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Particle Swarm Optimization and Long Short Term Memory Algorithms for Financial Brand Data Prediction under Internet of Things

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This study aims to improve the predictive ability of financial brand data, help investors and decision-makers better identify different financial brands' performance, and reduce unnecessary financial risks. The stock prices of various financial brands are undertaken as the experimental objects. The characteristics of financial data and the original model network structure are analyzed based on the Internet of Things (IoT). The long short-term memory (LSTM) neural and the particle swarm optimization algorithm (PSO algorithm) are adopted to optimize the model's parameters. The autoregressive integrated moving average model (ARIMA) algorithm is used to analyze the spatio-temporal data, and a data prediction model for the financial brand based on the ARIMA-PSO-LSTM algorithm is proposed. In addition, the validity and effectiveness of the proposed model are proved through the analysis and testing of specific example data. It is found that the model based on the IoT shows higher processing speed in contrast to the conventional method; the model proposed in this study shows smaller errors and improved accuracy in data prediction than the PSO-LSTM model and the LSTM model; the model presents better fitting effects and better performance compared with the latest research model. The experimental results reveal that combining the three algorithms can integrate the advantages of various algorithms, and the three algorithms can complement each other, thereby improving the ability of financial data analysis. The model established in this study shows high accuracy and good adaptability in identifying financial brands and predicting financial data.

Keywords: PSO algorithm, LSTM, financial brand, data prediction, model optimization

1. INTRODUCTION

The financial market plays a vital role in the national economic system, and the financial market's performance directly reflects the economic development of the entire country. A deep understanding of changes in the financial market and accurate prediction of development trends are essential in promoting the reform of the financial governance structure of a country [1]. At present, there are many different financial institutions with various capabilities. Various financial brands will offer investors different investment strategies to reduce risks and increase returns [2]. But even if different institutions give the same investment plan, they will have various services when subsequent investors lose money. Therefore, how to effectively screen different financial service brands has become

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the core of research in this field [3]. Besides, financial data is a common concern of all parties. Implementing a suitable model from existing data is of great value for financial investment and decision-making. The existing financial service structure is dedicated to the study of financial models. However, financial time series prediction (TSP) has encountered greater difficulties due to the gradual increase in the complexity of the financial market [4]. How to find a suitable financial institution from the existing financial market and realize effective prediction of financial data has also become a hot issue in this field.

With the rapid development of society, all industries have taken advantage of the data collection advantages of the Internet of Things (IoT) to create commercial value effectively. The deep integration of the IoT and finance enables the latter to rely on the IoT technology to improve service experience, reduce operating costs, and achieve the integration of capital flow, information flow, and entity flow, thereby transforming the financial credit system and controlling financial risks. The IoT will profoundly and far-reaching changes in the original models of banking, securities, insurance, leasing, investment, and many other financial fields, bringing about a new revolution in financial models. IoT finance is a new type of financial format in which financial institutions use IoT technology and information and communication technology to realize payment, financial communication, investment, asset management, and information intermediary services, and use data to control risks and eliminate information asymmetry. IoT finance has realized the integration of business networks and service networks at the financial level, making financial services automated and intelligent, and creating a variety of business models. The development of IoT finance promotes the development of IoT-related industries and improves the real economy's development. It can be said that IoT finance has found a breakthrough for IoT technology to better serve the real economy. The financial leasing industry can rely on sensors and other equipment to know all aspects of vehicle operation management, maintenance, *etc.* As a result, risks can be controlled, the lease subject is more, the bank can give more authorization, and the government can rely on bank credit funds to sequentially transfer public transportation. All vehicles are replaced by electric vehicles, fiscal and tax expenditures have dropped significantly, and the environment has been significantly improved. This is the role of IoT finance. In the future, there will be a series of changes in the investment field, playing a great beneficial role in the real economy, which is the application of IoT finance in serving the real economy.

Numerous scholars have undertaken research on IoT financial brands and market data prediction. These technologies have been applied to natural language processing, image recognition, and text detection, yielding promising research outcomes in data classification and prediction [5]. LSTM, as a specialized form of recurrent neural network (RNN) structure, has been enhanced through the selection of memory functions and the incorporation of specific unit structures, rendering it more suitable for financial data analysis [6]. The ARIMA algorithm, as a traditional time series analysis and prediction model, has the advantage of simple understanding and operation, and the algorithm also shows high performance in data prediction [7]. PSO has been gradually applied in data analysis owing to its robust parameter optimization capability [8]. Predicting financial brand data is of great significance to financial enterprises' decision-making and strategic formulation. The ARIMA model and PSO algorithm demonstrate better performance in data analysis. However, the construction of financial brand models has been a topic of limited exploration among current scholars, and the prediction accuracy of financial data prediction-related studies remains relatively low. Consequently, it is necessary to integrate the ARIMA model and PSO algorithm to study and analyze the data prediction model of financial brands to improve the ability of financial data analysis.

The statistical models, deep learning (DL) algorithms, and optimization algorithms are combined in this study, targeting at above problems. Based on the analysis of relevant literature, diverse financial brands are selected as the research objects to construct a data prediction model for financial brands using the ARIMA-PSO-LSTM algorithm. The performance of the proposed model is verified through specific example data and comparison with previous research. This study contributes novel methods and ideas for selecting the financial brand and realizing effective analysis of financial data. The composite model established in this study holds practical significance for the analysis and prediction of financial data. Combining the three algorithms can integrate the advantages of various algorithms, and the three algorithms can complement each other, thereby improving the ability of financial data analysis. Therefore, the compound algorithm concept proposed in this study represents a significant innovation in both technology and method.

2. RELATED WORKS

2.1 Studies on Data Prediction

As financial data prediction has a robust application and a wide range of applications, how to realize the intelligence of data prediction has become a hot issue in this field [9, 10]. With the continuous improvement of DL algorithms in recent years, more and more scholars have constructed the model using DL and found that the prediction effect of DL models is far superior to traditional machine learning algorithms [11]. Di and Honchar [12] found that structured financial products' final prediction accuracy rate can be as high as 72% by using RNNs and LSTM [12]. Pandey *et al.* [13] applied the radial basis function neural network (RBFNN) to predict exchange rates. They found that the complex nonlinear relationship between the dependent and independent variables was implicitly detected [13]. Qiu *et al.* [14] proposed a new hybrid LSTM model to predict stock price volatility, combining the LSTM model with various generalized autoregressive conditional heteroskedasticity (GARCH) generalized ARCH types. They believed that the hybrid model had the lowest prediction error in terms of mean absolute error (MAE) and mean square error (MSE) [14]. Wu *et al.* [15] used SPDRS&P500ETF data and selected a single model convolution neural network (CNN) and LSTM to measure the performance of the proposed model. The experimental results denoted that the feature fusion LSTM-CNN model was better than a single model in predicting the stock prices [15]. Qi *et al.* [16] proposed a hybrid model for feature fusion (LSTM-CNN model), which combined features learned from different representations of the same data. They found that the model showed better prediction accuracy [16].

