315 | 3692.8157 | 3715.3723 | 55748401900 | 696192000000 | 12.262 | 0.3311 |
| 2021/9/14 | 3715.3723 | 3709.6336 | 3723.8451 | 3655.6341 | 3662.6015 | 56495238600 | 693778000000 | -52.7708 | -1.4203 |
| 2021/9/15 | 3662.6015 | 3651.1583 | 3677.5265 | 3638.3225 | 3656.2232 | 47497000100 | 604232000000 | -6.3783 | -0.1741 |
| 2021/9/16 | 3656.2232 | 3664.841 | 3677.9198 | 3606.7276 | 3607.0922 | 54674147400 | 673955000000 | -49.131 | -1.3438 |
| 2021/9/17 | 3607.0922 | 3595.2715 | 3620.9575 | 3569.2707 | 3613.9663 | 51685021000 | 628834000000 | 6.8741 | 0.1906 |

**Table 3.** The closing price of other stock indexes

| Date | HSI | NASDAQ | DJIA | SZ |
|---|---|---|---|---|
| 2021/9/13 | 25813.81 | 15105.58 | 34869.63 | 14705.8272 |
| 2021/9/14 | 25502.23 | 15037.76 | 34577.57 | 14626.0848 |
| 2021/9/15 | 25033.21 | 15161.53 | 34814.39 | 14536.3136 |
| 2021/9/16 | 24667.85 | 15181.92 | 34751.32 | 14258.1299 |
| 2021/9/17 | 24920.76 | 15043.97 | 34584.88 | 14359.3583 |

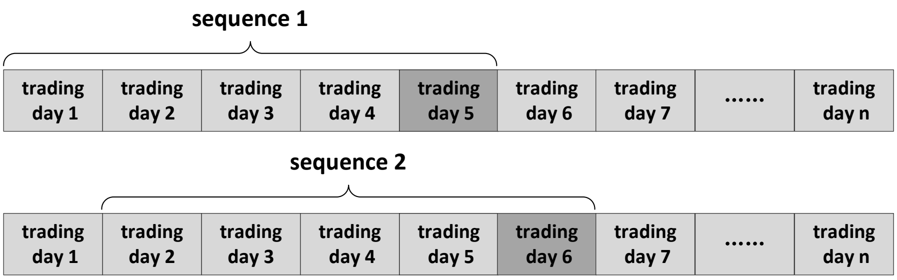


**Figure 5.** Time-series data construction

### 4.3 Data Preprocessing

(1) Data cleaning: In this paper, the moving average method is used to fill in the missing values of the data set and maintain the greatest correlation with the original data.

(2) Division of experimental data: In this paper, the first 6300 pieces of experimental data are used as training data, and the last 1100 pieces are used as test data.

(3) Building time-series data: Stock trading data are historically dependent. In combination with the regulation of stock trading days and experimental experience. As shown in Figure 5, this paper selects the stock trading data of the first four trading days as the input of the model and the stock closing price of the next trading day as the output.

### 4.4 Principal Component Selection

When studying complex problems like stock price prediction, only a few principal components can be considered by the PCA technique to simplify the problem and improve the efficiency of the analysis. The specific steps are as follows:

(1) Data standardization. Standardization can reduce the dimensional difference between the sample data without affecting the changing trend of the original data. The computation method is as shown in formula (7).

$$X = \frac{x_{ij} - \overline{x}_j}{\sigma_j}. \tag{7}$$

Where $\overline{x}_j$ is the average of characteristic $j$ and $\sigma_j$ is the standard deviation of characteristic $j$.

(2) Calculate the covariance; matrix R from the standard deviation matrix X, then calculate the eigenvalue $\lambda$ and the eigenvector $I$ of matrix R, and arrange the eigenvalues in descending order: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p$. The computation method is as shown in formula (8).

$$R = \frac{1}{n} XX^T, \ |\lambda I - R| = 0. \tag{8}$$

(3) Calculate the variance contribution rate. $\lambda_k$ is the k-th characteristic value, $\alpha_k$ is the variance contribution rate of the k-th principal component, and the computation method is shown in formula (9).

$$\alpha_k = \frac{\lambda_k}{\lambda_1 + \lambda_2 + \ldots + \lambda_p}. \quad \textbf{(9)}$$

(4) Calculate the cumulative variance contribution rate. The cumulative variance contribution rate of the first m principal components is calculated as shown in formula (10), $\lambda_i$ is the eigenvalue of the matrix.

$$sum = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{p} \lambda_i}. \quad \textbf{(10)}$$

(5) The eigenvectors corresponding to the first m eigenvalues form a coefficient matrix P. The original matrix X is multiplied by the coefficient matrix P to obtain the reduced dimension data.

