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Deep Learning-Based Stock Market Prediction and Investment Model for Financial Management

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ABSTRACT

This study explores the potential application of deep learning techniques in stock market prediction and investment decision-making. The authors used multi-temporary stock data (MTS) for effective multi-scale feature extraction in reverse cross attention (RCA), combined with improved whale optimization algorithm (IWOA) to select the optimal parameters for the bidirectional long short-term memory network (BiLSTM) and constructed an innovative RCA-BiLSTM stock intelligent trend prediction model. At the same time, a complete RCA-BiLSTM-DQN stock intelligent prediction and investment model was established by combining the deep Q network (DQN) investment strategy. The research results indicate that the model has excellent sequence modeling and decision learning capabilities, which can capture the nonlinear characteristics and complex correlations of the market and provide more accurate prediction results. It can continuously improve the robustness and stability of the model through adaptive learning and automatic optimization.

KEYWORDS

BiLSTM, DQN, Financial Management, Intelligent Trend Prediction of Stocks, Investment Decisions, IWOA, RCA, Stock Market Forecast

In today's financial market, the stock market has always been a hot topic and challenge about which investors are concerned. With the continuous development of technology and the rapid rise of artificial intelligence, deep learning technology is widely used as a powerful predictive analysis tool in various fields, especially in financial management and stock market forecasting (Ta et al., 2022). The volatility of the stock market in financial management is increasing, and investors often find it difficult to predict market trends and make scientific investment decisions (Lei, 2020). Scholars from various countries have explored the information patterns in the stock market through deep learning techniques, analyzed the volatility and related factors of the stock market, and proposed various stock market prediction models and investment decision-making strategies in financial management (Sun & Li, 2022).

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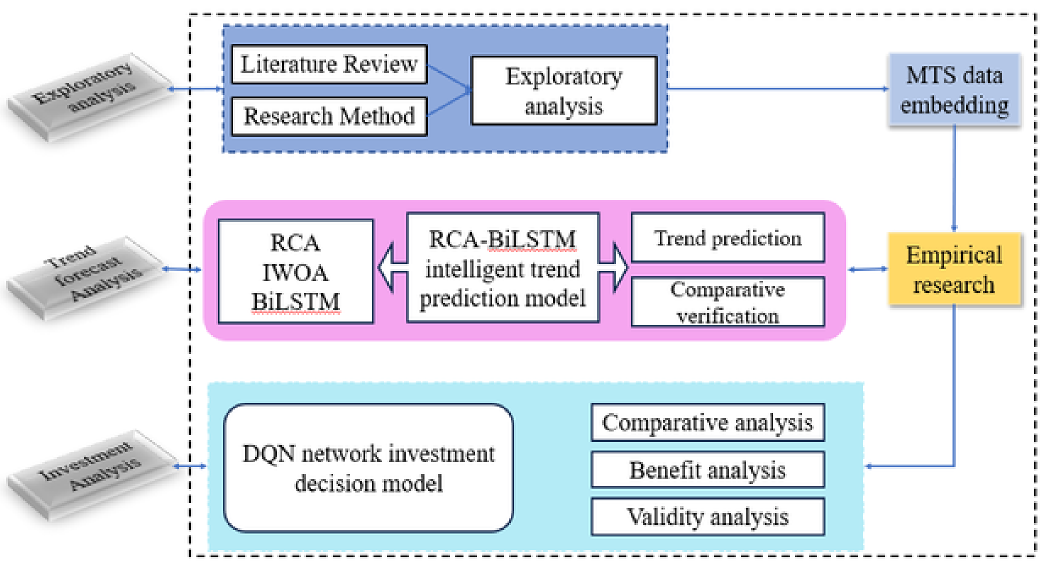
Among them, the Long Short Term Memory Network (LSTM) is currently one of the research hotspots for predicting stock market trends and making investment decisions (Chen et al., 2020). LSTM is a neural network model used for processing time series data; it can learn long-term dependencies and is helpful for predicting stock prices (Sonkavde et al., 2023). It considers multiple factors and can provide more accurate predictions and reliable decision-making recommendations, which is superior to traditional technical analysis. However, LSTM networks may encounter problems such as vanishing or exploding gradients when processing long sequence data, leading to unstable training and difficulty in convergence (Agrawal et al., 2022). By introducing reverse information flow, BiLSTM can, to some extent, suppress this problem, improve the stability and training effectiveness of the network, and more accurately capture patterns and trends in sequence data (Ji et al., 2021). Therefore, this article proposes an intelligent prediction and investment decision algorithm based on RCA-BiLSTM-DQN to address the aforementioned problems. The proposed algorithm uses RCA for multi-dimensional feature extraction, an IWOA algorithm for the calculation of optimal parameters in BiLSTM training for multi-scale feature stock prediction, and incorporates DQN decision strategy design. The framework is shown in Figure 1.

This study has made contributions to the literature in the following areas:

1. The intelligent prediction and investment decision algorithm of RCA-BiLSTM-DQN proposed in this article introduces the RCA mechanism, effectively extracting key features from sequence data. This approach enhances the model's ability to capture nonlinear and dynamic features in the stock market.
2. The utilization of a stock data representation method (MTS) that integrates multi-scale features solves the limitation of traditional methods, which have limited feature information and fail to capture temporal information. This improvement enhances the performance of prediction models.
3. In the intelligent model of RCA-BiLSTM-DQN, the biomimetic optimization algorithm IWOA is used to update the position of individual whales. This process yields optimal parameters that replace those in BiLSTM, enhancing the intelligence and automation of prediction and investment models.

Figure 1. Research Framework



4. This model demonstrates enhanced accuracy in the prediction of the future trend of the stock market and makes corresponding investment decisions based on the prediction results. This provides a feasible method for guiding investor behavior and offers new perspectives for research in the field of financial management.

LITERATURE REVIEW

Deep learning, as an important tool for stock market prediction and investment decision-making research in the current financial management field, has been explored by many scholars for the application of deep learning algorithm models in stock market prediction and investment decision-making. In stock market prediction in financial management, Nabipour et al. (2020) analyzed historical stock price data and predicted future trends by using Convolutional Neural Networks (CNN) and LSTMs. The research results showed that the combination of the two deep learning algorithm models outperformed other time series-based methods in terms of accuracy in stock market prediction. The research of Rouf et al. (2021) has shown that deep learning models perform well in terms of accuracy and stability in stock market forecasting and trading decisions. They used deep belief networks (DBN) and autoencoders (AE) for prediction and found that these models performed well in predicting market fluctuations and oscillations. At the same time, the accuracy of feature extraction is also crucial for the predictive performance of the model (Rouf et al. 2021). Therefore, some researchers use convolutional and pooling layers in CNN to capture the characteristics of time series data such as stock prices and trading volumes, thereby improving the accuracy of stock trend prediction (Lee et al., 2021). Feng et al. (2022) used adaptive compressive sensing (CS) technology for feature extraction and modeling of BILSTM models, and they successfully predicted the trend of the Shanghai and Shenzhen 300 Index.

In addition, by analyzing and predicting the trends of the stock market in financial management, investors can better understand market trends and possible development directions, making wiser investment decisions, guiding enterprises in investment, financing, and capital structure optimization decisions, and helping enterprises achieve more stable profits and risk management. However, when making investment decisions, investors need to consider multiple factors comprehensively and conduct in-depth analysis of relevant investment decisions in order to improve the efficiency and returns of stock market investments (Fan & Peng, 2022). Singh et al. (2022) used a combination model with feedforward (BP) neural network as the core technology to predict the return of Shanghai Stock Exchange and achieved good prediction results. In recent years, scholars have studied the use of reinforcement learning models to formulate investment decision strategies. Through interaction with the environment, the model gradually learns and improves strategies (Buczynski et al., 2021). Some researchers have used reinforcement learning models for stock investment decisions and achieved good results.