2.2 Studies on Brand Identification

The financial brand generally refers to the brand of a company or institution with certain popularity and influence in the financial field. These companies or institutions may provide various financial products and services, such as banking, securities, insurance, *etc.*

The influence of financial brands is related to market share, customer reputation, professional ability, service quality, and other factors. In finance, the financial brand is generally regarded as an essential part of corporate image and reputation, as well as one of the critical factors of corporate competitiveness and market share. With its inherent charm, a successful brand can attract consumers to repeat purchases and create stable profits for the company. Therefore, brand recognition is vital for corporate profit growth [17]. To establish a good brand image and build a well-known brand, the brand has to be recognized by consumers to leave a strong and unique impression. It is necessary to conduct in-depth research on the shaping of the brand image, to make the brand image play a role in the consumer's cognition [18]. Only a few scholars analyzed the research on brand recognition. Zhang [19] examined the impact of different brands on financial product risks by constructing various brand signal models and using relevant data. The results showed that liquidity, market risks, and the characteristics of cultural and creative industries had significant impacts on their idiosyncratic risks [19]. Lin and Huang [20] proposed a fusion of a feature learning framework and an improved Elman neural network (ENN) for the time series recognition of financial brands; the importance of data that was closer to the current time was higher than that was far away from the current time, so the random process was introduced into the model. It was found that the model's prediction ability was significantly enhanced in the time series data, which were lower than the brand [20]. Ry *et al.* [21] used the quantum PSO (QPSO) algorithm to search for the dynamic optimal weights and thresholds of the Region-CNN (RCNN). They found that the algorithm effectively was easy to fall into local optimization when optimizing the gradient algorithm [21].

2.3 Data Analysis of IoT Finance

IoT Finance is a new financial model based on Internet finance and traditional finance. It is an innovation of Internet finance and a new application model of IoT, which realizes the deep integration of IoT technology and Internet finance [22]. The IoT financial model is mainly based on the cloud-based large-scale IoT technology to learn the integration of capital flow, information flow, and physical flow for small and medium enterprises (SMEs), to reduce the financial risks brought by the virtual economy comprehensively, provide consumers with more convenient financial services, and give more financial service support to the economic development of the physical industry. The emergence of the IoT financial model solves the innovation in the IoT model and can promote the deep integration of the IoT and the financial field [23]. Domestic financial supervision faces lagging, untimely supervision measures, single management means, low efficiency, complex supervision, no evidence to rely on, difficulty in auditing, and high arbitrariness in operation. For instance, local SMEs have financial problems and deliberately apply for credit financing from the bank. If the bank credit fails, it will easily lead to the disconnection of the capital chain and restrict the development of SMEs. If the bank is not strictly audited, it is straightforward to accumulate financial risks [24].

2.4 Summary of Related Studies

Based on the aforementioned research advancements, it is observed that scholars have proposed more methods of financial time data prediction and brand recognition in different academic research fields. The applicability and potential for development of these methods in economics, finance, mathematics, and computer technology are highly promising. Under the current conditions of relying on the powerful computing power of computers, the absolute accuracy of model prediction cannot be fully guaranteed. Particularly, the current learning model still suffers from certain limitations in the prediction of long-term financial data. Consequently, different financial brand stock prices are undertaken as the experimental objects to analyze the characteristics of financial data and the structure of the original model network. The LSTM is introduced and the parameters of the model are optimized using the PSO algorithm. Furthermore, the ARIMA algorithm is used to analyze the spatio-temporal data, and the model's performance is evaluated through specific instance data. This study is of great value in fostering the advancement of related industries.

3. DATA PREDICTION MODEL FOR FINANCIAL BRAND

3.1 Construction of IoT Finance Platform

The IoT is an essential part of the new generation of information technology. The IoT takes the Internet as the core, based on which it extends to the information exchange among different things, that is, to connect any object to the Internet, conduct information exchange, and realize a series of measures such as intelligent identification, positioning, and tracking management. The structure of a financial data dynamic security depository system (DSD system) based on the IoT includes the perception, storage, and application layers. The structure of the DSD system consists of a perception layer, a storage layer, and an application layer. As the basis for the system to realize financial data collection, the perception layer is at the forefront of IoT applications. It plays a decisive role in the realization of IoT functions. The perception layer comprises a wireless sensor network, a radio frequency identification system, and a wireless video surveillance network, which is used for financial data collection, fusion, and completion of previous financial data transmission. The storage layer is the core part of the system, storing a large amount of financial data collected from the perception layer, and it can be divided into the IoT information storage center and the government IoT security center. The IoT information storage center will store a large amount of financial data organized by specific statistical standards through the cloud security storage service system. It will only be open to users who meet financial data access permissions. When a statistical user wants to query financial data through the system and registers for the first time, the IoT security center is responsible for calculating and generating a password, acquiring a password that matches the user's identity attribute, and ensuring that the user successfully accesses the statistical financial data. The application layer is based on different types of needs of users, obtains the corresponding financial data from the storage layer, completes the statistical business logic of user needs, and uses a graphical visual interface to display the statistical results of various businesses in Fig. 1.

3.2 Data Model of Financial Brand

Based on the above research, it is found that the ARIMA model can fit the linear relationship between time series and shows simple operation and strong applicability. However, the model often needs to be revised in the face of financial time series data.

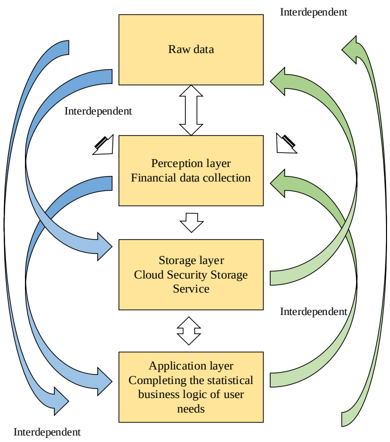

Fig. 1. Structure for data processing platform of IoT finance.

