RESEARCH ON THE DEVELOPMENT AND APPLICATION OF CNN MODEL IN MOBILE PAYMENT TERMINAL AND BLOCKCHAIN ECONOMY

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Reception: 17/11/2022 **Acceptance**: 17/01/2023 **Publication**: 15/02/2023

Suggested citation:

L., Hongyan (2023). **Research on the development and application of CNN model in mobile payment terminal and blockchain economy**. *3C Empresa. Investigación y pensamiento crítico, 12(1)*, 207-224. https://doi.org/10.17993/3cemp.2023.120151.207-224

ABSTRACT

As the most widely used payment method at this stage, mobile payment is more and more closely related to the blockchain economy. Traditional methods lack a certain degree of accuracy. This research proposes a feature-based and sequential-based Bilateral AM (BAM) and Convolutional Neural Network (CNN)-gated recurrent unit for the development and application of mobile payment and blockchain economy (Gated Recurrent Unit, GRU) hybrid model (BAM-CNN-GRU), select 5 feature parameters with high correlation with the blockchain for multivariate prediction. The introduction of BAM can automatically quantify the correlation between the input variables and the blockchain, and strengthen the expression of historical key information on the predicted output; the introduction of CNN can extract high-dimensional features that reflect the non-stationary dynamic changes of the blockchain. The proposed hybrid model achieves good results in both single-step and multi-step long-term series and multivariate input blockchain prediction. Compared with the other six methods, MAE is reduced by 75.45%, 64.74%, 62.84%, respectively. 59.41%, 45.54%, 44.16%. Compared with the BAM-GRU model, the CNN-GRU model, the GRU model, the LSTM model, the support vector machine SVM model and the BP model, the prediction accuracy of the hybrid model has been greatly improved, and it has a broader application prospect.

KEYWORDS

BAM-CNN-GRU; Mobile payment; Blockchain; Model comparison

https://doi.org/10.17993/3cemp.2023.120151.207-224

PAPER INDEX

1. INTRODUCTION

Mobile payment refers to a network payment method in which users use mobile smart devices to complete transaction payments. According to different supporting technologies, mobile payment is roughly divided into two modes: remote payment and near-field payment. Common payment methods include online banking payment and QR code payment [1-2]. At present, the two major characteristics of mobile payment are convenience and security, among which the core factor affecting the development of mobile payment business is security [3-5]. Mobile intelligent terminals are usually bound by software and hardware disadvantages such as computing power and storage capacity, which lead to great restrictions on the data processing capacity of the terminal equipment [6]. Therefore, most mobile application software programs have to implement the corresponding functions of the client by invoking remote cloud services [7]. As far as mobile banking is concerned, the mobile banking APP of the mobile client must complete the application functions such as transfer and wealth management by calling the cloud service of mobile banking remotely [8]. Usually, in the process of invoking cloud services from a mobile application, the remote application server will first verify the identity of the end user and even the legitimacy of the device to ensure the security of the transaction process.

In some developed countries abroad, such as Japan, South Korea, Europe and the United States, the development of NFC payment is very rapid [9]. The mobile payment service provided by NTTDoCoM, the largest mobile communication operator in Japan, uses the Felica technology developed by Scmy, which uses mobile phones with Felica chips. Its virtual wallet has contactless payment functions such as ticket purchase and bus ride [10]. At the beginning of the promotion of mobile wallets, NTTDoCoM installed NFC card readers for merchants for free, and made profits in the form of monthly rent [11]. In the same year, NTTDoCoM acquired one-sixth of the shares of Sumitomo's credit card business, so that the virtual wallet can be bound one-to-one with bank cards. Bank card payment [12]. In 2006, the company extended the NFC mobile payment service to the consumer credit field and launched the DCMX mobile credit card. It can be said that mobile phones and wallets have been equated in Japan, and shops of all sizes support NFC mobile payment [13]. In Europe, Nokia and Philips are the main leaders of NFC mobile payment. The unified currency model in the euro area has removed many obstacles to mobile payment. Some operators have independent bank-authorized payment authority, which is very beneficial for banking services, making Europe's near-field communication technology research and development ahead of the world [14]. The first NFC experiment in Europe was launched in March 2005 at the Frankfurt Metro, where passengers can use a Nokia 3220 mobile phone equipped with an NFC module to purchase tickets at subway stations. The world's first multi-application NFC experiment began in October 2005. Smartphones embedded with Philips' NFC chips were distributed to hundreds of French citizens of Ona participating in the experiment. During the experiment, they can be used in specific shopping malls, hotels and cinemas. After swiping the phone to pay, the experiment went on for six months. In Munich, Germany, local residents can use mobile phones equipped with NFC chips to swipe their cards to travel or enter