There is still no perfect algorithm model capable of accurate prediction of the trends and investment decisions in the stock market in financial management. The volatility and uncertainty of the stock market make it difficult to achieve precise predictions, and a model may exhibit errors in the forecasted outcomes. Based on the above research and deep learning technology, this paper proposes a new RCA-BiLSTM-DQN stock intelligent prediction and investment decision-making method. It integrates MTS stocks to represent multi-temporal features and employs RCA for feature extraction to capture market dynamics and trend information comprehensively. Then, the IWOA intelligent optimization algorithm is used to train BiLSTM and determine optimal parameters. The prediction results are then combined with the DQN network investment strategy model to construct a self-adaptive and universal RCA-BiLSTM-DQN stock intelligent model. This proposed model contributes to an improvement in prediction accuracy and informed investment decisions, yielding greater benefits.

MODEL DESIGN FOR STOCK MARKET PREDICTION AND INVESTMENT DECISION-MAKING

RCA-BiLSTM Intelligent Trend Prediction Model

RCA Model for Extracting Stock Trend Features

RCA, an improved algorithm based on Cross Attention (CA), is an attention mechanism in the Transformer model. Initially designed for machine translation, the Transformer model has proven highly effective (Lawal et al., 2020). This model is entirely constructed by the self-attention mechanism, which enables better capture of correlations among daily trend characteristics of stocks and the surrounding time steps, facilitating the extraction of token characteristics for each trading day in the stock market (Obthong et al., 2020). The Transformer model adopts a Seq2Seq model consisting of an encoder and a decoder. Information transmission between these two components is achieved through CA connections. The specific structure is shown in Figure 2 (a).

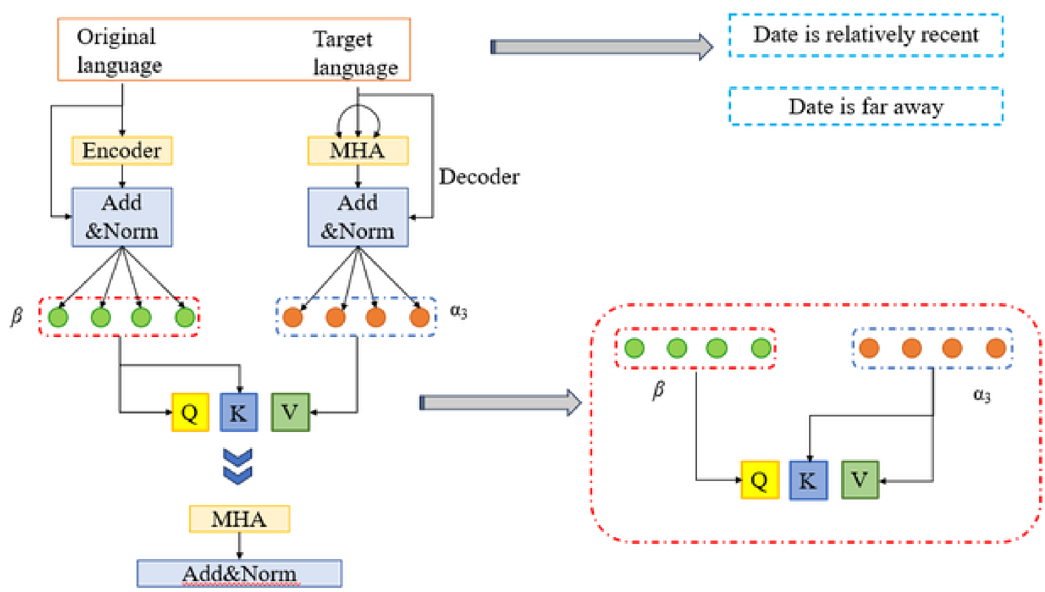
During the encoding process of CA, the data will be converted into an implicit vector through the Encoder β∘. This vector will serve as input for the $\boldsymbol{Q}$ and $\boldsymbol{K}$ values in the cross attention layer of the Decoder and participate in the calculation of the multi head attention layer (MHA):

$$Attention\left(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}\right) = softmax\left(\frac{\boldsymbol{Q}_e \boldsymbol{K}_e^T}{\sqrt{d_k}}\right)\boldsymbol{V}_d \tag{1}$$

In the formula, $\boldsymbol{K}_e$ and $\boldsymbol{Q}_e$ are the latent variables generated by the Encoder β, $\boldsymbol{V}_d$ is the latent variable generated by MHA in the Decoder α_3. When it is used as a traditional language translation model in Encoder, it places more emphasis on processing the original language input and allocates more attention to the hidden state of Encoder output β∘. However, in stock prediction tasks, data closer to the predicted date is usually more important, which is contrary to the focus of traditional

Figure 2. RCA Feature Extraction Algorithm

Note. The left side of the figure (a) shows CA and the right side (b) shows RCA.



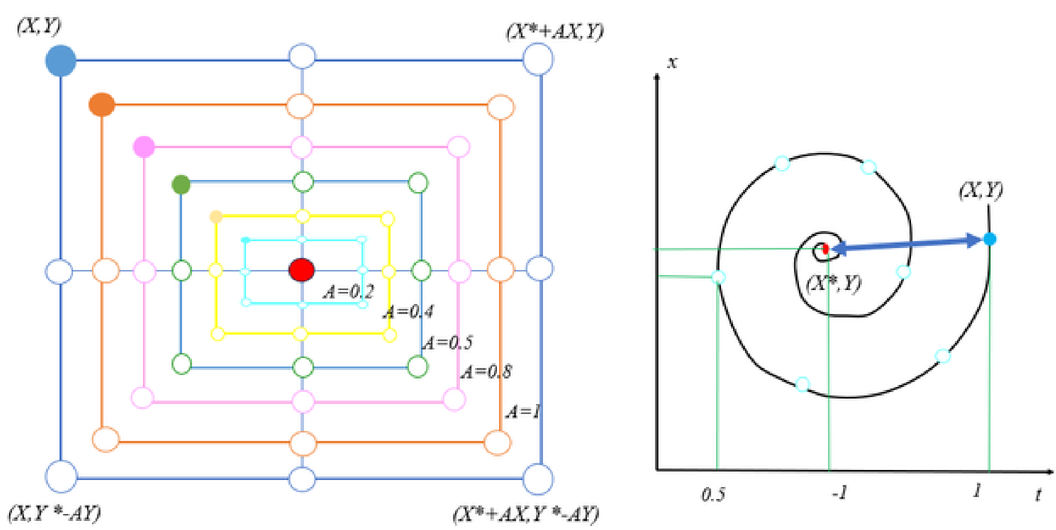
Transformer language translation models. Therefore, this article adopts a CA-based improvement method RCA, which mainly improves the cross attention layer in the Decoder. The specific structure is shown in Figure 2 (b). RCA differs from traditional cross attention layers by improving its input method and changing the order of generating hidden vectors. Specifically, one should use the output of the Encoder to generate the query vector $\boldsymbol{Q}$ and use the input of the Decoder to generate key value pairs $\boldsymbol{K}$ and $\boldsymbol{V}$. Through this approach, the model can focus more on the data in the decoder that is closer to the predicted date, enabling it to better learn information related to stock prediction (Guan, 2023). Compared to the regular attention (CA) algorithm, this model uses the relative distance attention (RCA) algorithm, which enables the model to focus on data with closer distances and achieve better predictive performance.

Optimized IWOA Intelligent Algorithm

IWOA is an intelligent optimization algorithm of the Whale Optimization Algorithm (WOA), a natural heuristic algorithm based on the predatory pattern of leading whales. The algorithm simulates the behavior of whale populations (Kumari et al., 2021). The predation process of the leader whale is divided into three stages: surrounding, attacking with foam net (using stage), and searching for prey (exploring stage). The schematic diagram of these stages is shown in Figure 3. By simulating these behaviors, WOA can demonstrate excellent performance in the resolution of various optimization problems (Day et al. 2023). However, WOA still exhibits shortcomings in terms of convergence speed and global search ability. To improve this situation, three improvement methods are introduced according to the original whale position update mode. These methods are combined to form a global search strategy to further enhance the intelligent optimization capabilities of the algorithm.