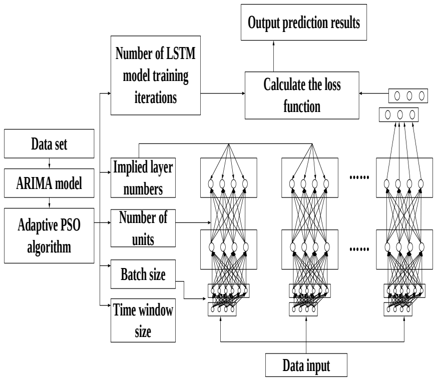

Fig. 2. The data prediction of financial brand based on PSO-LSTM.

LSTM can simultaneously process multiple pieces of information in time series prediction [25]. Changes in stock prices are affected by many factors, such as policies and economics, and are mixed with information that can't be fully quantified. They generally cover linear and non-linear models. The single linear and non-linear models can show lower prediction accuracy [26]. Therefore, a financial brand data analysis model is proposed, which combines the linear model ARIMA model and the nonlinear model PSO-LSTM model to extract secondary information from the financial time series. After the linear part of the ARIMA model is extracted, the PSO-LSTM model is used for the secondary modeling of the residual nonlinear information residual to improve the prediction accuracy.

The establishment of a hybrid model mainly covers three parts. Firstly, an ARIMA model is established using the unstandardized training set, and the appropriate model parameters are selected to ensure the accuracy of the established model in the prediction set. The residuals and predicted values on the training and test sets are outputted, and the standardized residuals are undertaken as the training set and test set of the PSO-LSTM model [27]. Secondly, the LSTM model is applied to extract the nonlinear part of the residual using the PSO algorithm for parameter selection. Finally, the data integration is realized, and the predicted value after the reverse transformation of the ARIMA model and the PSO-LSTM model is realized. When the ARIMA model predicts the data, the rolling forecast method is adopted, the value to be predicted is added to the true value sequence to remodel, and the established model is then to predict the data of a fixed number of days. In the whole process, the prediction and training sets of the PSO-LSTM model are derived from the output of the ARIMA model. The establishment of the ARIMA model and the test of the prediction effect are very important in Fig. 2.

3.3 Data Prediction based on LSTM

LSTM is an RNN, often used to process and predict important events with very long intervals and delays in time series [28]. An LSTM unit contains an input gate, an output gate, and a forgetting gate. The input gate controls the model's input, the output gate controls the model's output, and the forgetting gate calculates the degree of forgetting of the memory module at the previous moment [29]. The structure of the LSTM model is displayed in Fig. 3, and the specific calculation equation reads,

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

f_t and x_t represent the forgetting gate and input gate in the tth step in the sentence sequence. On each score, the forgetting gate controls the degree of forgetting of each score information, and the input gate controls the degree to which each score information is newly written into long-term information.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i \tag{2}$$

$$C = tanh(W_c \cdot [h_{t-1}, x_t] + b_c \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times C \tag{4}$$

The Sigmoid function is selected for the two gates f_t and x_t, and the value range is [0,1]. The value of the tanh function is [−1,1]. C_{t-1} and C_t refer to the state of the neuron at time $t-1$ and at time t.

$$h_t = o_t \times tanh(C_t) \tag{5}$$

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o \tag{6}$$

o_t represents the output gate to control the output degree of the long-term information of the word; h_t refers to the output of step t in the sentence sequence. The LSTM is introduced in this study, which can effectively solve the long-term dependence on data, thereby effectively processing the score data. The core of LSTM lies in the state of the cell layer throughout the entire forward process, and the characteristic information transmitted on the cell layer can remain unchanged for a long time (Fig. 3).

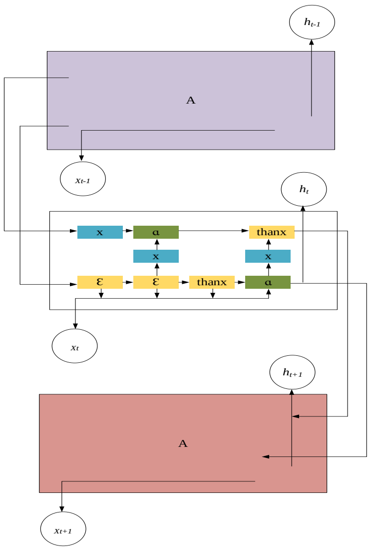

Fig. 3. The structure of the LSTM model.

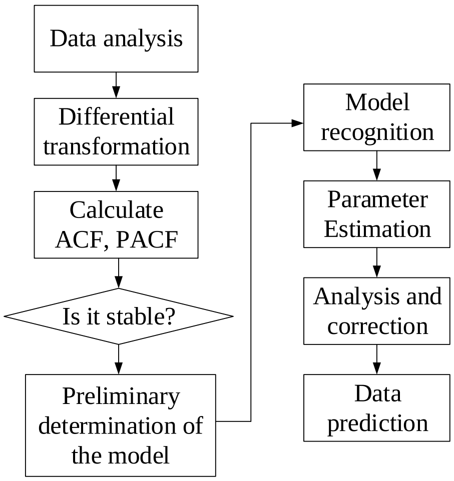

Fig. 4. Construction process of ARIMA model.

The input data of LSTM came from Tushare financial community. Daily stock price data from January 2000 to December 2014 and January 2015 to December 2019 were selected as the training and test sets, with a total of 3466 and 1200 pieces of data. The input of the LSTM model covers time step, input dimension, batch size, and other parameters, and the training set after data standardization as input data. Specific input variables and features are as follows:

1. Time step: It refers to the length of the input sequence, which corresponds to the number of previous trading days utilized to predict the lowest price of the next trading day. Here, the time step is set to 15, indicating that data from the last 15 trading days is utilized as input.
2. Input dimension: The dimension of the input data, representing the number of variables and features contained in the input data. According to the prediction time period, the prediction can be categorized into 5-day, 10-day, and 20-day predictions, with corresponding input dimensions of 5, 10, and 20, respectively.
3. Batch size denotes the number of samples employed in each update of the network parameters. Here, a batch size of 32 is utilized, implying that 32 samples are used during each iteration of network parameter updating.
4. Learning rate: It controls the step size of network parameter updates. The learning rate is set to 0.0005, accelerating the loss function's convergence.
5. Number of iterations: It represents the total number of times the network is trained. Here, the number of iterations is set to 50.
6. Output dimension: It means the dimension of the target variable predicted by the model, *i.e.* the predicted lowest price. The output dimension is 1, illustrating a single value is predicted.
7. Data standardization: It standardizes the data after merging the training and test sets to ensure that the range of input data is consistent and improve the effect of model training.