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tourist attractions[15]. After Google released HCE technology in 2013, foreign markets responded quickly: Spanish bank Bankmeter was the first to announce HCE support earlier in 2014: TH coffee shop offered HCE-based NFC payments, and the coffee shop invested People praised that the American coffee chain SimplyTapp also received a large amount of investment to study the development of HCE and set out to standardize HCE [16]. In the field of card organization, Royal Bank of Canada has put the development of HCE on the agenda, Zaputal One of North America and Barclays of the United Kingdom have all adjusted and applied HCE technology. Apple launched the Apple Pay service in IOS8, which supports the NFC+AppleID transaction method, which greatly promoted the development of NFC payment [17-18].

This paper proposes a hybrid model based on Bilateral AM (BAM) and CNN-GRU (Gated Recurrent Unit) to make multivariate predictions on the blockchain, an important factor influencing mobile payment, and selects the same as the blockchain. Other relevant feature performance parameters are used as input [19-20] and the blockchain is used as output. First, a feature AM is introduced on the input side to quantify the relationship between performance parameters and blockchain output; then, through the powerful feature extraction capability of one-dimensional (One Dimensional, 1D-CNN), the local information between the input information is mined. Finally, a time-series feature AM is introduced on the output side to strengthen the expression of important information at historical moments for the prediction output [21]. The purpose is to establish a prediction model that depends on each performance parameter under the time node, explore the connection between mobile payment and blockchain, and accurately predict the impact of blockchain on mobile payment.

2. PRINCIPLES OF DEEP LEARNING MODELS

2.1. 1D-CNN

The convolutional neural network performs high-dimensional feature mapping on the original data through local connection and weight sharing, and mines the feature information of the original data. 1D-CNN is mainly used to process time series, and its internal structure is shown in Figure 1. For processing time series, the convolution layer extracts the translation features of the data in the direction, and extracts the effective feature vectors on the time series. From an accurate point of view, the analysis is to perform cyclic product and summation on the data. The specific expression is as follows:

$$y(\mu)=w(\mu)*v(\mu)=\sum_{\tau=0}^{N} w(\mu-\tau)v(\tau)M \tag{1}$$

where y, w, v are sequences, μ is the number of convolutions, and M is the length of v.

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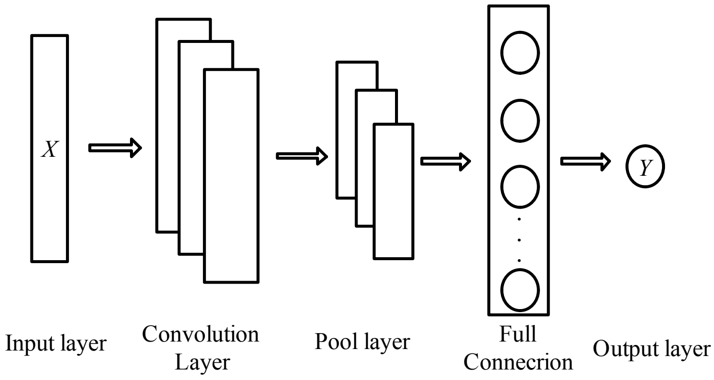

Fig.1 1D-CNN

2.2. ATTENTION MECHANISM (AM)

Attention mechanism (AM)is a reserve apportionment model that pretends the attention of the human brain. The human brain can pay attention to some important information of interest and ignore irrelevant information at a certain time node. The attention distribution of different information can be more important. The attention model assigns greater weight to important information through this probability distribution mode to different information, thereby improving the model's extraction of important information and improving the prediction accuracy of the model. In time series prediction, the AM can not only act on the input side to reflect the degree of correlation between each feature parameter and the predicted output, but also on the output side to weight the information at the historical moment to highlight the information related to the current prediction. Important time point information [22].