Adaptive Weight. In the early stage of algorithm search, weaken the impact of the optimal whale position on the current individual position adjustment to improve the algorithm's global search ability. As the number of iterations increases, the influence of the optimal whale position gradually increases, allowing other whales to converge to the optimal whale position faster and improving the convergence speed of the entire algorithm. Use the adaptive inertia weight composed of selected iteration times t to adapt to the changes in update times in the whale optimization algorithm (Chandola et al., 2023). The adaptive inertia weight is calculated as follows:

Figure 3. The Predation Process of the Leading Whale in WOA



$$w\left(t\right) = \frac{1}{5}\cos\left(\frac{\pi}{2}\cdot\left(1-\frac{t}{t\ \max}\right)\right) \tag{2}$$

The w introduced in the equation has the characteristic of nonlinear variation between [0,1]. In the early stages of the algorithm, the weights are small and change quickly; in the later stage, the speed of change is slowed down due to the larger weight. The design of this weight change can effectively ensure the convergence of the algorithm (Zhang et al., 2021). The IWOA position update formula is:

$$X\left(t+1\right) = \begin{cases} w\left(t\right)X^*\left(t\right) - A\cdot\left|C\cdot X^*\left(t\right) - X\left(t\right)\right| \\ w\left(t\right)X^*\left(t\right) + D\cdot e^{bl}cos\left(2\pi l\right) \end{cases} \tag{3}$$

$$X\left(t+1\right) = w\left(t\right)X_{rand}\left(t\right) - A\cdot \mid C\cdot X_{rand}\left(t\right) - X\left(t\right) \tag{4}$$

In the formula, t represents the number of iterations, A and C represent the coefficient vector, X^* is the current optimal whale position, X is the current whale position, b represents the spiral shape constant, l is a random number on the interval [-1,1], and $X_{rand}(t)$ represents the position of the random whale.

Variable Spiral Position Update. In traditional WOA, treating the control parameter b as a constant makes the spiral motion trajectory too simple, and each movement direction moves along the spiral towards the target, which can easily lead to the algorithm falling into local optima and becoming unable to search globally. Therefore, in order to expand the search range of the whale, the parameter b is adjusted to change with the increase of iteration times, and the shape of the spiral search is dynamically adjusted to enhance the whale's search ability, thereby improving the algorithm's ability in global optimization (Patalay & Bandlamudi, 2021). The expression for the spiral position update formula after combining adaptive weights is as follows:

$$\begin{cases} X\left(t+1\right) = w\left(t\right)X^*\left(t\right) + bD\cdot e^{l}cos\left(2\pi l\right) \\ b = e^{5\cdot\cos\left(\pi\cdot\left(1-\frac{t}{t_{\max}}\right)\right)} \end{cases} \tag{5}$$

In the spiral model, as the number of iterations increases, adjust parameter b to change the shape of the spiral dynamically. In the initial stage, a larger spiral shape is used to search for the global optimal solution, and in the later stage, a smaller shape is used to improve the optimization accuracy.

Optimal Neighborhood Perturbation. In order to increase search efficiency, the optimal neighborhood perturbation strategy is introduced, which randomly searches around the optimal value to find the global optimal solution, improves the convergence speed of the algorithm, and avoids premature convergence (Wang & Li, 2022). To increase the search space around and generate random perturbations at the optimal position, the formula for calculating neighborhood perturbations is as follows:

$$\tilde{X}\left(t\right) = \begin{cases} X^*\left(t\right) + 0.5\cdot rand1\cdot X^*\left(t\right), rand2 < 0.5 \\ X^*\left(t\right), rand2 \geq 0.5 \end{cases} \tag{6}$$

In the formula, *rand1* and *rand2* are uniform random numbers between [0,1]; $\tilde{X}(t)$ represents a new location for whales.

Greedy strategy is used to determine whether the generated neighborhood positions are preserved. The calculation formula is as follows:

$$X^{*}(t)=\begin{cases}\tilde{X}(t), f(\tilde{X}(t))<f(X^{*}(t))\\ X^{*}(t), f(X^{*}(t))\le f(\tilde{X}(t))\end{cases} \tag{7}$$

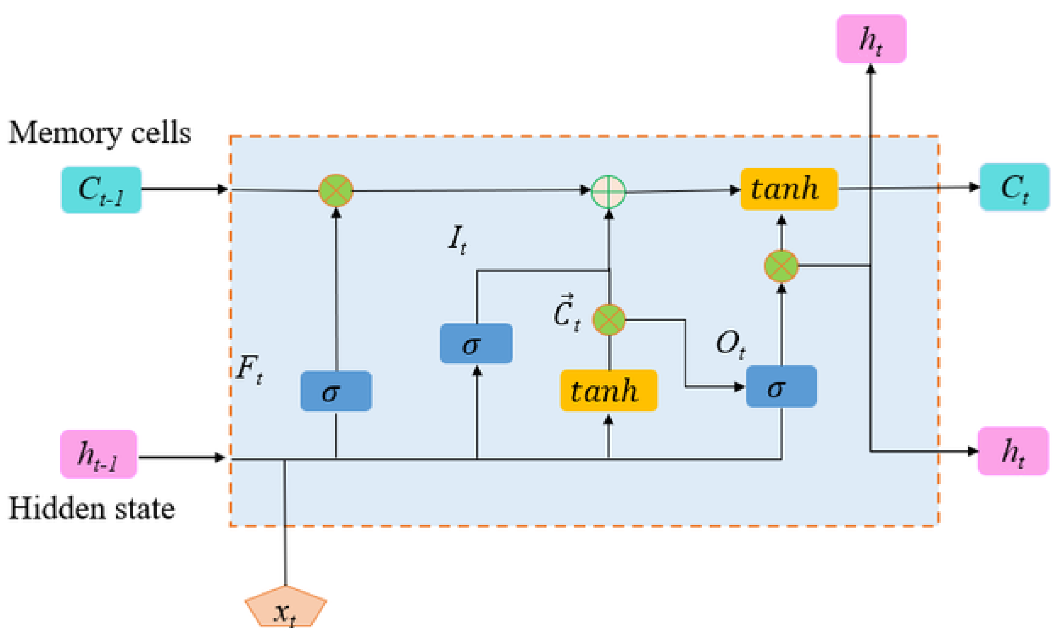
In the formula, *x* represents a position, and its fitness value is given by *f (x)*. If the generated position has better fitness than the original position, then this position will be considered globally optimal and replace the original position. On the contrary, keep the original optimal position unchanged.

BiLSTM Prediction Algorithm

BiLSTM is a variant of Recurrent Neural Networks (RNNs) used for processing sequence data. Traditional RNNs can only rely on previous input information for prediction when processing sequence data (Lei et al., 2022). When confronted with long sequences, they are prone to problems such as vanishing and exploding gradients, making it difficult to transmit earlier input information to subsequent time steps. Although the proposal of LSTM has somewhat solved these problems, the LSTM model only considers unidirectional timing concerns. In the presence of long sequence inputs, it often ignores certain information in the previous segment, resulting in information loss (Zheng et al., 2019). The unit structure diagram is shown in Figure 4.

By contrast, the structure consists of two LSTM loop layers that transmit information in both chronological and reverse-chronological order, allowing for simultaneous consideration of forward

Figure 4. LSTM Unit Structure Diagram



and backward sequences and utilizing past and future information to avoid information loss. It is composed of two LSTM networks, forward and backward. The forward network processes the input sequence in normal chronological order, while the backward network processes it in reverse. At each time step, the hidden states of the forward and backward networks are combined to form the final output, making them widely used in various fields (Mohapatra et al., 2022). Through bi-directional processing of sequential data, BiLSTM can better utilize contextual information and improve model performance and accuracy.