3.4 Time-Space Analysis Based on ARIMA

In this study, *R* language is taken as the platform for fitting the time series. The main steps for implementing the ARIMA model are given as follows. The stability of the original series is judged by graph-checking and hypothesis-checking methods. If it is unstable, a data difference operation must be performed until it reaches a stable state. The model's order is determined by selecting the appropriate parameters p and q for model establishment according to the tailing properties of the sample's autocorrelation and partial autocorrelation functions. An appropriate method for parameter estimation is selected to solve the estimated value of the autocorrelation coefficient and the moving average coefficient in the model. The model is tested to check whether the residual is a white noise sequence and whether the model is valid. If the model does not pass the above test, Step 2 can be ignored. The various possible combinations of p, d, and q should be considered fully, and the fit has to be realized multiple times. The model with the best fitting effect is selected among the many models that have passed the test. The fitted model is adopted to predict the future trend of the sequence, thereby testing whether the model has a good application effect on the prediction set [30, 31]. The ARIMA model regards the data sequence formed by the forecast object over time as random and uses a certain mathematical model to approximate the sequence. Once the model is determined, it can predict future values based on the past and current values of the time series. However, financial time series have high dynamic instability and long-term dependence. Hence, ARIMA can't well dig out the hidden information behind dynamic financial data. The traditional ARIMA model is not suitable for predicting financial data. However, the advantage of the ARIMA model to stabilize non-stationary series is integrated, and the ARIMA model is combined with the LSTM model to establish a multi-layer prediction model to realize the prediction of non-stationary time series in this study. The forward LSTM and the backward LSTM are combined to form a Bi LSTM, which encodes and processes information in a two-way manner. However, the financial data is highly dependent on time series. Therefore, this study only considers the forward coding and processing of financial data to predict future changes in financial laws. Consequently, financial data processing and prediction can be realized through LSTM without using Bi LSTM in Fig. 4.

The specific process of time series data analysis of ARIMA is as follows, (1) Determination of the stationarity of the time series: the wide and strict stationary of the time series are calculated; (2) Determination of parameters of the ARIMA model: moment estimation, least squares estimation, and maximum likelihood estimation are used to determine the parameters of the ARIMA model; (3) Fitting ARIMA model: the model is fitted according to the determined ARIMA model parameters, and the fitting effect is tested; (4) ARIMA models are used for prediction.

3.5 Parameters Optimization of PSO

PSO is inspired by bird swarm foraging behavior [32]. In the group of PSO algorithms, individual particles evaluate their position information in each round of evolutionary iterations by searching for solutions to multi-dimensional problems in space. During the entire process of the group, the particles share their "optimal" position information, adjust their own speed and position based on the memory, constantly compare and follow the candidate space solutions, and then find the optimal solution or the local optimal solution [33]. The specific structure is presented in Fig. 5. The evolution equation of the basic PSO is given as follows,

$$v_{ij}(t+1) = \lambda v_{ij}(t) + c_2 \cdot r_2 \cdot (b_{ij}(t) - p_{ij}(t)) + c_2 \cdot r_2 \cdot (g_{ij}(t) - p_{ij}(t)), \tag{7}$$

$$x_{ij}(t+1) = v_{i_{ij}}(t+1) + x_{ij}(t). \tag{8}$$

Based on the particle search path analysis, the particles are constantly approaching their local attractors in the process of particle search to ensure the convergence of the particle swarm algorithm. The equation is defined in Eq. (9).

$$p_{ij}(t+1) = p_{ij}(t) + \beta \cdot v_{ij}(t+1) \tag{9}$$

t means the current iteration number; v_{ij} represents the velocity of particle i in dimension j; $v_{ij} \in [-v_{max}, v_{max}]$; v_{max} refers to the maximum speed that the particle is allowed to and move; p_{ij} stands for the position of particle i in dimension j, $p_{ij} \in [-p_{max}, p_{max}]$; p_{max} denotes the maximum space position that the particle is allowed to move; λ is the inertia weight, which is used to balance global search and local search; b_{ij} and g_{ij} indicate the individual extreme value and global extremum of particle i on the dimension j; $c1$ and $c2$ are acceleration factors 3 that represent the ability of particles to self-summarize and learn from high-quality particles in the group; $r1$ and $r2$ represent random numbers between [0, 1]; β implies a constraint factor to control the weight of the speed.

Compared with other biological intelligent evolutionary algorithms, the biggest advantage of the particle swarm optimization (PSO) algorithm lies in simple algorithm design and fast convergence speed. Although the PSO algorithm is easy to fall into the local optimum, adding this algorithm to the ARIMA LSTM model can significantly improve the calculation accuracy of the model.

The PSO algorithm simulates the swarm intelligence behavior of various animals in the natural world, and uses the mutual cooperation and communication of individuals in the group to achieve the goal of optimization. PSO algorithm and wolf swarm algorithm (GWO) are two common algorithms, and they have their own ranges of adaptation. GWO is more prominent in predicting and optimizing multiple input multiple output systems. Combining PSO and GWO with other algorithms can significantly improve the prediction accuracy of the composite model. However, compared with GWO, PSO is prone to fall into a local optimum during the optimization. In the processing and prediction of financial data, a large amount of data needs to be globally optimized. The GWO algorithm faces the fatal problem of weak global search ability and slow convergence speed. Thus, the PSO algorithm is employed to improve the prediction accuracy of the multi-layer model, as indicated in Fig. 5.

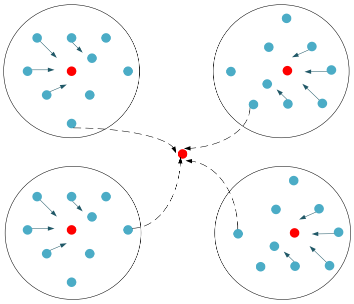

Fig. 5. Structure optimization of PSO algorithm and early warning system driven by big data.

