ABSTRACT

Based on the deep learning (DL) theory, the study takes the multinational corporation Technology Company A as the research target and explores the impact of information technology (IT) management capabilities on the sustainable competitive advantage of the company. Firstly, the proposed method summarizes the connotation and characteristics of IT management capabilities and analyzes the nature and functions of enterprise IT management capabilities. Secondly, the study expounds three different theories of sustainable competition theory. Then, it briefly elaborated the principles of artificial neural network (ANN) algorithms and the classification and definition of DL algorithms. Finally, long short-term memory (LSTM) is selected as the training algorithm of the model. The stock price trend of Technology Company A is used as the basis for judging competitiveness, and the influence of IT management ability on the company’s sustainable competitiveness is quantitatively analyzed.

KEYWORDS

Deep Neural Network, LSTM Model, Stock Price, Sustainable Competitiveness

INTRODUCTION

Information technology (IT) management has increasingly become an important factor affecting productivity (R. Baldwin, 2018; B. Begovi, 2017). IT profoundly affects the economic development of a country or region. The emergence of informatization has changed the pattern of traditional enterprises and the form of competition. The emergence of informatization has led to the continuous expanding scope of competition between enterprises, the competitive environment has become more and more complex, and the competition has become more and more fierce (M. Chi & J. Zhao et al, 2017). Enterprises hope to effectively solve the difficulties through investment in IT management. The investment in IT management can not only help enterprises obtain good benefits but also help enterprises enhance the competitiveness of the industry (V. Sambamurthy & S., Venkataraman, et al, 2017). However, after a period of time, large-scale investment in IT management capabilities did not create sustainable competitive advantages for enterprises as expected (I. Muda & D. Y. Wardani et al, 2017; J. Luftman & K. Lyytinen et al, 2017). Therefore, the ability of IT management determines to a large extent whether an enterprise can have sustainable competitiveness. IT management capabilities
will affect the development of a company’s sustainable competitiveness. This study uses stock information to evaluate the impact of IT management capabilities on the sustainable competitiveness of enterprises (J. A. Brink & R. L. Arenson et al., 2017; T. N. Varma & D. A. Khan, 2017).

Recently, the application of deep learning (DL) algorithms in business management has become more and more mature (Ilker and Ercanli, 2020). This type of algorithm can help companies better formulate development strategies and help companies predict future trends (L. A. Peng & J. B. Wei et al., 2020). In a general sense, the main content of stock analysis is to evaluate the fluctuations of stock prices in the stock market environment. In a broader sense, stock analysis is the analysis and evaluation of the overall change law and trend of stock prices within a certain period. Approaches to stock analysis are technical as well as statistical analysis (Q. Wang & Y. Zhu et al., 2017; A. S. Cordis & C. Kirby, 2017). These traditional methods play an active role in the development of stock analysis. Traditional stock analysis has promoted the development of the stock market to a certain extent. In recent years, stock analysis methods by computer technology have developed rapidly, and more and more scholars have begun to use DL neural networks (NNs) for stock analysis research. Deep neural network (DNN) is born since traditional NN. Compared with Artificial Neural Network (ANN), DNNs have more hidden layers (Alanis & Y. Alma, 2018; P. Bangalore & L. B. Tjernberg, 2017). The principle of DNN is the multi-level processing of information by the human brain (E. Isik & M. Inalli, 2018). The biggest features of the raw data can be learned by the means of hierarchical training and solve classification problems. In addition, hierarchical initialization can be adopted to reduce the NNs’ training difficulty to a large extent (S. Li & M. Fairbank et al., 2017). As a kind of complex dynamic system, stock market contains many data that are generated during transaction. The structural features of NN can be adopted for the analysis of stock market, which is quite appropriate (M. Safa & S. Samarasinghe et al., 2018) and is unmatched by traditional analysis methods.

Technology company A is used as the research object to analyze and process the stock information data. The stock data information of company A in the past three years is used as the original data set, a Long Short-Term Memory (LSTM) neural network evaluation as well as forecasting model is implemented, and the LSTM model is trained using the data set. Finally, the proposed method uses the LSTM model to predict the stock trend of technology company A and compares it with the traditional forecasting model.