2.3. GRU

GRU network is an improved mode of LSTM network [23]. By optimizing the gate structure inside the LSTM network, the input gate and the forget gate are combined into an update gate, and the state of the neuron is mixed with the state of the hidden layer. The update gate inputs the combined matrix of the input vector and X_t and the state memory variable h_{t-1} of the previous moment into the update gate after the nonlinear transformation of the activation function, and determines the degree to which the information of the previous moment is retained to the current state [24]. The reset gate combines the previous state information with the current state information in the manner of $1 - z_t$ times h_{t-1} and z_t times $\tilde{h}_t$ as the output of the current state information. The GRU structure network is exposed in Fig. 2, and expression is revealed in Equation (2) [25].

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$$\begin{cases} r_t = \sigma\left(W_r \cdot [h_{t-1}, X_t]\right) \\ z_t = \sigma\left(W_z \cdot [h_{t-1}, X_t]\right) \\ \tilde{h}_t = \tanh\left(W_{\tilde{h}} \cdot [r_t \times h_{t-1}, X_t]\right) \\ h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \end{cases} \tag{2}$$

In Figure 2 and equation (2): X_t, h_{t-1}, r_t, z_t, $\tilde{h}_t$, h_t are the input information, the state information of the previous moment, the update gate, the reset gate, the input vector and the previous hidden layer state information, respectively. Summary, the output of the current hidden layer state; W_r, W_z, $W_{\tilde{h}}$ are the trainable weight matrices of each gate state; σ is represented as the Sigmoid function.

3. MOBILE PAYMENT AND BLOCKCHAIN PREDICTION MODEL BASED ON BAM AND CNN-GRU HYBRID MODEL

3.1. MOBILE PAYMENT AND BLOCKCHAIN PREDICTION MODEL

Mobile payment is not only carefully associated the operation of various components in the system, but also related to the blockchain environment, such as the sharing economy, etc., but these are external factors and will indirectly affect the operation status of each component in the system , and then make the mobile payment security change. Therefore, according to the internal operation rules of mobile payment, we select sharing economy N_1, Internet of Things N_2, cloud computing W_f, artificial intelligence p_o and digital economy T_o, five performance parameters that are highly correlated with mobile payment as input parameters, and establish the following parameters at each time point. The relevant performance parameters are dependent on the predictive model.

Note that the time series set of mobile payment is $Y = [y1, y2, \ldots, yT] \in RT$, and the time series of the five blockchain-related features of the input terminals N1, N2, Wf, po and To are X = [x 1, x 2, ..., xT] = [x(1), x(2), ..., x(5)]′, the specific expansion can be represented by equation (3). Where $xt = [xt(1), xt(2), \ldots, xt(5)]$ represents a set of five related feature parameter variables measured at time t, $x(k) = [x1(k), x2(k), \ldots, xT(k)]$ is represented as the measured value sequence of the k-th relevant feature parameter at T historical moments.

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$$\boldsymbol{X} = \begin{bmatrix} x_1^{(1)} & x_1^{(2)} & \cdots & x_1^{(5)} \\ x_2^{(1)} & x_2^{(2)} & \cdots & x_2^{(5)} \\ \vdots & \vdots & \ddots & \vdots \\ x_T^{(1)} & x_T^{(2)} & \cdots & x_T^{(5)} \end{bmatrix} \in \boldsymbol{R}^{T\times 5} \tag{3}$$

where k (1≤k≤5) of x(k) represents the number of features. (t 1≤t≤T) of xt represents the value of the corresponding feature at time t.

According to the five characteristic performance parameter variables related to the blockchain as the input, and the blockchain at the corresponding time as the output of the model, the multi-variable prediction of mobile payment in the future time and time is carried out. Let the mapping function of the entire model be Fθ, then the predicted value represents for:

$$\hat{x}_{T+1} = F_\theta\left(x_1, x_2, \ldots, x_T\right) \tag{4}$$

In order to obtain the relationship between each feature performance parameter and the blockchain at the current moment and the dependency in the time series information, a bilateral attention and CNN-GRU hybrid model combining the feature AM and the time series AM are adopted. Multivariate forecasting methods. A feature AM is presented on the input side to calculate the degree of correlation between the exhaust gas temperature value to be measured and other related performance parameters, so that the features with strong correlation are assigned greater weights, while the weak or irrelevant features are weakened. information. CNN mines the high-dimensional features of the input information through operations such as convolution pooling, and effectively reduces the error caused by manual feature extraction. The time series AM is introduced at the output, independently select the information of the historical key moment with high correlation with the current moment, and solve the problem of GRU network for long-term sequence.