In the calculation process, the hidden state $\vec{h}_t$ of the forward LSTM depends on the current input x_t and the previous hidden state $\vec{h}_{t-1}$, while the hidden state $\overleftarrow{h}_t$ of the reverse LSTM depends on the current input x_t and the subsequent hidden state $\overleftarrow{h}_{t+1}$. The final bidirectional LSTM result is determined by the outputs of both forward LSTM and reverse LSTM. The relevant calculation formulas for $\vec{h}_t$ and $\overleftarrow{h}_t$ are as follows:

$$\vec{h}_t = LSTM\left(\vec{h}_{t-1}, x_t\right) \tag{8}$$

$$\overleftarrow{h}_t = LSTM\left(\overleftarrow{h}_{t+1}, x_t\right) \tag{9}$$

$$h_t = \left(\vec{h}_t, \overleftarrow{h}_t\right) \tag{10}$$

DQN Network Investment Decision Model

DQN is an algorithm that combines deep learning and reinforcement learning using Q-learning ideas on the basis of deep learning. The DQN model utilizes the powerful learning ability of neural networks to train the model and obtain the optimal value in a specific environment (Wu et al., 2021). To facilitate model training, it is necessary to define a loss function that measures the deviation between the target label and the model output. The model is trained by minimizing this deviation, gradually converging towards the optimal solution. Therefore, the DQN algorithm enables high-performance reinforcement learning in complex environments (Mahalakshmi et al., 2022). The calculation of the action state function value $Q*$ for updating the network is as follows:

$$Q^*\left(s,a\right) = Q\left(s,a\right) + \alpha\left(r + \lambda \max_a Q\left(s_{t+1}, a\right) - Q\left(s_t, a_t\right)\right) \tag{11}$$

When the environmental state is s, $Q\left(s,a\right)$ represents the corresponding network output, and $Q^*\left(s,a\right)$ represents the action value function based on the optimal strategy. The deviation of DQN refers to the difference between $Q\left(s,a\right)$ and $Q^*\left(s,a\right)$, which can be calculated using a loss function. Therefore, the goal of DQN is to train the network model so that the output value $Q\left(s,a\right)$ in the current state gradually approaches the target label $Q^*\left(s,a\right)$. Among them, the loss function L is calculated as follows:

$$L\left(w\right) = E\left[r + \lambda \max_a Q\left(s', a', w'\right) - Q\left(s, a, w\right)\right] \tag{12}$$

In the formula, w represents the weight parameter of the network model. So, once the loss function is determined, the DQN network can be trained to learn investment strategies autonomously that can enable investors to gain more returns. In order to obtain higher returns and make better trading decisions, this article adds the prediction results of the trend prediction module as an additional N+1 dimensional feature on the basis of the original N-dimensional classification features (Ahmed et al., 2022). Finally, a dataset containing N+1 dimensional features will be input into the investment decision module to support more accurate investment decisions.

RCA-BiLSTM-DQN Intelligent Prediction and Investment Model

The intelligent trend prediction and investment model of RCA-BiLSTM-DQN constructed in this article consists of the RCA-BiLSTM intelligent trend prediction model and the DQN network decision model. The model process is shown in Figure 5. The RCA-BiLSTM intelligent trend prediction model employs RCS to extract features from financial management stock market data. Then, BiLSTM is trained using the IWOA intelligent optimization algorithm to obtain optimal parameters for stock market prediction. RCA feature extraction discovers correlations between features and enables the extraction of more informative and representative features, thereby improving the performance of the model. During BiLSTM training, the biomimetic optimization algorithm IWOA is applied to compare fitness values to determine the optimal fitness of individual whales and whale populations. The position of individual whales is then updated to obtain the best parameters, which replace the parameters in BiLSTM. With the optimal parameter configuration, training the BiLSTM model enables the learning of features and stock data to more accurately predict future stock market trends and discover potential investment opportunities. These predictions contribute to wiser investment decisions. The pseudocode studied is shown in Table 1.

Model Evaluation Indicators

This study uses evaluation indicators such as root mean square error (RMSE) (Patel et al., 2015), mean absolute error (MAE) (Mehta et al., 2021), mean absolute percentage error (MAPE) (Thakkar & Chaudhari, 2021), and coefficient of determination (R^2) (Sonkavde et al., 2023) to predict stock market trends in financial management. Investment decisions are evaluated using the rate of return (P) evaluation indicator (Guan, 2023). The specific calculation is as follows, where y_i is the true value, $\overline{y}_i$ I is the average value of y_i, and $\hat{y}_i$ is the predicted value of the model; the larger the difference between the two, the poorer the predictive ability of the model. B_m represents the balance of the investor's account, and V_m represents the amount invested by the investor:

$$RMSE\left(y,\hat{y}\right)=\sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(\hat{y}_i-y_i\right)^2} \tag{13}$$

$$MAE=\frac{1}{n}\sum\nolimits_{i=1}^{n}\left|\hat{y}_i-y_i\right| \tag{14}$$

$$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i^{'}-y_i\right|}{y_i} \tag{15}$$

$$R^2=1-\frac{\sum\nolimits_{i=1}^{n}(\hat{y}_i-y_i)^2}{\sum\nolimits_{i=1}^{n}\left(\overline{y}_i-y_i\right)^2} \tag{16}$$

$$P=\frac{B_m-V_m}{V_m}\times 100\% \tag{17}$$

The larger the indicator values of MAPE, MAE, and RMSE, the lower the prediction accuracy of the model, while the opposite is true for R^2. A larger P-value indicates a higher rate of return.

Figure 5. Intelligent Stock Prediction and Investment Model of RCA-BiLSTM-DQN

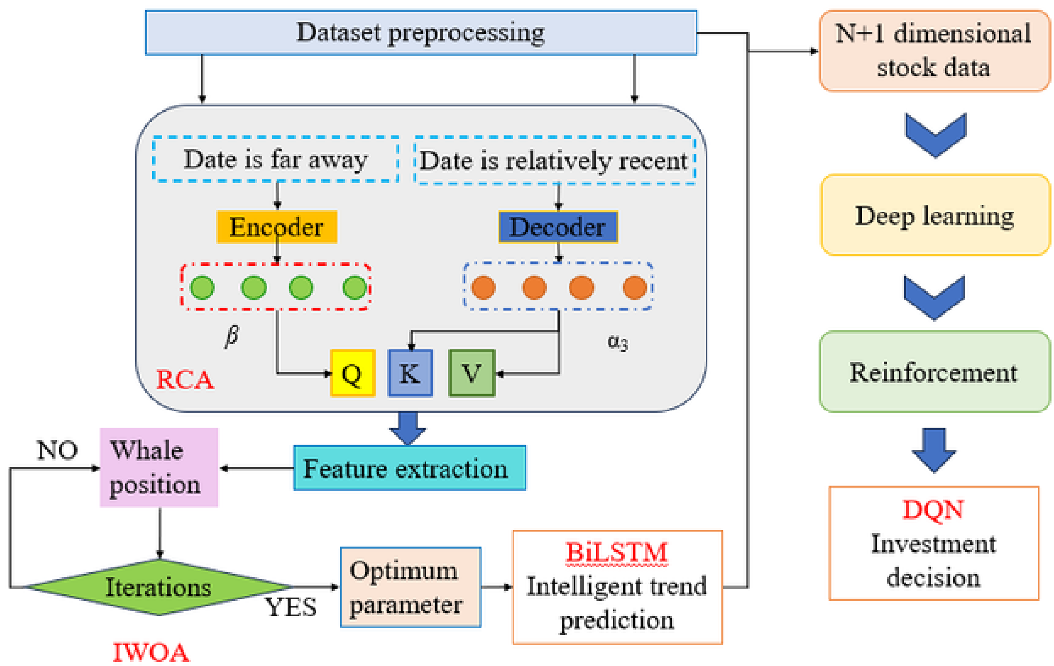


Table 1. Schematic Diagram of Pseudocode Research

Input: The hidden variables q, k, v generated by Encoder, Vd generated by MHA in Decoder, feature weight w, adaptive inertia weight w (t), IWOA position update value X (t+1), helix shape constant b, and random number l on the interval [-1,1].
Hidden variable V_d generated by MHA in Decoder
Calculate Attention (Q, K, V) using eq-1
for all t= 1 to R **do**
$w(t)=1/5\cos(\pi/2\cdot(1-t/t_{max}))$
The introduced w has a value between [0,1]
Calculate $X(t+1)$ using eq-3
for $X(t+1)1: N$
$X(t+1)=w(t)X^*(t)-A\cdot\|C\cdot X^*(t)-X(t)\|, p<0.5$
if $p\geq 0.5$
$X(t+1)=w(t)X^*(t)+D\cdot e^{bl}\cos(2\pi l)$
Determine the loss function
else
Output the newly added N+1 dimensional feature as the prediction result
end for
end for