RESEARCH METHODS AND RELATED THEORIES

IT Capability

IT Capability Definition

IT capability (ITC) is the capacity of an organization to utilize and allocate its own resources (P. Foroudi & S. Gupta et al., 2017; Ming-Feng et al., 2018), and the ability of an enterprise to manage and control IT resources. The joint effect of ITC and other resources as well as the interactive informatization application effects and organizational goals enable enterprises to obtain sustainable competitive advantages since informatization, and enable the sustainable development of IT resources of corporate informatization projects combined with the dynamic characteristics formed within them. Figure 1 shows the classification of ITC (L. Li & F. Su et al., 2018).
ITC Features

Figure 1. ITC classification

ITC has the following four characteristics (C. J. Torrecilla-Salinas & O. D. Troyer et al., 2019): 1) ITC is a dynamic mechanism for multinational high-tech industries to achieve better performance and competitive advantage; 2) high-tech multinationals ITC is based on information, including organizational cultural knowledge, etc.; 3) ITC of multinational high-tech industries is closely related to corporate activities. ITC is not only the collection and integration of information, but also a complex mode of activity that is coordinated between people and information resources, and between people and the corporate environment formed within the enterprise; 4) ITC of the high-tech multinational corporations is extremely strong. Corporate informatization construction is a slowly rising process, and it cannot be achieved directly by purchasing software and hardware. The key tacit knowledge is formed in the development of the enterprise. This tacit knowledge is the key for the enterprise to maintain its competitive advantage. Additionally, this knowledge also restricts the adjustment of the corporate ITC. In addition, corporate ITC is a long-term cumulative learning, and learning is also gradual and cannot be accomplished overnight. TC is also accompanied by the development of enterprises. Moreover, it can be said that it is the product of long-term development of enterprises (Y. Liu & W. Wu et al., 2020). ITC is a complementary asset that is irreversible investments under the established capabilities of the enterprise. Only when they are connected to specific product technologies and specific processes can they generate value (L. Raymond & S. Uwizeyemungu et al., 2018).

Related Theories Of Sustainable Competitiveness

The two terms “Competitive Advantage” and “Competitiveness” frequently appear in the research of enterprise problems (S. N. Morioka & I. Bolis et al., 2017), but the difference between the two is not clearly given. Some studies have pointed out that both competitive advantage and competitiveness are the standard for evaluating enterprises, and both can be used to measure the development status of enterprises. Enterprises with strong competitiveness have greater competitive advantages (J. E. Delery & D. Roumpis, 2017). Companies with large competitive advantages have greater competitiveness, which shows that there is no clear distinction between “Competitive Advantage” and “Competitiveness”, and the research on competitiveness is always inseparable from the theory of competitive advantage. At present, domestic scholars mostly combine competition with competitive advantage. It is believed that when it comes to issues related to competitiveness, it must be related to competitive advantage, and the two are inseparable. Judging from the existing research results, the theory of corporate competitiveness can be divided into three different theories:
Relationship Theory

Relationship theory holds that the reason why a company maintains its competitiveness is that the company has above-average performance in the industry. For example, in terms of sales, the company’s products account for a large market share. The competitive advantage of an enterprise depends on the competitive strategy formulated by the enterprise, such as low-cost strategy, differentiation strategy, and target clustering strategy (V. P. Malyshev & A. M. Makasheva, 2020).

Resource Capability Theory

Resource capability theory holds that the reason why a company maintains its competitiveness lies in the maturity of the industry’s core technology that the company has mastered. For example, when a company masters a core technology that is not mastered by any potential competitors, the company has a huge competitive advantage in the present fierce market competition. Competitive advantage comes from the heterogeneous resources or capabilities possessed by the enterprise. This heterogeneous resource cannot be easily obtained, nor can it be easily imitated by competitors, and cannot be easily replaced in a short period of time (S. Gupta & X. Qian et al., 2019; V. C. Gu & B. Zhou et al., 2021).

Hierarchy Theory

Hierarchy theory holds that competitiveness refers to: in the competitive market of the industry or related products, companies can bring better services or better products to the market than peer companies, and can obtain long-term benefits in this state of development (X. J. Xing & X. Y. Jia, 2019; S. C. Tefan & T. C. Popa et al., 2020).