3.2. FEATURE AM

In order to obtain the degree of correlation between the five feature parameters and the blockchain to be tested, a feature AM is introduced on the input side, and the multi-layer perceptron calculation method is used to quantify the attention weights of various features. The model is shown in Figure 2 [26].

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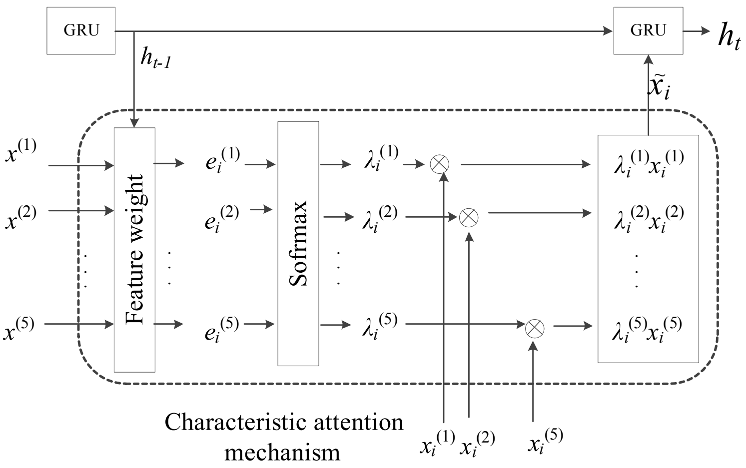

Fig. 2 Characteristic attention model

The five feature parameters at time t are combined with the hidden layer state ht - 1 at the preceding time as the input of the feature AM. The weight of each feature parameter at this time is calculated by formula (5), and the Softmax function is used. Normalize e(k) t according to formula (6), namely:

$$e_t^{(k)} = \boldsymbol{V}_\mathrm{e}^\mathrm{T} \mathrm{relu}\left(\boldsymbol{W}_\mathrm{e}\boldsymbol{h}_{t-1} + \boldsymbol{U}_\mathrm{e} x^{(k)} + \boldsymbol{b}_\mathrm{e}\right) \tag{5}$$

$$\lambda_t^{(k)} = \frac{\exp\left(e_t^{(k)}\right)}{\sum_{k=1}^{5} \exp\left(e_t^{(k)}\right)} \tag{6}$$

where V_e, W_e and U_e are the weight matrices of the feature AM, and be is the corresponding bias term.

The feature parameter weight λ(k) t assigned according to the feature AM is multiplied by the corresponding feature input x(k) t to obtain the associated features x̃ with different feature contribution rates, so as to perform strong and weak correlation for each feature Different expressions can be specifically expressed as:

$$\tilde{x}_t = \left(\lambda_t^{(1)} x_t^{(1)}, \lambda_t^{(2)} x_t^{(2)}, \ldots, \lambda_t^{(5)} x_t^{(5)}\right)^\mathrm{T} \tag{7}$$

Finally, the input information $\tilde{x}$ is iterated by formula (8) to ensure that the hidden layer state h_t at each time t contains the associated feature x:

$$\boldsymbol{h}_t = f_{\mathrm{GRU1}}\left(\boldsymbol{h}_{t-1}, \tilde{x}_t\right) \tag{8}$$

where f_{GRU1} represents the network unit of the input side GRU.