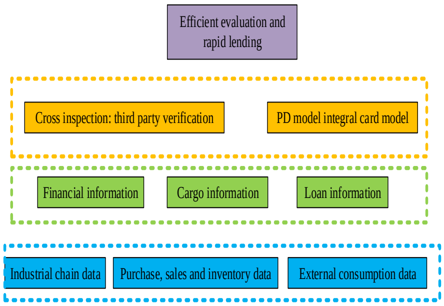

Fig. 6. IoT financial credit evaluation.

The specific process of the PSO algorithm optimization model parameters is as follows:

(1) The parameters that must be optimized are determined, including batchsize, epoch, and step.
(2) The parameter values are set, the minimum values are 10, 5, and 3, and the maximum values are 60, 50, and 30. The learning factor is set to 2, the maximum inertia weight is 0.8, the minimum inertia weight is 0.2, and the number of particles is 20, for a total of 30 searches.
(3) The length of the prediction time period is set to 5 days, 10 days, and 20 days, respectively.

(4) The MSE function is employed to measure prediction accuracy. Before calculating the MSE value, the true value and the predicted value are reversed to ensure the validity of the MSE value.

3.6 Experiment Design and Performance Evaluation

The data used here came from the Tushare financial community. The daily stock price data from January 2000 to December 2014 was selected as the training set, with a total of 3466 data, and the data from January 2015 to December 2019 was used as the test set, with a total of 1200 data. This experiment aims to obtain the predicted value of a fixed number of days. Considering the correlation between time series, it is necessary to preprocess the dataset, split it into fixed-length intervals, and take this interval as a whole to achieve the result of directly outputting fixed-length predictions. The tensorflow open source platform is applied as the DL platform, and Python2.7 is applied to write the programs of LSTM and PSO. The ARIMA model is to output the predicted value sequence as the first part of the combined model output. The standardized residuals are performed with data division according to the original proportions, which are deemed as the training set and the test set of the PSO-LSTM model. The data set is divided into many intervals of the corresponding length according to the difference in the length of the prediction time period, and the intervals are taken as a whole. The processed training set is considered as the input of PSO-LSTM to establish a financial data prediction model. The adaptive moment estimation algorithm is defined as the optimization algorithm for training the internal parameters of LSTM, and the learning rate is set to 0.0005. The parameter settings of the PSO algorithm remain unchanged. According to the different lengths of the prediction period, it is divided into three periods: 5-day, 10-day, and 20-day predictions.

The batchsize, epoch, and step are fixed. Due to the actual situation of a single-layer LSTM, a single-layer LSTM with 56 hidden neurons is established firstly through repeated experiments, and the dropout function is introduced to add a second hidden layer. After the model parameters are selected completely, 3466 pieces of training data are split into a sequence with a fixed length of 5 and a data input dimension of 5. In addition, the ARIMA-PSO-LSTM model is constructed and trained. The 240 test sets of length 5 are predicted. A double-layer LSTM with 50 and 32 hidden neurons is constructed based on the PSO algorithm, the model parameters are determined, and the structure of the LSTM is established.

Due to the large noise of financial data, a normalization method is adopted in this study to reduce the data noise, unify the data dimension, facilitate gradient calculation, and speed up the convergence. In addition, the MIN-MAX method is applied to normalize the data, as illustrated in Eq. (10).

$$X_{scaled} = \frac{X - X_{\min}}{X\ \min_{\max} \cdot (max - min) + min} \tag{10}$$

The prediction accuracy of different models is compared using a quantitative method to measure the prediction effect of each model. The MSE, root mean square error (RMSE), and MAE are selected to evaluate the performance of each model in financial data prediction [34]. MSE refers to the expectation of the square of the difference between the model's predicted value and the true value, which can be used to measure the degree of difference between the true value and the estimated value and to evaluate the predictive ability of the model. The larger the MSE, the worse the ability to fit the experimental data. The calculation equation reads.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2 \tag{11}$$

RMSE is the arithmetic square root of the MSE. The smaller the RMSE, the stronger the ability to fit the data. It can be written in Eq. (12):

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

MAE is the expectation of absolute error. MAE can prevent the positive and negative offset of the error, and can better reflect the actual situation of the deviation between the predicted value and the true value. The smaller the value, the stronger the ability to fit the data. The calculation equation is expressed in Eq. (13),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| y_i' - y_i |\,. \tag{13}$$

3.7 IoT Financial Evaluation System

The essence of internet finance is still finance, and the core of internet finance is still credit. Credit risk is currently the biggest risk in Internet finance. Both traditional finance and current Internet finance are subjective credit systems, and their credit evaluation is mainly based on manual evaluation. The IoT finance is an objective credit system, which mainly uses intelligent sensing equipment to collect objective information to form an objective credit system, which can fully resolve the current credit crisis in Internet finance. The IoT introduces a novel model that facilitates the active perception and interaction of the physical world. It realizes the behavior of the virtual economy in the time and space dimensions of the real economy, to accurately predict the development trend of the real economy. Thereby, the combination of the virtual economy and the real economy will be realized, and the reform of Internet finance will be promoted [35]. Then, a new model of the IoT emerges, which is called IoT finance. IoT finance is a new financial model based on Internet finance and traditional finance in Fig. 6. It is an innovation of Internet finance and a new application model of IoT, realizing the deep integration of IoT technology and Internet finance [36].

3.8 Data Confidence Interval Construction

Confidence Interval (CI) refers to the estimated interval of overall parameters constructed by sample statistics. In statistics, the CI of a probability sample is the interval estimate of a certain overall parameter of the sample. The CI shows the degree to which the true value of this parameter has a certain probability to fall around the measurement result. It gives credibility to the measured value of the measured parameter, that is, the calculation steps of “a probability” required above are as follows:

Firstly, it has to find the mean of a sample.

Secondly, it can calculate the sampling error.

It is generally believed that the sampling error of 100 samples is ±10%; the sampling error of 500 samples is ±5%; and the sampling error of 1,200 samples is ±3%.

Thirdly, the "sampling error" calculated in the second step is added or subtracted from the "sample mean" obtained in the first step to obtain the two endpoints of the CI. The calculation process is shown in Eq. (14),

$$Pr = (C_1 \leq \mu \leq C_2) = 1 - \alpha. \tag{14}$$

α indicates the significance level (0.05 or 0.10); $(1 - \alpha)$ means the confidence level (for example, 95% or 90%); (C_1, C_2) refers to the CI.