ANN

ANN is often referred to as NN for short. It uses the biological characteristics of the nervous system in biology to process and understand the information input to the human brain, and then reflect the input abstract information and external stimuli, and it is based on network topology knowledge. ANN is actually a mathematical model. In this model, how does the nervous system in human brain deal with the complicated message is simulated (W. Wu & A. D. Li et al., 2018; D. G. Giovanis & I. Papaioannou et al., 2017; Huang & Sun, 2020; Yu et al., 2021; Liu et al., 2021). The model can perform parallel as well as distributed processing, which has high fault tolerance as well as intelligence and can learn by itself. In addition to the role of information processing, it also has the function of storage. Multiple fields pay close attention to it because of its special knowledge representation as well as intelligent adaptive learning ability. Actually, it is a complicated system including multiple simple components that are interconnected. There is a high nonlinearity in the model and the model has the ability of conducting complicated logic operations as well as nonlinear correlations to achieve the system (C. Hartmann & D. Opritescu, and W. Volk et al., 2019; Shen, 2020).

A NN is a model including many interconnected nodes, which are also called neurons (R. Beedel, 2020; Madueke et al., 2020; Xu, 2019). Each node or neuron indicates a specific “Output function” that is named “activation function” as well. As mentioned above, there is a connection between each two neurons. The connection indicates a weight value, which is taken as the weight of the signal that goes through the connection. The NN is to simulate the memory of human in such way (B. Suffoletto & P. Gharani et al., 2018; Lei et al., 2021; Kumar et al., 2019). The network structure, the connection method between neurons, the weight value between nodes as well as the activation function jointly determine the output of the NN. Networks are usually approximations of natural algorithms or functions, or expressions of logical strategies. Due to the inspiration from the operation method of biological NNs, NN is constructed. In ANN, the realization of biological NNs are combined with the model of mathematical statistics and they are implemented through the devices of mathematical statistics. In artificial intelligence (AI), mathematical statistics are used to make neural networks
have similar decision-making capabilities and simple judgment capabilities to humans. It is a further promotion of traditional logical calculus.

In the processing unit of ANN, each neuron can usually be used to represent a different research object, like the characteristics of certain research objects, some English letters, specific concepts, or abstract concepts with practical significance. A complete NN structure has 3 types of structural units, namely input layer, output layer, and hidden layer, which differ from each other. The main function of the input layer is to receive data and signals, and perform preliminary processing on the data and signals. The data received by the input layer and the newly processed data will be output from the input layer, and then these newly output data and signals will be used as the hidden layer’s input. The hidden layer is responsible for connecting the input as well as the output layer, and the data as well as signals output by the input layer will be output as the hidden layer. Then the hidden layer deeply digs the hidden information contained in these data and passes the hidden information of the data and signal to the output layer. The hidden layer usually has multiple hidden layers in a NN structure. The hidden layer plays the role of an intermediate unit, which can connect the neurons as well as the whole NN in series. The weights between neurons can show the strength between the units. ANN is a non-programmed, self-adaptive, information and data processing method similar to the human brain. The essence of this process is to simulate how the human brain system processes the complicated message at different levels.

Figure 2 shows a NN unit. Among them, the dendrite is the input unit of the neuron, and the axon is the output unit of the neuron, and represents a cell body between the dendrite and the axon. Figure 3 shows the structure of the ANN.

**DL Algorithm**

After the 1950s, DL was proposed by American scholars. Its original purpose is to explore the degree of a learner’s learning input and the degree of knowledge mastery. In the learning process, different learners will adopt different strategies to achieve mastering knowledge. There are two kinds of learning methods, namely, DL and shallow learning. DL refers to: learners think about, understand, and ask their own questions during the learning process. Shallow learning does not pay attention to the understanding of knowledge, but acquires knowledge through passive memory. Obviously, DL is better than shallow learning (Y. Chen & Z. Lin et al., 2017; Wu et al., 2021). The DL and shallow learning are further compared, as shown in Figure 4.
At present, there is no unified definition of DL. According to related literature, most scholars define DL from the following four aspects, as shown in Figure 5.

DL uses the data characteristics of a large amount of data to mine the internal attributes and hidden features between the data through DL theory. DL is mainly used for data analysis and prediction. The biggest feature of DL is that it has more hidden layers. Function transformation is adopted for passing the input data to the first layer. Then, Eq. (1) can be adopted to represent the output:
In Eq. (1), $R_1$ refers the output matrix of the first hidden layer, $f$ refers the activation function, $W_1$ refers the weight matrix, and $B_1$ refers the threshold matrix.