3.3. CNN LAYER

The introduction of the 1D-CNN network is to extract the feature of the relationship information processed by the feature AM, map the relationship information to the high-dimensional feature space, mine the deep-level feature information, and extract the key node information in the feature variables [27]. The convolutional layer extracts features, the pooling layer filters the information, and the dropout layer discards some neurons to prevent the network from over-fitting due to over-reliance on some local features [28]. In this paper, at the connection between 1D-CNN and GRU, the maximum pooling layer and dropout layer are used to replace the fully connected layer. This operation not only reduces the data dimension input to the GRU network, reduces the network training time, but also preserves the time series information of the input features to the greatest extent, ensuring the prediction accuracy of the model. The output feature vector Rφ of the 1D-CNN network can be expressed as:

$$\boldsymbol{C} = \mathrm{relu}\left(\boldsymbol{H} \otimes \boldsymbol{W} + \boldsymbol{b}_1\right) \tag{9}$$

$$\boldsymbol{P} = \text{[illegible]}\left(\boldsymbol{C}\right) + \boldsymbol{b}_2 \tag{10}$$

where H is the set of hidden layers of the input side GRU, the outputs C and P are the outputs of the convolutional layer and the pooling layer, respectively; W and b_1 are the weights and bias terms of the convolutional layer; b_2 is the bias of the pooling layer. set item; the output of the CNN layer is:

$$\boldsymbol{R}_{\varphi} = \left[r_1, r_2, \ldots, r_{t,}, \ldots, r_{\varphi}\right] \tag{11}$$

3.4. TEMPORAL AM

Since the predicted value of the blockchain is greatly affected by the historical state, and the hidden layer state information at different times has different effects on the output of the current network, in addition, the network output is more inaccurate due to the increase in the length of the time series. In order to enable the predicted value to process historical state information autonomously and to strengthen the expression of important historical moment information with high output relevance at the current moment, this paper introduces a time-series AM for the output side of the GRU network. The specific structure is shown in Figure 4 [29].

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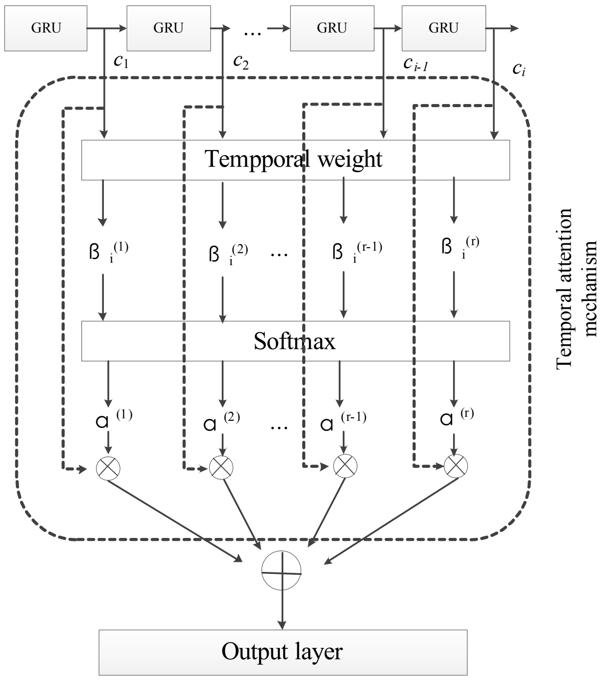

Fig.4 Temporal attention model

The time series information of the hidden layer state including the relationship information processed by the CNN is the vector Rφ, which is used as the input of the GRU network, and its output is expressed as C, and the output at time t is expressed as:

$$c_t = f_{\mathrm{GRU2}}\left(c_{t-1}{}^{,} r_t\right) \tag{12}$$

where f_{GRU2} represents the network unit of the output side GRU.

The input of the time-series AM is the output vector C processed by the GRU network on the output side. According to the AM, the historical state information at each time point is weighted and expressed, and the Softmax function is continued to normalize the weight βtT, and record each moment in history. The correlation degree of the hidden layer state information to the output at the current moment is αφt [30].

$$\beta_t = V_c^{\mathrm{T}} \mathrm{relu}\left(W_c c_t + b_c\right) \tag{13}$$

$$\alpha_t = \frac{\exp\left(\beta_t\right)}{\sum_{j=1}^{T} \exp\left(\beta_t\right)} \tag{14}$$

where V_c and W_c are the corresponding weight matrices of time-series attention, and b_c is the bias.

αt indicates that the correlation degree of each hidden layer state information in the history to the prediction output at the current time is quantified, and all α φt and the corresponding hidden layer state information are weighted and summed, and the output of the time series AM at time t is l_t express.