4. RESULTS OF DATA PREDICTION OF FINANCIAL BRAND

4.1 Performance Analysis of Single Model

The single LSTM model shown in Fig. 7 for financial data prediction presents different levels of effectiveness over different prediction time periods. Figs. 7 (a)-(c) represent the prediction results of 5, 10, and 15 days, respectively. For 5-day predictions, the model expresses promising performance, accurately capturing long-term trends in the data and adapting to short-term trends with large changes. The MSE for this prediction time period is 0.2358. However, the prediction results for the 10-day are relatively unsatisfactory. The

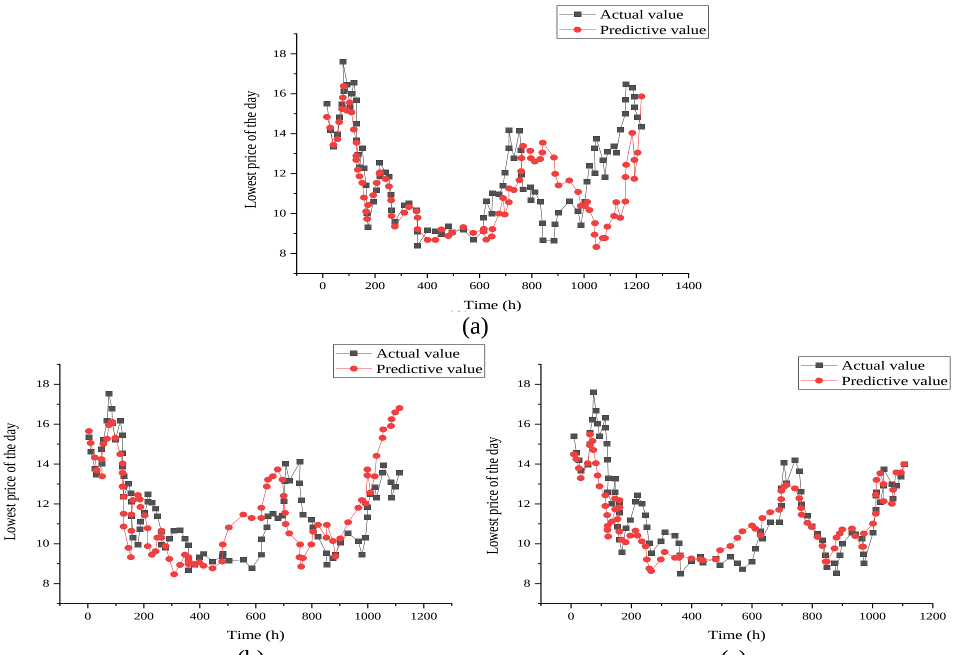

Fig. 7. Prediction results of single model at different time periods; (a) 5 days prediction results for a single model; (b) 10 days prediction results for a single model; (c) 15 days prediction results for a single model.

model tends to produce higher predictions during the first 200 days and 800 to 1000 days. Over the next 200 days, there are too many fluctuations in the forecast results, and the model has difficulty accurately adapting to those regions that had undergone large changes. The MSE for this prediction time period is 0.509. For the 20-day prediction time period, the overall effectiveness of the model decreases further. The prediction results perform poorly during periods of sharp fluctuations in the lowest price. The model cannot accurately capture real data's upward or downward trend, resulting in inconsistent and delayed predictions. The MSE for this prediction time period is 0.612.

4.2 Performance Analysis of Multi-layer Model

Fig. 8 presents the results of the PSO-LSTM model for different prediction time periods. Specifically, Figs. 8 (a)-(c) represent the prediction results for 5 days, 10 days, and 15 days, respectively. The following observations can be made. For the 5-day prediction, the PSO-LSTM model demonstrates an overall improvement in fitting performance, with an MSE of 0.196. However, there are discrepancies in the predicted values during the initial 200 days, where the model generates lower predictions. The prediction results for 15 days show significant fluctuations in the predicted values between 800 and 1200 days. There is a noticeable discrepancy between the predicted and actual values in regions where the real data undergo substantial changes. The MSE for this prediction time period is 0.509. As for the 20-day prediction, the model shows a relatively poorer fitting performance. The predicted values tend to be either lower or higher. Although the predicted values are relatively stable in certain regions, capturing short-term trends remains challenging. However,

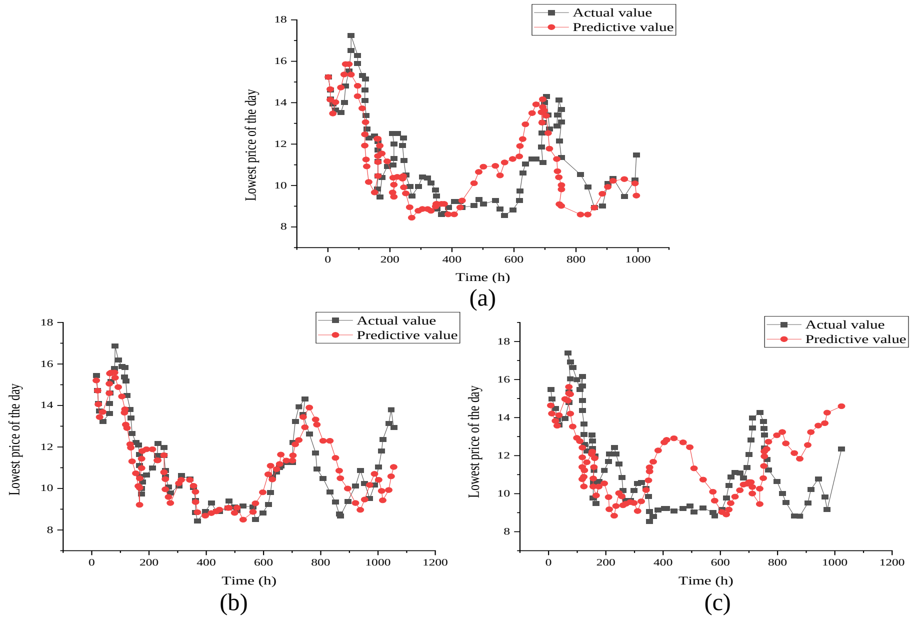

Fig. 8. Prediction results of multi-layer model at different time periods; (a) 5 days PSO-LSTM model prediction results; (b) 10 days PSO-LSTM model prediction results; (c) 15 days PSO-LSTM model prediction results.

compared to the LSTM model, the PSO-LSTM model demonstrates improvement in predicting delayed effects. The MSE for this prediction time period is 0.571. Based on the provided data, it can be concluded that incorporating the PSO algorithm, as in the PSO-LSTM model, significantly enhances the model's accuracy.