Then, Eq. (1) can be adopted to represent the output of the $m$-th hidden layer.

$$R_m = f(W_m \cdot R_{m-1} + B_m)$$

In the same way, the final output is Eq. (3):

$$y_k = g(W_{n+1} \cdot R_n + B_{n+1})$$

In Eq. (3), $g$ is the classification function of the output layer.

The study uses LSTM neural network algorithm as the training algorithm of the model. As a kind of DL algorithm, the LSTM algorithm has a memory function that other algorithms do not have, that is, the hidden layer information can be transmitted to the output terminal as well as passed to the hidden layer of the next time, and then have an impact on the weight of the next time. The LSTM algorithm steps are as follows:

1. Calculation of the output value of the hidden layer

   $i_t$ indicates the input gate; $f_t$ donates the forget gate; $c_t$ refers to the cell state; $o_t$ donates the output gate. $w$ as well as $b$ are the weight coefficient matrix as well as bias, respectively. The activation functions are logistic function and tanh function. The forgetting channel determines whether the output at time $t-1$ as well as the input at time $t$ meet the settings of the cell.
In Eq. (4), \( i \) indicates the input gate; \( f \) donates the forget gate; \( c \) refers to the cell state; \( o \) donates the output gate. \( w \) as well as \( b \) are the weight coefficient matrix as well as bias. \( \sigma \) is the logistic function, \( t \) is the activation vector of the cell, and \( h \) is the cell output vector.

The input layer generates new values through activation functions, as shown in Eq. (5):

\[
i_t = \sigma\left(w_i [h_{t-1}, x] + b_i \right) \\
c_{1,f} = \tanh\left(w_c [h_{t-1}, x] + b_c \right)
\]

Use the updated value to update the cell state, as Eq. (6):

\[
c_t = f_t * c_{t-1} + i_t * c_{1,f}
\]

The output value of the model is obtained through the logistic function and the tanh function, as shown in Eq. (7):

\[
o_t = \sigma\left(w_o [h_{t-1}, x] + b_o \right) \\
h_t = o_t * \tanh\left(c_t \right)
\]

(2) Calculation of the error of each cell

It is assumed that \( z_k \) is the desired output. The global error between desired output and actual output is \( L \), as shown in Eq. (8):

\[
L = \frac{1}{2} \sum_{k=1}^{k-1} (z_k - z_k')^2
\]

The expression of the error transmitted to the hidden layer reads:

\[
L = \frac{1}{2} \sum_{k=1}^{k-1} f\left( \lambda_k \right) - z_k' \right|^2 = \frac{1}{2} \sum_{k=1}^{k-1} \left[ f\left( \sum_{j=1}^{k-1} w_{jk} y_j + b_k \right) - z_k' \right]^2
\]

The reverse transmission to the input layer is shown in Eq. (10):

\[
L = \frac{1}{2} \sum_{k=1}^{k-1} \left[ f\left( \sum_{j=1}^{k-1} w_{jk} y_j + b_k \right) - z_k' \right]^2 = \frac{1}{2} \sum_{i=1}^{k-1} \left[ f\left( \sum_{j=1}^{k-1} w_{ij} a_j + b_i \right) + b_k \right) - z_k' \right]^2
\]
Eq. (10) shows that the network error is a function of the weight $w_{ij}$. Hence, the change of the neuron weight can result in the change of error $E$, as shown in equations (11) and (12):

$$\Delta w_{ij} = -\varepsilon \frac{\partial L}{\partial w_{ij}} \left( i = 1 \ldots m, j = 1 \ldots n \right)$$  \hspace{1cm} (11)$$

$$\Delta w_{jk} = -\varepsilon \frac{\partial L}{\partial w_{jk}} \left( j = 1 \ldots n, k = 1 \ldots t \right)$$  \hspace{1cm} (12)$$

In equations (12) and (13), $\varepsilon$ represents the gradient descent rate.

According to the above description, backpropagation can be adopted for the calculation of the error $\delta$ of each LSTM cell.