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$$l_t = \sum_{i=1}^{T} \alpha_t c_t \tag{15}$$

Finally, the output information is dimensionally transformed through the fully connected layer network, and the final blockchain prediction value ỹT + 1 is obtained:

$$\tilde{y}_{T+1} = F_\theta\left(x_1, x_2, \ldots, x_T\right) = \tanh\left(W_y l_t + b_y\right) \tag{16}$$

where W_y and b_y are the weights and biases for dimensional changes in the network.

3.5. HYBRID MODEL BASED ON BAM AND CNN-GRU

The structure of the entire prediction model is shown in Figure 5. After the input information is processed by the feature AM, relevant information with different weights is obtained, and then it enters the GRU network for learning. The output of the network is used as the input of 1D-CNN. In the processing of the pooling layer and dropout layer, the information enters the GRU network on the output side, and the hidden layer state is used as the input of the timing AM on the output side. . In the training process of this model, the Adam (Adaptive Moment Estimation) optimization algorithm is selected to update and learn various parameters, and the loss function of the model adopts the mse function, as shown in formula (17) [31].

$$Loss = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \tilde{y}_i\right)^2 \tag{17}$$

In the formula, n is the number of samples; y_i is the actual value of the blockchain, and $\tilde{y}_i$ is the blockchain value predicted by the model.

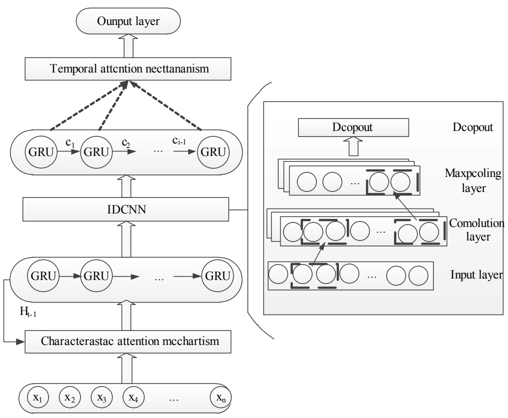

Fig.5 Model structure based on BAM and CNN-GRU

3.6. ERROR ANALYSIS

In this paper, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used as indicators to evaluate the prediction accuracy of each model. The expressions are as follows shown [32]:

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$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{19}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}\times 100\% \tag{20}$$

4. MODEL PREDICTIONS

For the sample data, the mixed model of BAM and CNN-GRU, BAM-GRU model, CNN-GRU model, GRU model, LSTM model, BP model and SVM model proposed in this paper are used to predict the output. The training and test sets are split in a ratio of 4:1. The GRU network and LSTM network structure in the above models all use the same hyperparameters (the number of hidden layer neurons is 128, the sliding window is 6, the number of iterations is 400, and the batch_size is 256); the AM uses relu as the internal structure[33-34]. Activation function, and use Softmax function to normalize it; the convolution layer of CNN network is set to 64, the convolution kernel is 1, the maximum pooling layer is 4, and the dropout is 0.3; BP network adopts the number of hidden layer neurons is a network structure of 8; the SVM network adopts radial basis kernel function.

According to the three evaluation indicators selected in this paper, the prediction performance and accuracy of different models 566 are evaluated. The experimental comparison results are shown in Table 1.

Table 1 Comparison of prediction accuracy of different models

Model	AE	RMSE	MAPE
BP	4.48	4.57	0.67
SVM	3.12	3.76	0.48
LSTM	2.96	3.47	0.46
GRU	2.71	3.17	0.42
CNN-GRU	2.02	2.98	0.32
BAM-GRU	1.97	2.39	0.30
Proposed	1.10	1.81	0.17

From the information in Table 1, it can be concluded that the prediction accuracy of the algorithm in this paper is better than that of the other 6 algorithms. Compared with the other 6 methods, MAE is reduced by 75.45%, 64.74%, 62.84%, 59.41%, 45.54%, 44.16%; RMSE Compared with the other 6 methods, the reductions were 60.39%, 51.86%, 47.84%, 42.90%, 39.26%, 24.27%, respectively; compared with the other 6 methods, MAPE decreased by 0.50%, 0.31%, 0.29%, 0.25%, 0.15%, 0.13%.