EMPIRICAL RESEARCH AND ANALYSIS

Experimental Data and Preprocessing

Dataset

This article uses the following three financial management stock market prediction datasets, which cover both high market value and low market value stocks in the A-share market of financial management. The stock data used in the experiment is from April 12, 2012 to December 30, 2022, mainly including closing price, highest price, lowest price, opening price, and other information. Each dataset is divided into training and testing sets, with a segmentation ratio of 7:3. The information of the dataset is as follows:

1. The Center for Research in Securities Prices Dataset (CRSP): CRSP is a research institution under the Booth School of Business at the University of Chicago, focusing on providing data and historical prices for stocks and securities markets.
2. Compustat Dataset (COM): Compustat is a provider of financial and economic analysis data for institutional investors and companies. This dataset mainly includes financial and economic data of listed companies.
3. Wharton Research Data Services Dataset (WRDS): WRDS is a database from the Wharton School of Business at the University of Pennsylvania which supports advanced data analysis and research, and it can be used for academic and business analysis.

Data Preprocessing

The data obtained from the stock market is generally incomplete and noisy, so it needs to be preprocessed. This article mainly processes the data in three aspects:

1. Data cleaning: There may be some inconsistencies in the obtained data, such as missing or duplicate values. Therefore, it is necessary to clean the data, treat the data before and after market closures and trading suspensions as continuous, remove missing data, and ensure that the analysis of stock price data takes into account the actual market situation to avoid unreasonable impact on the analysis results. Furthermore, data cleaning ensures the accuracy and consistency of the data, providing a reliable foundation for subsequent data analysis (Mohapatra et al., 2022).
2. Dataset partitioning: In deep learning modeling, datasets are typically divided into training and testing sets. The training set is used to fit the model and learn the inherent rules of the data, while the test set is used to evaluate the performance of the algorithm (Buczynski et al., 2021). According to the time span, the dataset is divided into training and testing sets, with the training set accounting for about 70% of the total data and the testing set accounting for about 30%. The specific division of the dataset is shown in Table 2.
3. Data normalization: When performing stock prediction tasks, in order to convert data from different ranges and units into a unified range, avoid the impact of differences between feature values on the model, improve the iteration convergence speed and prediction accuracy of the model, one should consider normalizing the stock price time series. This article uses the Min Max normalization method to linearly map data to the interval 0-1 between the specified minimum and maximum values.

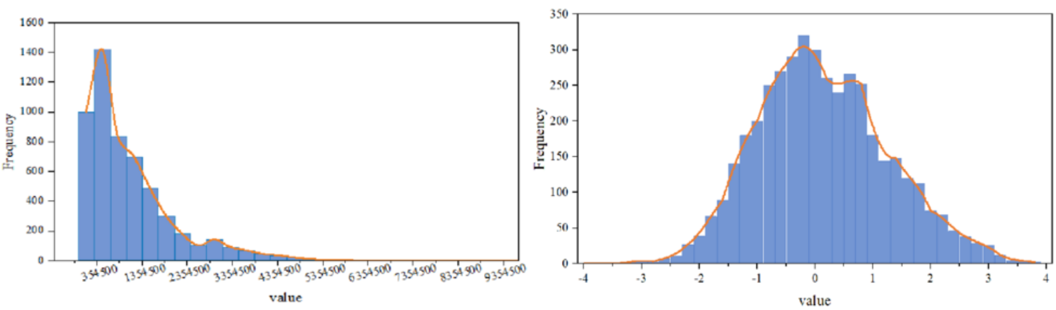
Figure 6 (a) shows the minute level trading volume distribution of a stock in the CRSP dataset over 100 trading days. As can be seen from the graph, the trading volume data is generally distributed in small numerical intervals, and as the value increases, its distribution decreases, until it reaches a very large numerical interval. The sample distribution becomes very rare and even cannot be represented in the bar chart. After normalization of preprocessed data, the distribution of trading volume data is

Table 2. Dataset Partitioning Table

Dataset	Time Range	Time Span/Days
Training Set	2012/4/12-2020/12/13	2737
Test Set	2020/12/14-2022/12/30	1174

Figure 6. Normalization Processing of Data

Note. The left graph (a) shows original transaction volume data and the right graph (b) shows preprocessed transaction volume data.



a normal distribution with 0 as the mean, as shown in Figure 6 (b), which can accurately represent whether the daily hourly trading volume status of the stock is decreasing or increasing compared to the overall situation over a long time span.

Integration of MTS Stock Data Representation

The traditional stock daily candlestick chart cannot accurately represent the temporal characteristics of stock trading; it only focuses on the opening price, highest price, lowest price, and closing price (Day et al., 2023). This article proposes a stock data representation method (MTS) that integrates multi-scale features, as shown in Figure 7. Starting from the temporal trend of stock prices, it solves the problem of traditional methods having limited feature information and being unable to capture temporal information, which results in poor performance of prediction models. This method aims to reflect the trading status of stocks on each trading day accurately, treating each trading day as a token. The existence of extended time steps also enriches the features represented by tokens. The advantage of using multi temporal features is that they can capture market dynamics and trend information more comprehensively, thereby improving the expression ability and prediction accuracy of stock data, laying a foundation for the following work.

To verify the effectiveness of the MTS method, traditional data representation (TRA) and MTS data representation were used in this experiment, and regression experiments were conducted using stock prediction models based on deep learning such as RNN-CNN (Guan, 2023), BiLSTM (Mohapatra et al., 2022), GRU (Buczynski et al., 2021), ARIMA BiLSTM (Huang, 2023), TCN (Singh et al., 2022), RCA-BiLSTM, and more. Traditional data representation includes opening, highest, lowest, and daily trading volume on closing prices. The objective of the experiment is to predict the percentage increase or decrease in the opening, highest, lowest, and closing prices of the next trading day compared to the previous day's closing price, forming a vector of length 4. In order to avoid overfitting, the experiment adopted an early stop mechanism, and the results are shown in Figure 8.