4.3 Performance Analysis of Hybrid Model

Figs. 9 (a)-(c) demonstrate the results of the ARMI-PSO-LSTM hybrid model over different time periods, corresponding to 5-day, 10-day, and 20-day predictions, respectively. The following conclusions can be drawn. For 5-day predictions, the hybrid model shows a relatively good fitting effect and can capture the overall trend of data changes. However, in the first 200 days, there are significant differences in the predicted values, and the model produces lower predictions compared to the actual values. The MSE in this time period is 0.186. In the 15-day predictions, the hybrid model can generally adapt to the changing trend, and the predicted value curve is relatively close to the actual value. However, there are clear biases in some places, and the predicted data are both higher and lower than the real data. The loss function values are higher compared to the 5-day prediction, indicating a relatively poor overall fit. The MSE for this prediction time period is 0.408. The 20-day prediction shows the model's weak ability to capture the overall trend, resulting in a relatively poor overall fit. The loss function values are higher compared to the 5-day and 10-day predictions. The MSE for this prediction time period is 0.558. Based on the information provided, it can be concluded that the ARMI-PSO-LSTM hybrid model exhibits reasonable fitting over a shorter prediction range. However, it faces challenges in accurately predicting long-term trends, resulting in large biases and high MSE values.

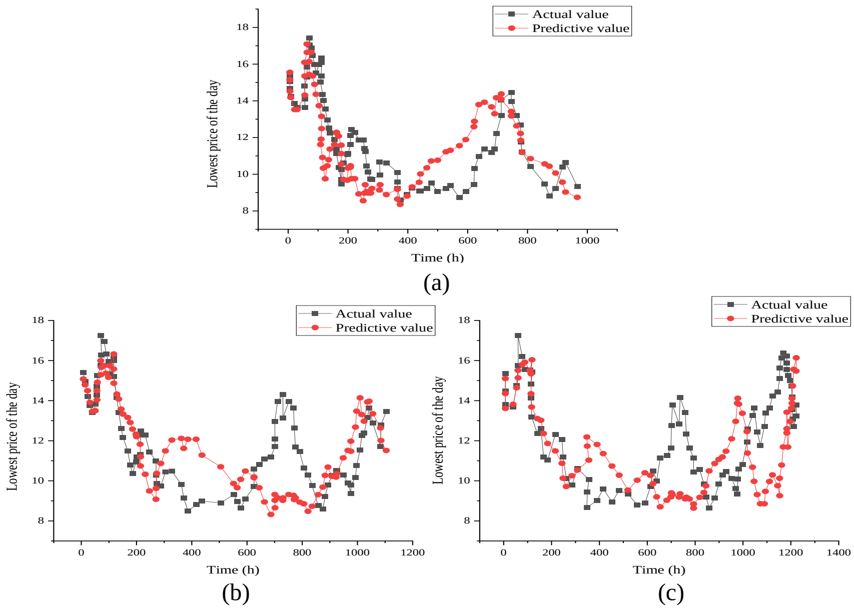

Fig. 9. Prediction results of hybrid model at different time periods; (a) 5 days prediction results of ARIMA-PSO-LSTM hybrid model; (b) 10 days prediction results of ARIMA-PSO-LSTM hybrid model; (c) 15 days prediction results of ARIMA-PSO-LSTM hybrid model.

Figs. 10 (a)-(c) provide a vertical comparison of the LSTM, PSO-LSTM, and ARIMA-PSO-LSTM models for the prediction results of 5, 10, and 20 days. The following are the main conclusions. Compared to the PSO-LSTM model, the ARIMA-PSO-LSTM model exhibits a reduction in MSE, RMSE, and MAE values across all time periods. Specifically, for the 5-day prediction, the ARIMA-PSO-LSTM model presents a decrease of 9.93%, 5.09%, and 7.25% in these indicators compared to the PSO-LSTM model. For the 10-day prediction, these indicators decrease by 14.57%, 7.57%, and 7.56%, respectively. For the 20-day prediction, the indicators decrease by 5.87%, 2.98%, and 6.55%, respectively. These reductions indicate that the introduction of the ARIMA model effectively enhances the prediction accuracy of the PSO-LSTM model, resulting in improved overall prediction results. When comparing the LSTM, PSO-LSTM, and ARIMA-PSO-LSTM models for 5-day, 10-day, and 20-day predictions, it can be observed that as the prediction range increases, the MSE, RMSE, and MAE values gradually increase. This observation suggests that the proposed models may not have been sufficiently trained. The limitation primarily stems from the limited size of the provided dataset, resulting in fewer model training iterations. In summary, the results reveal that the ARIMA-PSO-LSTM hybrid model outperforms the PSO-LSTM model in terms of prediction accuracy for different time periods. However, the insufficient training due to the small dataset size highlights the need for more extensive training to enhance the overall performance of the proposed model.