The error term is passed back to the upper layer along the network:

$$\delta = \left( \delta^T_f w_{fx} + \delta^T_c w_{cx} + \delta^T_o w_{ox} \right) \cdot f'(net_{f}^{-1})$$  \hspace{1cm} (13)$$

The error term is transmitted in the reverse direction of time, $\delta_t$, $\delta_{t-1}$ and $\delta_k$ represent the error term at time $t$, $t-1$, as well as $k$.

$$\delta^T_t = \frac{\partial E}{\partial h_t}$$  \hspace{1cm} (14)$$

$$\delta^T_{t-1} = \frac{\partial E}{\partial h_{t-1}} = \frac{\partial E}{\partial h_t} \frac{\partial h_t}{\partial h_{t-1}} = \delta^T_t \frac{\partial h_t}{\partial h_{t-1}}$$  \hspace{1cm} (15)$$

$$\delta^T_k = \prod_{i=t}^{t-k} \delta^T_o w_{oh} + \delta^T_f w_{fh} + \delta^T_i w_{ih} + \delta^T_c w_{ch}$$  \hspace{1cm} (16)$$

(3) Calculation of the gradient of each weight on the basis of the error as shown in Eq. (17):

$$\frac{\partial E}{\partial w_{olt}} = \sum_{a,j}^{j-1} \delta^T_{a,j} h^T_{a,j-1}$$  \hspace{1cm} (17)$$
\[ \frac{\partial E}{\partial w_{ff}} = \sum_{j=1}^{j-1} \delta_{j,f} h_{j-1}^T \]  

(18)

\[ \frac{\partial E}{\partial w_{ih}} = \sum_{j=1}^{j-1} \delta_{j,i} h_{j-1}^T \]  

(19)

\[ \frac{\partial E}{\partial w_{ch}} = \sum_{j=1}^{j-1} \delta_{j,c} h_{j-1}^T \]  

(20)

\[ \frac{\partial E}{\partial b_o} = \sum_{i=1}^{i-1} \frac{\partial E}{\partial b_i} = \sum_{i=1}^{i-1} \delta_{i,o} x_t^T \]  

(21)

\[ \frac{\partial E}{\partial w_{ox}} = \frac{\partial E}{\partial \text{net}_{o,t}} \frac{\partial \text{net}_{o,t}}{\partial w_{ox}} = \delta_{o,t} x_t^T \]  

(22)

\[ \frac{\partial E}{\partial w_{ft}} = \frac{\partial E}{\partial \text{net}_{f,t}} \frac{\partial \text{net}_{f,t}}{\partial w_{ft}} = \delta_{f,t} x_t^T \]  

(23)

\[ \frac{\partial E}{\partial w_{ix}} = \frac{\partial E}{\partial \text{net}_{i,t}} \frac{\partial \text{net}_{i,t}}{\partial w_{ix}} = \delta_{i,t} x_t^T \]  

(24)

\[ \frac{\partial E}{\partial w_{cx}} = \frac{\partial E}{\partial \text{net}_{c,t}} \frac{\partial \text{net}_{c,t}}{\partial w_{cx}} = \delta_{c,t} x_t^T \]  

(25)

In equations (17)-(25), E represents the weight error item; \( w \) indicates the weight; \( x_t^T \) represents the input value; \( \text{net} \) stands for the related item; \( \delta \) denotes the error of the LSTM cell.

(4) Update the weight according to the gradient, as shown in Figure 6.
LSMT algorithm structure is shown in Fig. 7.

CORPORATE SUSTAINABLE COMPETITION

ANALYSIS BY DL NETWORK MODEL

Indicators and Data Selection

Selection of Survey Subjects

As a multinational company, technology company A is the research object, and the impact of technology company A’s ITC on the company’s competitive advantage is analyzed by investigating the
stock information of technology company A. The data come from Shanghai Stock Exchange, Shenzhen Stock Exchange, as well as Cninfo Consulting Network. Evaluation indicators include: three-year operating income growth rate, three-year asset-liability ratio, three-year research and development of investment ratio, total share capital, number of outstanding shares, whether to increase shares in the past three years, whether it is state-owned, the largest shareholder’s shareholding ratio, three-year dividend distribution, listing time, issue price, whether to reorganize in the past three years, the number of senior executives, the number of major lawsuits, the listing location, public donations, key pollutants, and the release of social responsibility reports. The stock category is the actual output, and 9 financial indicators and 10 non-financial indicators are selected. A total of 19 factors are included in the evaluation system. Table 1 is the indicator meaning.