Figure 7. Fusion of Multi-Temporal Feature Stock Data (MTS)

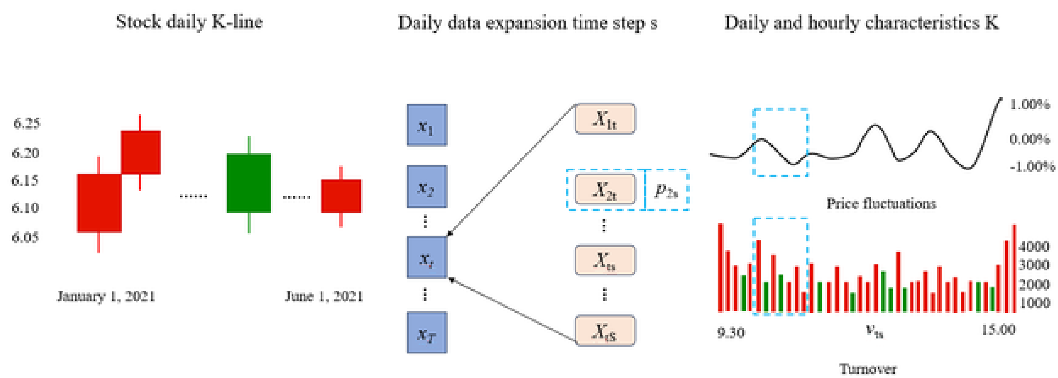
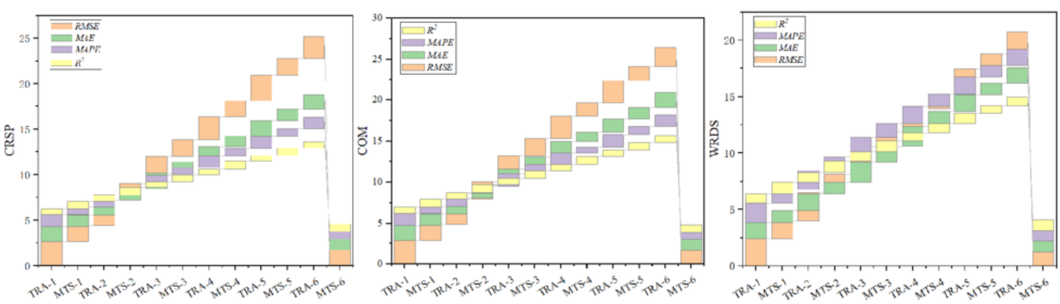


Figure 8. Regression Experimental Results of Different Datasets on Traditional and MTS Representation Methods

Note. 1 represents RNN-CNN, 2 represents BiLSTM, 3 represents GRU, 4 represents ARIMA-BiLSTM, 5 represents TCN, and 6 represents RCA-BiLSTM).



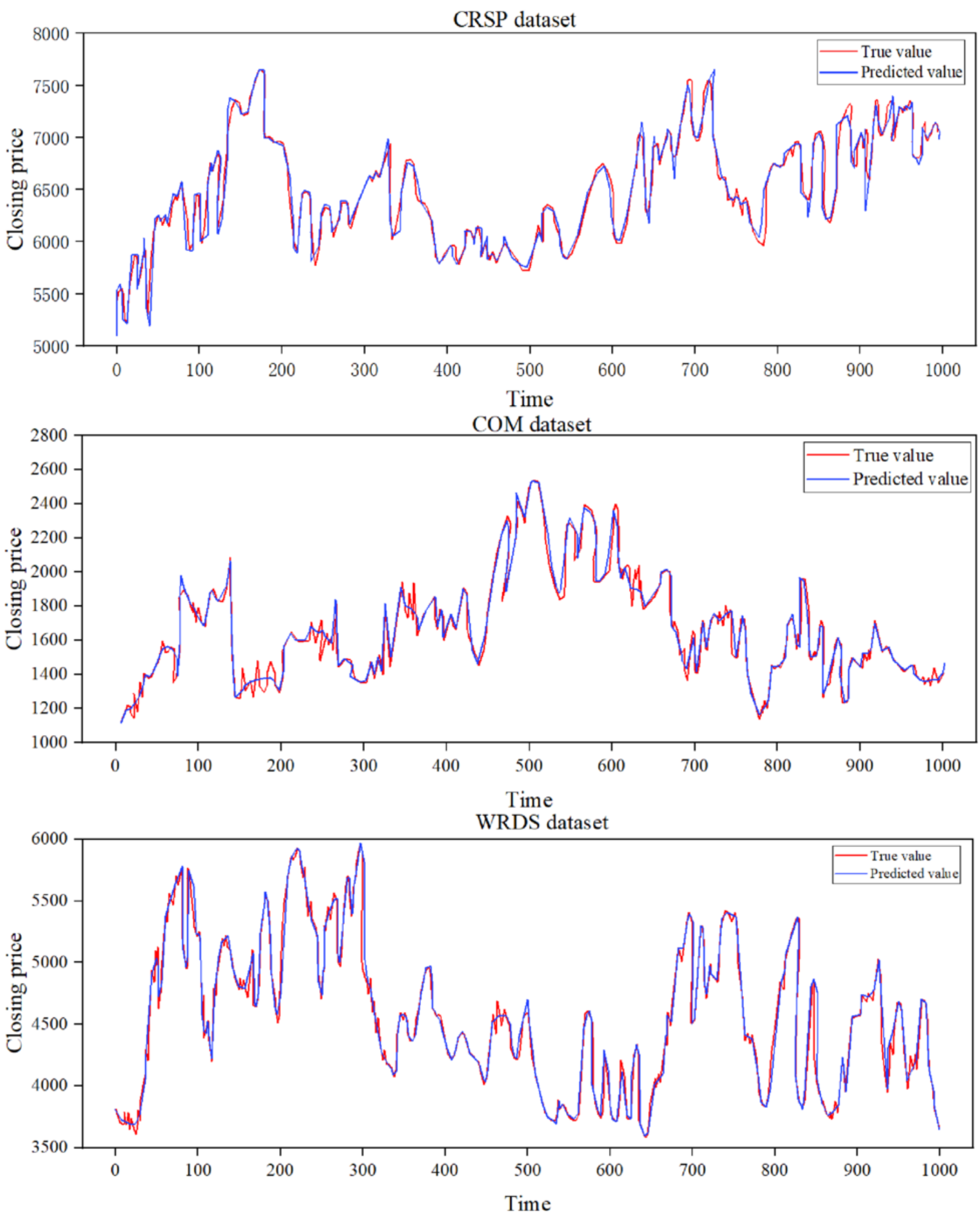
According to the results shown in Figure 8, among all of the algorithms in the experiment, the prediction model using the MTS method exhibits superior performance in terms of RMSE, MAE, MAPE, and R^2 indicators compared to traditional methods. GRU shows suboptimal performance with traditional feature representation methods but excels when using MTS feature representation methods. RCA-BiLSTM, BiLSTM and RNN-CNN demonstrate favorable performance under MTS feature representation methods but exhibit poorer results under traditional feature representation methods. Specifically, in the RCA-BiLSTM model, the RMSE, MAE, and MAPE obtained using traditional methods were 2.43, 1.25, and 1.58, respectively. However, with the MTS method, these values decrease to 1.72, 0.81, and 1.23, respectively, along with an increase in R2 indicator values from 0.69 to 0.85. Similarly, under multiple prediction models such as RNN-CNN, BiLSTM, GRU, ARIMA-BiLSTM, TCN, and more, the MTS method significantly outperforms traditional methods. Notably, these advantages are observed in the COM and WRDS datasets.

The MTS method demonstrates outstanding performance across different datasets and various prediction models, showing superior results in RMSE, MAE, MAPE, and R^2 metrics. This is attributable to the MTS representation method, which provides models with more refined and rich feature representations. In summary, the following conclusion can be drawn: Using the MTS method for feature representation of stock data can significantly improve the performance of prediction models; this method is superior to traditional methods in multiple evaluation indicators.

Trend Prediction Results and Analysis

By validating the effectiveness of the fused MTS stock data representation mentioned above, we can predict stock market trends for financial management. The test sets from the three test datasets introduced in Experimental Data and Preprocessing were placed into the trained RCA-BiLSTM model, and the fitting trend of the financial management stock closing price data obtained is shown in Figure 9.

Figure 9. Trend Prediction of RCA-BiLSTM on Stock Datasets Under Different Financial Management



In Figure 9, the prediction results demonstrate that on the three datasets, the predicted values of the RCA-BiLSTM model in this paper are relatively close to the actual test data values, showing a favorable fitting effect. On the CRSP dataset, despite slight deviations in the predicted values at different times, the overall fitting effect stands out as the best, indicating a relatively small corresponding prediction error value for the model. The fitting curves on the other two datasets also exhibit favorable clustering effects compared to actual values.