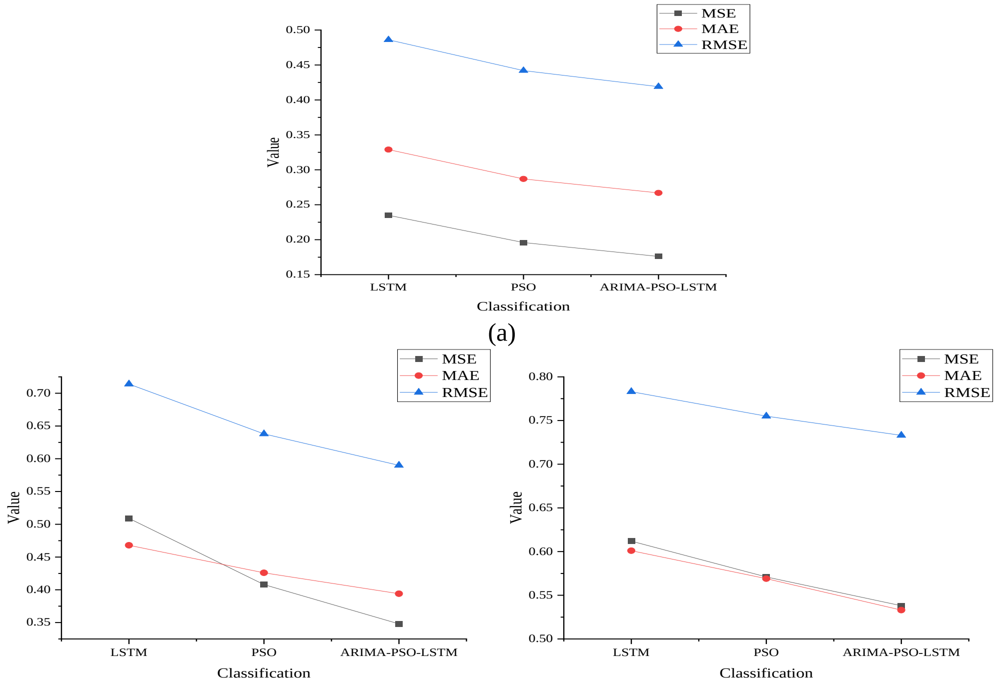

Fig. 10. Prediction results of different hybrid models at various time periods; (a) Longitudinal comparison of 5-day prediction results for LSTM, PSO-LSTM and ARIMA-PSO-LSTM models; (b) Longitudinal comparison of 10-day prediction results for LSTM, PSO-LSTM and ARIMA-PSO-LSTM models; (c) Longitudinal comparison of 15-day prediction results for LSTM, PSO-LSTM and ARIMA-PSO-LSTM models.

4.4 Performance Analysis of IoT

In Table 1, the number of financial data gradually increases when the number of users is 10~30; Subsequently, the number of financial data records starts to decline when users reach 30 to 100. However, the number of financial data increases instantly once users exceed 100, primarily due to the start and stop time expansion. The response time increases greatly when there are more than 30 users. This finding confirms that the system can effectively support up to 30 concurrent users for simultaneous financial data uploads within the current architectural framework, with a financial data upload rate of approximately 208.9/min and an average throughput of 2 MB/s. When the number of concurrent users is 10~100, the number of failed transactions of the financial data uploaded by this system is 0, and no abnormal phenomenon has occurred. This outcome demonstrates that the proposed system can maintain stable operation during high-pressure scenarios for financial data uploading.

Table 1. Financial data IOT upload test results.

Scenes	Number of users	Success rate	Failure rate	Response time	Financial data	Volume of data / MB	Lasting time	Throughout (/ MB/s)
1	10	568	0	4.678	1 047	535.545 95	6	1.711 080 135
2	20	628	0	12.092	1 167	602.204 35	6	2.011 017 101
3	30	708	0	13.531	1 327	667.725 55	6	2.151 677 756
4	50	699	0	23.075	1 299	650.787 25	6	2.101 882 222
5	100	758	0	24.075	1 427	715.032 55	6	20.056 768 337
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4.5 Discussion

This study takes data of different financial brands as research objects, adopts IoT framework modeling, and uses DL algorithms to establish single, combination, and mixed models. Additionally, the improved PSO algorithm is utilized to select the parameters of the LSTM model, leading to the construction of the ARIMA-PSO-LSTM model. The prediction results of the models are evaluated by comparing the evaluation indicators of the three models, such as MAE, MSE, and RMSE. In financial data prediction, scholars have proposed diverse methods and models that have found applications in economics, finance, mathematics, and computer technology. However, due to the complexity and uncertainty of financial data, the absolute accuracy of model prediction cannot be fully guaranteed. Compared with previous studies, the proposed model demonstrates smaller errors, higher prediction accuracy, better fit, faster response processing speed, and superior performance than the latest research models. This study offers a new method to predict the data of different financial brands, which can help financial institutions better understand the market trend and predict future market changes, and provide references for investors, which has important application value.

5. CONCLUSIONS

The different financial brand data are taken as the research objects. The IoT framework is selected as the basis of modeling to implement different IoT financial data analysis models with corresponding algorithms as the research core.

This study focuses on analyzing data from various financial brands as the research objects. A DL framework is adopted to model the selected data, and the single, combined model, and hybrid models are established are tested under different data sets. An improved PSO algorithm is utilized to select some parameters of the LSTM model, and the ARIMA-PSO-LSTM model is constructed. In addition, model evaluation is conducted using MAE, MSE, and RMSE as indicators, and the prediction results of the proposed model are compared with those of the other models. It is found that the performances of different models have been tested, which further proves that the proposed model has smaller error, greatly improved data prediction accuracy, better fitting effect, faster response processing speed, and higher performance in contrast to the latest research models. Furthermore, the proposed model demonstrates superior fitting effects and outperforms the latest research models in terms of performance. However, this study still has several limitations. Firstly, the traditional statistical and DL models are combined, and the improved PSO algorithm is introduced to optimize the model parameters. But there are alternative methods to optimize the PSO algorithm, such as GARCH in addition to the ARIMA model. Secondly, 30 days of data are utilized for analysis only here, which limits the spatiotemporal analysis results of the model built to a certain extent. Subsequent research will delve deeper into these two aspects and continuously refine the financial data and brand prediction model. In this study, the DL framework is combined with the improved PSO algorithm to establish the analysis model of different financial brand data, and model performance is evaluated using indicators such as MAE, MSE, and RMSE. The experimental results reveal that the performance and accuracy of the model are improved, which has a certain role in promoting research in the field of financial data analysis. Finally, this study provides a new method to predict the data of different financial brands, enabling financial institutions to better understand market trends and predict future market changes. Besides, this study offers references for investors, which has vital application value. This study has some contributions in both academic and practical fields. First, from an academic perspective, it uses the IoT framework and DL algorithm, combined with the improved PSO algorithm, to establish a model to analyze the data of different financial brands. By comparing the evaluation indexes of the model, it is demonstrated that the proposed model exhibits smaller errors, higher data prediction accuracy, better fitting effect, and faster response processing speed compared with the latest research model. This introduces a new method and tool for the field of financial data analysis, enriches the theoretical framework of academic research, and provides a reference for further research. Second, in terms of practical application, the proposed model equips financial institutions with enhanced capabilities to comprehend market trends and predict future market changes. By analyzing the data of different financial brands, financial institutions can obtain more accurate forecast results, to better develop investment strategies and risk management programs. Furthermore, this study offers vital references for investors to enable them to make more informed investment decisions. Thus, this study has important contributions in both academic and practical applications. Consequently, this study expands the theoretical framework in the field of financial data analysis while providing a feasible method and tool to assist financial institutions and investors in comprehending and responding to market risks, thus improving the accuracy and efficiency of decision-making. This improvement in accuracy and decision-making efficiency positively impacts promoting the development of the financial industry and facilitating economic stability.

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