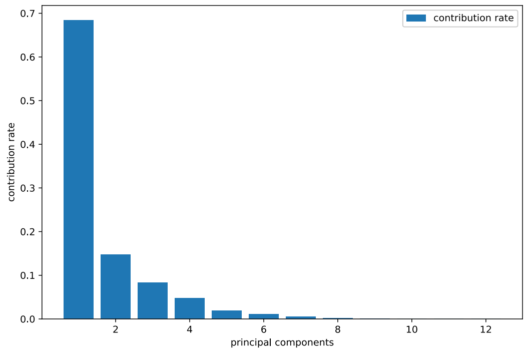


**Figure 6.** Variance contribution rate of each component.

Figure 6 is a histogram showing the contribution rate of variance for each component. Table 4 shows that the variance contribution rate of the first six principal components has accumulated to 99%, representing most of the original information. At the same time, it reduces the data dimension and the redundancy of the model's input data. Therefore, $Y_1$-$Y_6$ are selected as the principal components of the influencing factors of the stock closing price in this paper. The calculation results of PCA are shown in Table 5.

**Table 4.** Cumulative variance contribution

| Component | Variance contribution | Cumulative contribution rate |
|---|---|---|
| $Y_1$ | 0.6836 | 0.6836 |
| $Y_2$ | 0.1479 | 0.8315 |
| $Y_3$ | 0.0834 | 0.9149 |
| $Y_4$ | 0.0473 | 0.9622 |
| $Y_5$ | 0.0191 | 0.9813 |
| $Y_6$ | 0.0105 | 0.9918 |

**Table 5.** The calculation results of PCA

| | $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ | $Y_5$ | $Y_6$ |
|---|---|---|---|---|---|---|
| Pre | 0.334 | 0.334 | 0.333 | 0.334 | 0.294 | 0.292 |
| Opening | -0.026 | -0.019 | -0.010 | -0.010 | 0.037 | 0.033 |
| Highest | -0.281 | -0.281 | -0.283 | -0.280 | 0.357 | 0.336 |
| Lowest | 0.007 | 0.007 | 0.014 | 0.002 | 0.507 | 0.560 |
| Volume | 0.016 | 0.018 | 0.009 | 0.006 | -0.005 | 0.007 |
| Turnover | -0.164 | 0.166 | -0.165 | -0.164 | -0.200 | -0.054 |
| Rise & Fall | 0.165 | 0.167 | 0.170 | 0.162 | 0.136 | -0.027 |
| Rate | 0.026 | 0.033 | 0.029 | 0.021 | -0.540 | 0.542 |
| HSI | -0.057 | -0.057 | -0.080 | -0.040 | -0.421 | -0.436 |
| NASDAQ | -0.631 | -0.339 | -0.576 | 0.392 | -0.005 | 0.004 |
| DJIA | -0.589 | 0.794 | 0.109 | -0.099 | 0.004 | -0.004 |
| SZ | -0.074 | -0.046 | -0.632 | 0.769 | 0.014 | -0.003 |

### 4.5 Model Evaluation Indexes

To compare the PCA-IGRU model proposed in this paper with baseline models, we select three evaluation indexes, Mean Absolute Error (MAE), Directional Symmetry (DS), and R-squared ($R^2$).

MAE is used to measure the error between the predicted value and the true value. The smaller the MAE, the higher the accuracy of the model [14].

Financial time-series prediction not only requires minor errors but also predicts the direction of change as accurately as possible. DS is used to measure the consistency of the change direction between the predicted value and the true value [28-29].

$R^2$ is used to measure the goodness of fit between the predicted value and the true value, and the closer its value is to 1, the higher the goodness of fit is [14].

### 4.6 Analysis of Experimental Results

The prediction results of the PCA-IGRU model are shown in Figure 7. The abscissa is the time, and the ordinate is the stock closing price. The predicted value and the true value are basically consistent, achieving a good prediction effect.

According to Table 6 and Figure 8, compared with SVR, $R^2$ of LSTM increases by 0.0221; MAE decreases by 12.095; DS increases by 3.78%; and training time decreases by 1.4498s. Compared with the traditional regression model, LSTM can solve the time series problem better. It uses the characteristics of the serial structure to make the hidden layer at the current time not only be determined by the input layer at the current time, but also be affected by the hidden layer at the previous time. Compared with LSTM, $R^2$ of GRU increases by 0.003; MAE decreases by 1.8806; DS increases by 1.11%; and training time decreases by 0.0734s. GRU has a simpler model structure and better prediction effect, which is more suitable for the prediction of the stock closing price.