Table 1. Index Significance

| Number | Index symbol | Index                                                                 |
|--------|--------------|----------------------------------------------------------------------|
| 1      | At           | Earnings per share                                                   |
| 2      | Bt           | Revenue growth                                                       |
| 3      | Ct           | Asset liability ratio                                                |
| 4      | Dt           | Dividend allotment                                                   |
| 5      | Et           | R & D investment                                                     |
| 6      | Ft           | Issue price                                                          |
| 7      | Gt           | Total share capital                                                  |
| 8      | Ht           | Number of outstanding shares                                         |
| 9      | It           | Whether to increase shares in recent three years                     |
| 10     | Kt           | Shareholding ratio of the largest shareholder                        |
| 11     | Lt           | Industry                                                             |
| 12     | Mt           | Time to market                                                       |
| 13     | Nt           | Has it been reorganized in the past three years?                     |
| 14     | Ot           | Number of senior managements                                         |
| 15     | Pt           | Number of major lawsuits                                             |
| 16     | Qt           | Listing location                                                     |
| 17     | Rt           | Public welfare donation                                              |
| 18     | St           | Key pollutant discharge units                                         |
| 19     | Tt           | Social Responsibility Report                                          |

Data Preprocessing

Among the 19 evaluation indicators, the impact on the evaluation target is different. For the purpose of improving the model accuracy, the indicators are processed by dimensionality reduction, and the correlation degree of each index is compared through $r$. $r \in [-1,1]$, $r>0$ means positive correlation; $r<0$ means negative correlation; $|r|<0.1$ means no correlation, $0.1<|r|<0.3$ means weak correlation, $0.3<|r|<0.5$ means moderate correlation, and $0.5<|r|<1$ means strong correlation. Then, standardize
the data. The data standardization processing method used is normalization processing. There are three commonly used normalization processing methods:

- The logarithmic function form is as Eq. (26):

\[ X_i = \log x_i \]  

(Eq. 26)

- The arc cotangent function method is as Eq. (27):

\[ X_i = \frac{2 \tan^{-1} x_i}{\pi} \]  

(Eq. 27)

- The Min-Max method is as Eq. (28):

\[ X_i = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

(Eq. 28)

In Eq. (28), \( x_{\text{min}} \) donates the dataset' minimum value; \( x_{\text{max}} \) refers to the dataset' maximum value.

According to the characteristics of the analysis data and the evaluation target, the Min-Max method is used to normalize the data.

**Establishment of LSTM Neural Network Evaluation as Well As Prediction Model**

**Steps for Establishing the LSTM Neural Network Evaluation As Well As Prediction Model**

LSTM neural network model establishment steps are shown in Figure 8.
**Prediction Model Structure Design**

The NN model structure design is relatively free, and the input or output value of the model needs to be set. The selection of the number of model layers will affect the error and accuracy of the network, and even lead to overfitting of the model. A three-layer network structure is selected. Finally, the nodes quantity of the input layer, hidden layer and output layer are 18, 15 and 3, respectively. The NN evaluation model designed is shown in Figure 9.

**Selection of Activation Function**

In the NN structure, the output value of the previous layer is the input value of the next layer. Moreover, the output node of the previous layer is the input node of the next layer. The activation function is the functional relationship between these nodes, and is usually called the activation function. The choice of activation function is an important part of building a NN. Non-linear features can be introduced through the activation function to make the NN more powerful. There are three types of activation functions used by NNs, as shown in equations (29), (30) and (31):
Logistic function: 
\[ Sigmoid(x) = \frac{1}{1 + e^{-x}} \] (29)

Tanh function: 
\[ Tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{1 - e^{-2x}}{1 + e^{-2x}} = -1 + 2Sigmoid(x) = -1 + \frac{2}{1 + e^{-2x}} \] (30)

Relu function: 
\[ ReLU(x) = \max(0, x) = \begin{cases} 0, & \text{otherwise} \\ x, & \text{if} \ x > 0 \end{cases} \] (31)

The function images of Logistic function, Tanh function, and Relu function activation function are shown in Figure 10.

Logistic function, Tanh function, and Relu function have their own advantages and disadvantages. Among them, Relu function and Logistic function are the most used activation functions, and the convergence speed of Relu function is 6 times that of Sigmoid. The Relu function is characterized by gradient unsaturation, so the Relu function can rapidly modify the parameters as well as the gradient disappearing process. Therefore, the study selects the Relu function as the activation function.