In addition, to verify the effectiveness of the RCA BiLSTM model compared to other prediction models (RNN-CNN, BiLSTM, GRU, ARIMA BiLSTM, TCN) in stock trend prediction experiments, this experiment used the same MTS data representation method, and different prediction models were tested on three different datasets. The task was to predict the opening, highest, and lowest prices of the next trading day A vector of length 4 composed of the percentage increase or decrease of the lowest and closing prices. At the same time, in order to make the fitting effect of the model clearer, the comparison of indicators between the RCA-BiLSTM model and other algorithm models is shown in Figures 10-12.

From the comparison of indicators between the RCA-BiLSTM model and other algorithm models, the RCA-BiLSTM model exhibits the smallest RMSE, MAE, and MAPE values across all three datasets, along with largest R^2 indicator value, which indicates that the prediction error of the algorithm model is the smallest. Specifically, in the CRSP dataset, the RMSEs for six models, RNN-CNN, BiLSTM, GRU, ARIMA-BiLSTM, TCN, and RCA-BiLSTM, are recorded as 1.74, 1.81, 1.91, 1.72, 1.86, and 1.71, respectively. The GRU model exhibits relatively poor performance, possibly due to the difficulty in capturing long-term dependencies. In terms of MAE, MAPE, and R^2 indicators, the RCA-BiLSTM model also outperforms other models, including newer models such as ARIMA-BiLSTM and RNN-CNN, indicating the superiority of prediction results based on time series and deep learning to those of a single BiLSTM deep learning algorithm. This is attributable to the temporal dependencies and trends in time series data, effectively captured by deep learning models. Time series-based deep learning models, characterized by multiple levels of neural networks, can better capture nonlinear relationships and long-term dependencies in data. Therefore, the experimental results show that the RCA-BiLSTM model has improved predictive performance compared to other

Figure 10. Comparison of Indicators Between RCA-BiLSTM Model and Other Models on CRSP Dataset

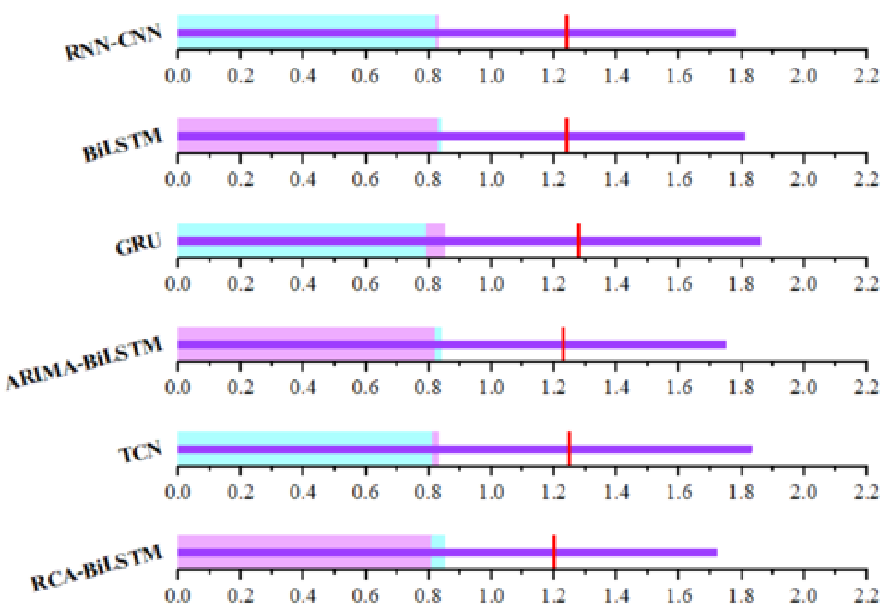


Figure 11. Comparison of Indicators Between RCA-BiLSTM Model and Other Models on COM Dataset

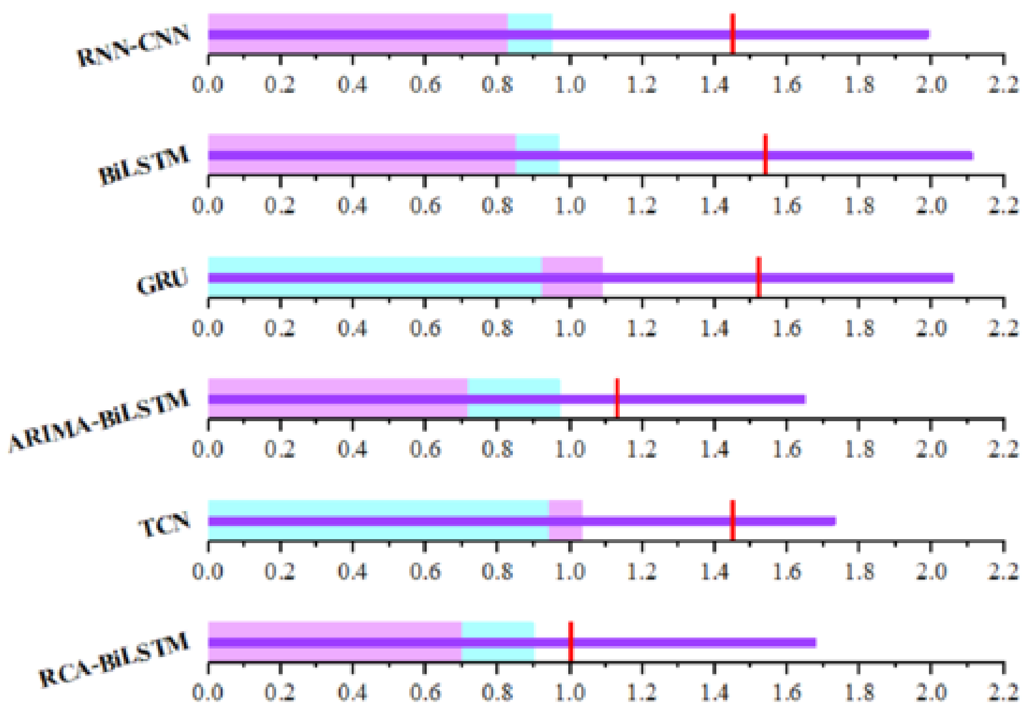
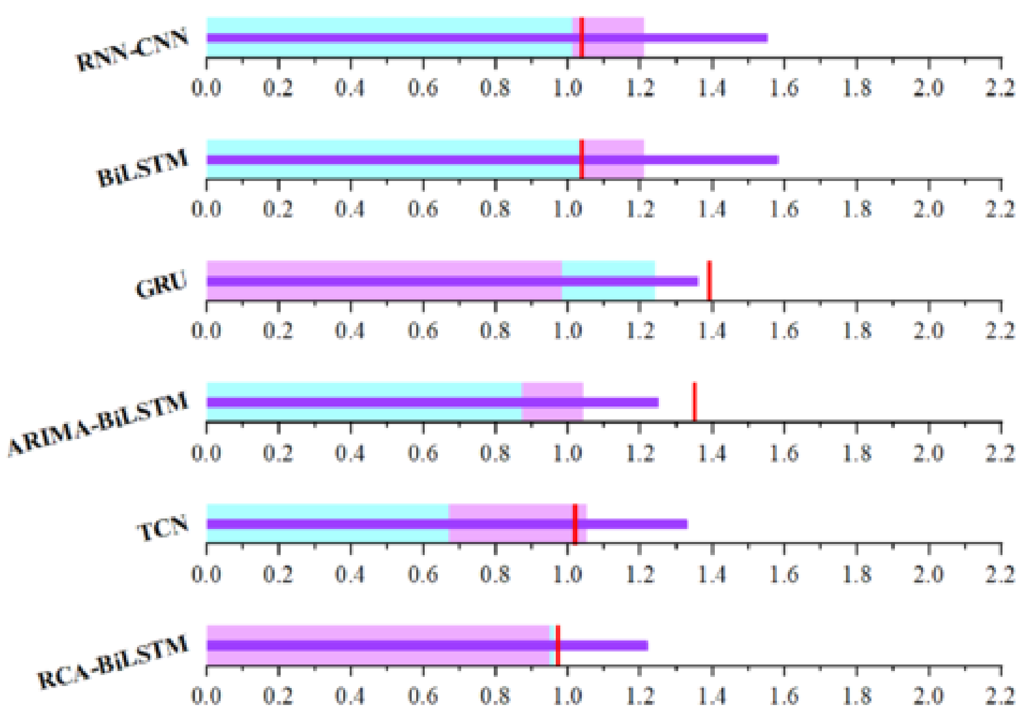


Figure 12. Comparison of Indicators Between RCA-BiLSTM Model and Other Models on WRDS Dataset



models under different evaluation indicators on different datasets. This improvement is attributed to the superior ability of RCA to learn the characteristics of stock data, coupled with the acquisition of optimal parameters of BiLSTM through the IWOA intelligent optimization algorithm, thereby achieving superior predictive performance.