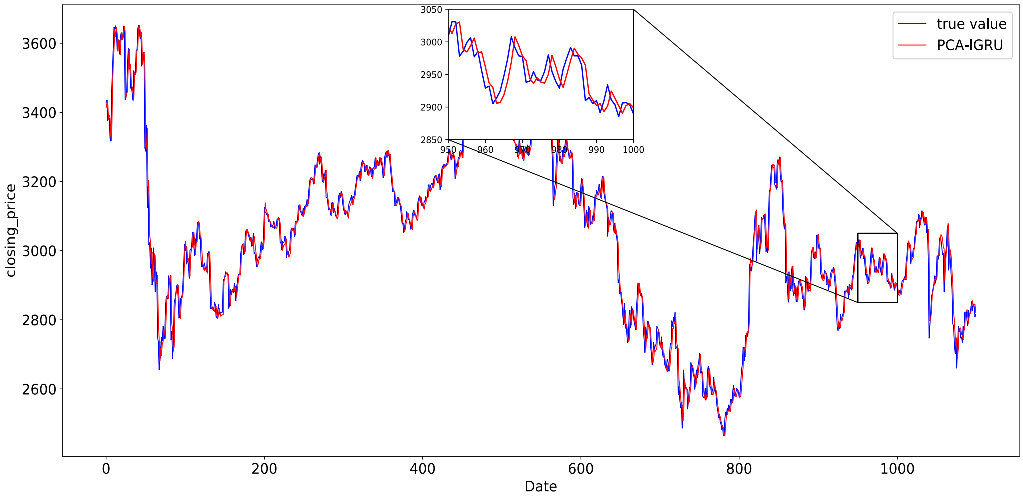


**Figure 7.** Prediction results of PCA-IGRU

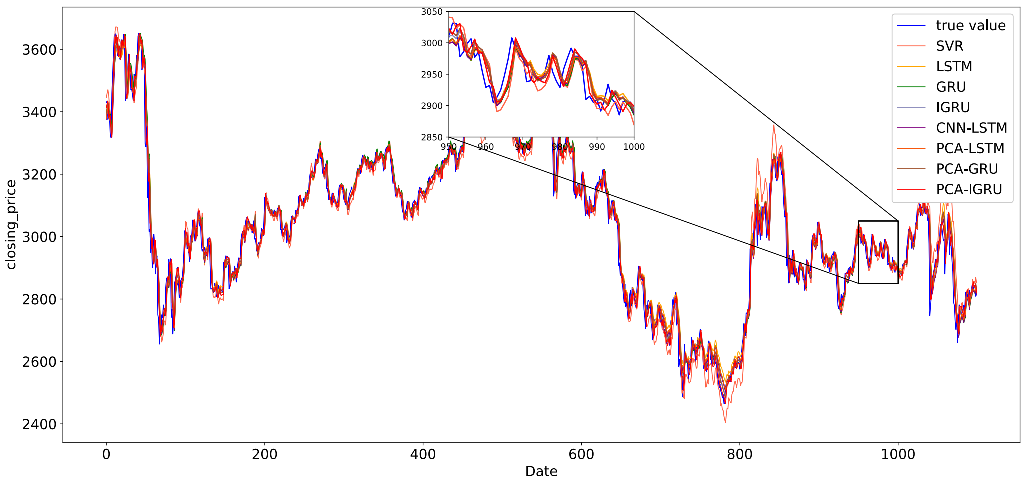


**Figure 8.** Comparison of prediction results of all models

**Table 6.** All models' prediction results

| Models | MAE | DS (%) | $R^2$ | Training time (s) |
|---|---|---|---|---|
| SVR | 46.5048 | 66.45 | 0.9419 | 16.2723 |
| LSTM | 34.4098 | 70.23 | 0.9640 | 14.8225 |
| GRU | 32.5292 | 71.34 | 0.9670 | 14.7491 |
| IGRU | 30.1711 | 73.52 | 0.9698 | 14.4521 |
| CNN-LSTM | 31.1926 | 71.97 | 0.9677 | 16.3365 |
| PCA-LSTM | 30.6361 | 72.13 | 0.9681 | 12.8426 |
| PCA-GRU | 28.8409 | 73.44 | 0.9694 | 12.1381 |
| PCA-IGRU | 24.7577 | 73.86 | 0.9772 | 12.1071 |