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Comprehensive analysis, the algorithm in this paper has obvious reduction in the three error evaluation indicators, indicating that the algorithm in this paper has a relatively good prediction performance. According to the analysis of the error results, the machine learning methods (BP, SVM) are not as outstanding as the deep learning methods (LSTM, GRU, CNN-GRU, BAM-GRU, Proposed) in terms of prediction effect. From Table 1, it can be seen that the CNN-GRU model and the BAM-GRU model have a significant decrease in the three error evaluation indicators compared with the single deep learning model, indicating that the CNN network can be performed by the high-dimensional local dependence on the multivariate input performance parameters. Mining to improve the prediction performance of the model. By introducing BAM, the degree of correlation between input features and output is quantified on the input side, and the contribution rate of each performance feature is adaptively extracted, which effectively avoids the output expression of non-critical information and secondary feature information, and strengthens important information for prediction. The output side strengthens the correlation expression of historical important information for the current prediction output, reduces information omission and memory decay, and solves the prediction lag problem of LSTM and GRU single network models.

The comparison of the prediction output curves of each model on the test set is shown in Figure 6 and Figure 7. It can be seen from Figure 6 that the traditional machine learning method has a poor prediction effect, and the predicted output value has a low degree of fitting with the actual value. The error is large.

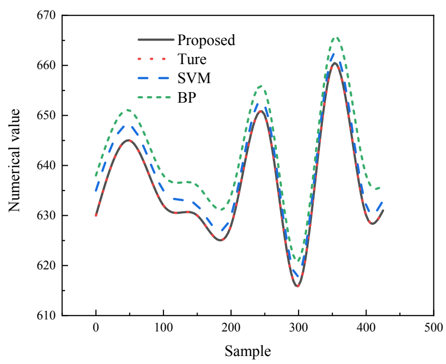

Fig. 6 Comparison of predicted values between the proposed model and the machine learning model

Figure 7 shows that the prediction output of the deep learning model has a high degree of fitting with the actual value, which proves the advantages of deep learning in time series prediction. The hybrid model of BAM and CNN-GRU proposed in this paper can not only accurately predict in a slightly smooth interval, but also accurately capture the changing law of mobile payment in high and low peak time periods. The other four learning methods can also accurately predict the blockchain in some intervals, but there is still a certain gap between their prediction performance and the method proposed in this paper when the blockchain peaks and fluctuates violently. It shows that the model proposed in this paper has good performance in establishing long-term dependencies of time series and effectively capturing the dynamic changes

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of blockchain. By accurately predicting the blockchain, the change rule of the blockchain can be known in advance, and compared with the corresponding baseline value to check whether the difference is within the maximum range allowed for operation, and then take the corresponding maintenance strategy. In addition, when it is found that there is a sudden and substantial rise and fall of the blockchain within a certain predicted time period, it is necessary to consider whether the mobile payment operation is normal, and investigate the reasons in time to avoid security accidents.

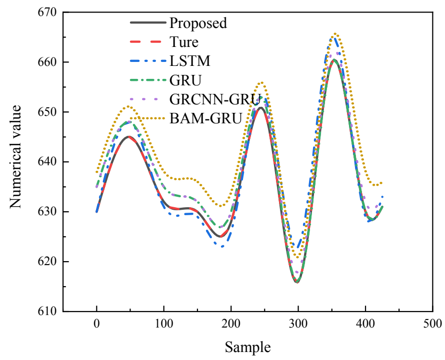

Fig. 7 Comparison between the predicted value of the proposed model and the deep learning model

5. CONCLUSION

Aiming at the relationship between mobile payment and blockchain economy, this paper proposes a hybrid model based on BAM and CNN-GRU to improve the prediction accuracy and stability of the long mobile payment model. The following conclusions are drawn: (1) The prediction accuracy of the hybrid model of BAM and CNN-GRU proposed in this paper is better than that of the other six algorithms. Compared with the other six methods, the MAE is reduced by 75.45%, 64.74%, 62.84%, respectively. 59.41%, 45.54%, 44.16%; (2) The hybrid model of BAM and CNN-GRU proposed in this paper can not only accurately predict in a slightly smooth interval, but also accurately capture the change law of mobile payment in high and low peak periods; (3) The CNN network can improve the prediction performance of the model by mining the high-dimensional local dependencies of multivariate input performance parameters.

6. CONFLICT OF INTEREST

The authors declared that there is no conflict of interest.

https://doi.org/10.17993/3cemp.2023.120151.207-224

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