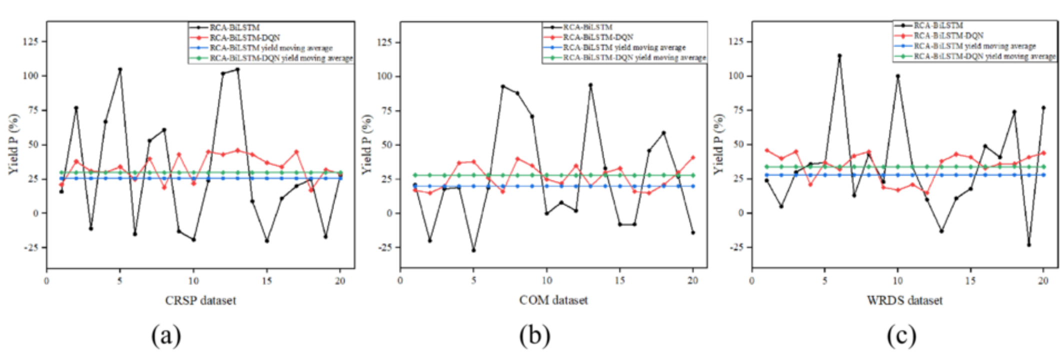
Investment Decision Results and Analysis

The accuracy of the RCA-BiLSTM model trend prediction mentioned earlier can provide guidance on when to buy or sell a particular stock. If the forecast shows that a specific stock or industry may show an upward trend, investors may increase their investment to achieve higher returns when prices rise. On the contrary, by reducing investment, losses can be avoided or reduced. This investment decision-making experiment used 20 stock data from the three datasets in Experimental Data and Preprocessing as experimental data. The experimental data is still divided into training and testing sets in a 7:3 ratio. The DQN investment decision model designed in this paper (RCA-BiLSTM-DQN) is trained and tested and compared with the turning point investment strategy predicted in this paper (RCA BiLSTM). The P (%) evaluation index is used to compare and analyze the investment strategy. The comparison results are shown in Figure 13.

The results in Figure 13 show the significant differences in stock returns if buying and selling are directly carried out based on trend prediction turning points in each dataset. However, in the experiment, the DQN investment strategy based on trend prediction produces a small difference in returns (P) between buying and selling. The P values is near the mean within a certain range, indicating the DQN investment decision model's robust universality and adaptability. In addition, using the RCA-BiLSTM investment strategy yields an average return (P) of 25.6310%, 20.8635%, and 28.3970% on three datasets, respectively. After adding the DQN decision model, the average return (P) increases to 28.8428%, 27.8683%, and 34.4927%, a respective 3.2118%, 7.0048%, and 6.0957% improvement. Therefore, compared to direct investment at the turning point of stock price trend prediction, adding DQN investment strategy to trend prediction can achieve greater returns. This further demonstrates the importance of the investment decision-making module in RCA-BiLSTM-DQN.

Based on the comparative analysis of financial management in stock market trend prediction and investment decision-making, it can be concluded that the RCA-BiLSTM-DQN model proposed in this paper has been validated for its effectiveness and feasibility from multiple perspectives. The stock market trend prediction experiment demonstrates the superior predictive performance of the RCA-BiLSTM model compared to current mainstream algorithms. Direct investment at the predicted turning point of this model yields enhanced returns. The comparative analysis of investment decision-making solidifies the following conclusion: After trend prediction in the RCA-BiLSTM model and the following experiments on the investment strategy model of the DQN network, the direct prediction algorithm can achieve higher returns through point investment, which indicates the adaptability and

Figure 13. Comparison of Investment Decision Results



universality of the financial management designed in this article in terms of trend prediction and investment decisions in the stock market. This can reduce investment risks and enable investors to obtain increased profits.

DISCUSSION

In today's stock market, investors must be equipped with scientific analysis methods and prediction skills to succeed in intense competition. In the field of financial management, there is a growing focus on stock market prediction and investment decision-making based on machine learning technology. This article explores the application of deep learning technology for stock market prediction and investment decision-making. The analysis employs the RCA-BiLSTM-DQN algorithm. This algorithm has two main characteristics: Firstly, it combines autocorrelation and cross-correlation information, which enhances the prediction accuracy of stock market changes; secondly, it incorporates deep reinforcement learning to enable informed investment decision-making and management.

The research shows that the stock market prediction model using RCA-BiLSTM-DQN yields more stable and accurate prediction results, with a significantly improved prediction effect compared with the single model. In terms of investment decision-making and management, we applied this model for empirical analysis and found that the RCA-BiLSTM-DQN algorithm assists investors in better analysis of the stock market to formulate scientifically-grounded investment strategies and improve the accuracy and efficiency of investment decisions. For example, the use of this model for stock market risk prediction enables investors to make targeted asset allocations. However, this model comes with certain limitations. Firstly, this study adopts the analysis of historical data. Although historical data provides some reference for the future, unforeseeable factors such as market conditions and policy changes require timely market trend monitoring. Secondly, the effectiveness of the RCA-BiLSTM-DQN algorithm requires a large amount of data and computing resources, making it difficult for individual investors to implement.

In summary, this article focuses on the application of RCA-BiLSTM-DQN in financial management. This model can help investors better analyze the stock market and improve the accuracy and efficiency of investment decisions. However, we also need to be vigilant about its limitations, comprehensively consider market changes and other factors, formulate reasonable investment strategies, and make wiser decisions.

CONCLUSION

This study focuses on stock market prediction and investment decision-making in the field of financial management and proposes a method based on RCA-BiLSTM-DQN. This method combines multiple technologies and algorithms to analyze stock market trends and key features, achieving prediction of stock prices and informed investment decision-making based on prediction results. More specifically, our goal is achieved through the combination of RCA, Bidirectional Long Short-Term Memory Network (BiLSTM), and Deep Q Network (DQN). This method not only captures the temporal dynamics of historical stock prices but also handles the high uncertainty and complexity of the stock market.

The experimental results show the effectiveness of the RCA-BiLSTM-DQN method in the prediction of stock market prices and the generation of high investment returns. Our proposed investment strategy, based on the RCA-BiLSTM-DQN prediction results, outperforms investment strategies based on traditional technical analysis and simple linear regression prediction models. In addition, our analysis extends to investment decisions under different market conditions. Experimental results have shown robust performance of investment strategies based on RCA-BiLSTM-DQN in these situations. Therefore, the stock market prediction and investment decision-making method based on RCA-BiLSTM-DQN proposed in this article exhibits superior accuracy and practicality compared to existing methods and can provide useful references and guidance for stock investment in the field of financial management. However, this article only explores the prediction and investment of stock market data in the field of financial management using this method. To bolster the applicability of the model, it is necessary to extend its application to sequence prediction and decision-making problems in other fields. Future research will study and verify the applicability of the model in other contexts. Future research will also continue to expand the application scope of this method to improve its performance and ensure sustained stability.

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