It can be seen that the performance of IGRU is improved compared with GRU, $R^2$ increases by 0.0028, MAE decreases by 2.3581, DS increases by 2.18%, and training time decreases by 0.297s. It shows that the introduction of ACM effectively improves the comprehensive performance of the model. Compared with CNN-LSTM, $R^2$ of PCA-LSTM increases by 0.0004; MAE decreases by 0.5565; DS increases by 0.16%; and training time decreases by 3.4939s. The results show that PCA is better than CNN. PCA-IGRU, PCA-GRU, and PCA-LSTM compared with IGRU, GRU, and LSTM, $R^2$ increases by 0.0074, 0.0024, and 0.0041, MAE decreases by 5.4134, 3.6883 and 3.7737, DS increases by 0.34%, 2.1%, and 1.9%, and training time decreases by 2.345s, 2. 611s, and 1.9799s respectively. It shows that the introduction of PCA improves the comprehensive performance of the model.

It can be seen that the performance of PCA-IGRU is improved compared with PCA-GRU and PCA-LSTM, $R^2$ increases by 0.0078 and 0.0091 respectively, MAE decreases by 4.0832 and 5.8784 respectively, DS increases by 0.42% and 1.73% respectively, and training time reduces by 0.031s and 0.7355s respectively. Overall, PCA-IGRU has a better performance in stock closing price prediction.

## 5 Discussion

The experiment concludes that the PCA-IGRU model is better than other models in predicting stock closing price and has excellent comprehensive performance. Compared with LSTM, GRU reduces the number of gate structures, simplifies the model, and has better prediction accuracy. Compared with GRU, IGRU introduces ACM into the original structure of GRU and adjusts the value selection mode of the reset gate, making the model more sensitive to learning information from the previous time. Compared with IGRU, PCA-IGRU reduces redundancy between input data. The data processed by PCA makes the computation of the model easier, improves prediction accuracy, and shortens the training time.

The main reasons for the improvement of the comprehensive performance of PCA-IGRU are as follows:

(1) PCA can effectively capture the key information between variables, reduce the redundancy of input data, and condensed input data can reduce the amount of neural network computation.

(2) IGRU introduces ACM into GRU to prevent oversaturation and improve the sensitivity of the model to historical information learning. While inheriting the advantages of GRU, IGRU alleviates the problem of the weak ability to capture historical information caused by too many network layers and improves prediction accuracy.

(3) This paper not only considers the impact of the historical trading data of the SCI on the closing price of the stock but also considers the impact of the NASDAQ, DJIA, HSI and SZ closing price on the closing price of the SCI. To a certain extent, they reflect the impact of international economic fluctuations on the closing price of the SCI.

## 6 Conclusion

A PCA-IGRU model is proposed in this paper to predict stock closing price. To avoid the input redundancy caused by excessive influencing factors, the model uses PCA to reduce the dimension of the input data. And the model algorithm is improved based on GRU to improve the sensitivity of model learning. PCA-IGRU provides investors with a simple and efficient method to predict the stock closing price and enriches the research on financial time-series prediction. Stock price prediction is a significant research direction, and future research is mainly divided into the following two aspects:

(1) The daily closing price prediction method proposed in this paper can help investors to make decisions. But the stock price is changeable, so future research should include hourly stock price prediction. The hourly stock price prediction method is of great significance to short-term investors. It can provide a more accurate reference for investors to avoid risks and improve the return on investment.

(2) Stock price prediction is a complex nonlinear problem affected by many factors. Future research will add more influencing factors to predict stock price trends, such as economic policies, natural disasters, and epidemics.

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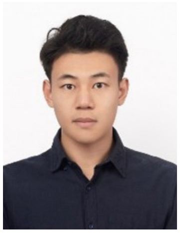
## Biographies

**Jingyang Wang** is currently a Professor with Hebei University of Science and Technology, Shijiazhuang Hebei, China. His research interests include deep learning and computer vision.



**Daoqun Liu** is currently pursuing the master's degree with the Hebei University of Science and Technology. His research interests include machine learning and deep learning.

**Lukai Jin** is currently pursuing the master's degree with the Hebei University of Science and Technology. Her research interests include machine learning and deep learning.

**Qiuhong Sun** received the Dr. Ing. degree in circuit and system from Yanshan University, China, in 2017. She is currently an assistant Professor with Hebei University of Science and Technology, Shijiazhuang Hebei, China. Her research interests include machine learning, big data processing and computer vision.

**Zhihong Xue** is currently an associate professor with Hebei University of Science and Technology, Shijiazhuang Hebei, China. His research interests include machine learning, natural language processing, deep learning, action recognition, artificial intelligence, process parameter monitoring and intelligent control.