**Model Evaluation Criteria**

Five evaluation indicators are selected, namely \( R^2 \), mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), as well as average absolute percentage error (MAPE), which can assess the prediction effect of the model. The smaller the value of the above four errors, the smaller the deviation between the model’s prediction result and the true value, the more accurate the prediction result, and the higher the model’s prediction accuracy. The closer \( R^2 \) to 1, the better the fitting effect of the model, and the more accurate the prediction result of the model. The five evaluation criteria are specifically expressed as in equations (32)-(36):
\[ RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\hat{y}_n - y_n)^2} \]  

(32)

\[ MAPE = \frac{1}{N} \sum_{n=1}^{N} \left| \frac{\hat{y}_n - y_n}{y_n} \right| \]  

(33)

\[ MAE = \frac{1}{N} \sum_{n=1}^{N} |\hat{y}_n - y_n| \]  

(34)

\[ MSE = \frac{1}{N} \sum_{n=1}^{N} (\hat{y}_n - y_n)^2 \]  

(35)

\[ R^2 = \frac{\sum_{n=1}^{N} (\hat{y}_n - y)^2}{\sum_{n=1}^{N} (y_n - y)^2} \]  

(36)

RESULT ANALYSIS

Analysis of LSTM Model Prediction Results

According to the model implemented and the LSTM training steps, after repeated training, the nodes quantity in the hidden layer is 50, and the simulation results are carried out by Matlab. To ensure the evaluation effect of the model, the study uses the existing NN model suitable for stock information evaluation (ARIMA: autoregressive integral moving average model; SVM: support vector machine; MLP: multilayer perceptron; RNN: Recurrent Neural network; BPNN: BP neural network) to simulate and analyze the data set. They are compared with LSTM model. The result is shown in Figure 11.

Figure 11 shows that the red line is the predicted value of the model, and the black line is the actual value. The trend of stocks represents the trend of corporate competitiveness over a period of time. Experiments reveal that the model implemented can predict the stock trend of technology company A in a more accurate way, thereby evaluating its corporate competitiveness.
Comparison of Prediction Results Between LSTM Model and Traditional Model

The traditional network model is used to simulate the company’s stock trend, and the results are shown in Figures 12, 13, 14, 15 and 16.

Figures 12, 13, 14, 15 and 16 show that the above five models can predict the stocks of technology company A to varying degrees. But compared with the LSTM model, the LSTM model implemented is more accurate than the traditional network model. After statistical analysis of the LSTM model and traditional model evaluation indicators, the results are shown in Figure 17.
Figure 13. ARIMA model prediction results

Figure 14. MLP model prediction results

Figure 15. RNN model prediction results
(a) LSTM; (b) ARIMA; (c) SVM; (d) MLP; (e) RNN; (f) BP

Figure 17 shows that the LSTM model implemented predicts that the four errors (RMES, MAPE, MAE, and MSE) are lower than those of the traditional model. In the determination coefficient $R^2$ evaluation standard, the calculation result of this model is closer to 1 than other the prediction model, indicating that the prediction performance of the LSTM model implemented is better than that of the traditional prediction model. In addition, under the MAPE evaluation index, the LSTM model is 71% lower than the MAPE value of the ARIMA model and 31% lower than the MAPE value of the RNN model. In short, the LSTM model implemented can better predict the sustainable competitiveness of technology company A.

**CONCLUSION**

By the theory of DL, the study takes the multinational company, technology company A, as the research object to explore the impact of IT management capabilities on the company’s sustainable competitive advantage. Meanwhile, taking the stock price trend of technology company A as the basis
for judging the competitiveness, the study implements the LSTM model to predict the stock price of company A and draws the following conclusions:

(1) Stock price trends can be used to measure the development trend of corporate competitiveness. The competitiveness of enterprises is positively correlated with the trend of stock changes.

(2) The four prediction errors (RMES, MAPE, MAE and MSE) of the LSTM model implemented are all lower than those of the traditional model. In the determination coefficient $R^2$ evaluation standard, the calculation result of this model is closer to 1 than other prediction models, indicating that the prediction performance of the LSTM model implemented is better than that of the traditional prediction model. In addition, under the MAPE evaluation index, the LSTM model is 71% lower than the MAPE value of the ARIMA model and 31% lower than the MAPE value of the RNN model. Therefore, the LSTM model has more advantages in predicting the competitiveness of enterprises.

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