Sustainable Reuse Strategies of Enterprise Financial Management Model Following Deep Learning Under Big Data

Na Ta, Peking University, China
Bo Gao, Communication University of China, China*

ABSTRACT

The study aims to help enterprises to formulate a financial sustainable development strategy. A financial crisis forecast system based on deep learning (DL) is proposed to assist enterprises in checking their financial bills in time, knowing about their financial situations, formulating corresponding strategies, and realizing financially sustainable development. First, the relevant theories of financially sustainable development and DL are reviewed. Second, a long short-term memory (LSTM) neural network model based on DL is implemented, and the normal sample data are compared with the unbalanced sample data. Finally, the performance of the model is analyzed according to the experimental results. The experiments show that the performance of the financial crisis forecast system is the best when the time step is T-3. The accuracy rate of the LSTM model is more than 93%, and the highest value of AUC (area under the curve) is 93.67%. The AUC value of the LSTM neural network model is compared with that of the fully connected neural network model and logistic regression model.

KEYWORDS

Big Data, Deep Learning, Financial Crisis, LSTM Neural Networks, Sustainable Development

INTRODUCTION

With the development of modern society, big data emerge as the product of high-tech. According to big data, enterprises can know about their financial situations in detail through the statistical analysis, which is the basis for establishing appropriate financial management modes and formulating financial development strategies, achieving the reuse of financial management modes.

For the sustainable reuse of financial management mode, scholars in China and abroad have conducted a lot of researches. Xu et al. (2020) explored the relations between innovation investment and financial sustainability in the energy industry and the roles of executive incentives. The results show that innovation investment has a heterogeneous impact on the business performance of different energy enterprises in different periods. Cheah et al. (2019) established a framework to evaluate the impact of the most prominent internal resources (i.e. entrepreneurial orientation, social significance, and business planning) regulated by the financial and social performance of social enterprises. Qi et al. (2020) used Back Propagation Neural Networks (BPNN) to evaluate the credit risk and personal information risk of network finance. The results show that credit risks and personal information risks are the most important factors affecting the future development of network finance. In turn, they may hinder the development of Internet finance in some cases. Zhang et al. (2021) used long-
short term memory (LSTM) to forecast the change in stock price. Compared with artificial neural networks (ANN), LSTM is more suitable for dealing with nonlinear, non-stationary, and complex financial time series. Investor attention agents are used as market variables to improve the forecast accuracy, such as price, trading volume, and other technical indexes. The empirical results show that the LSTM model using the online investor attention agent is better than other models, and has the highest forecast accuracy and reasonable time consumption. Zhang et al. (2019) developed a personal financial scoring model based on a hybrid support vector machine (SVM) using three technologies to evaluate the candidates’ short-distance return score from the candidates’ information highlights.

The sustainable development of corporate financial management mode is a hot topic. If enterprises want to maintain sustainable financial development, they should employ an efficient financial management mode and long-term smooth operation. In this case, a financial crisis forecast system is established based on deep learning (DL). Through the financial data collected by LSTM, the financial situation of enterprises is analyzed, which provides a reference for enterprise management and promotes the sustainable development of corporate financial management mode.

MATERIALS AND METHODS

Related Theories of Financially Sustainable Development

Financially Sustainable Development Theory

Since the actual situation of each enterprise is different, their sustainable financial development theories are also different (Shin & Lee, 2019). Here, four representative theories are introduced.

Sustainable operation theory: the premise for any enterprise to achieve financial growth and sustainable development is that the enterprise can operate smoothly. And the enterprise management level should consider how to survive and how to run continuously first, and then think about the financially sustainable development of enterprises (Wang et al., 2020).

Enterprise life cycle: once an enterprise can operate smoothly, it needs to estimate the enterprise life cycle. The life circle of enterprises can be divided into four periods: the enterprise development period, enterprise growth period, enterprise maturity period, and enterprise recession period (Llerena Caña et al., 2021). Sustainable financial development should be discussed in the development period and growth period of enterprises, and it is realized by analyzing the enterprise life cycle in-depth (Yang et al., 2021).

Stakeholder Theory: there are many stakeholders in the enterprise. Some are from the enterprise, some from the outside, and their interest needs are also different. Sustainable financial development can effectively alleviate the conflict between different stakeholders, so that all stakeholders can gain benefits and ensure the development of enterprises (Waheed & Zhang, 2020).

Control right theory: the subjects of the control right theory and interest theory are humans. And reasonable control management calculation is beneficial to the sustainable development of enterprises (Cao, 2020).

Influencing Factors of Financially Sustainable Development

The influencing factors of financially sustainable development should be analyzed, avoided, or reused, and they fall into internal factors and external factors (Ahmed et al., 2021; Wu et al., 2022).

External factors are national laws and policies, macroeconomic level, and industry competition. These factors will affect the financially sustainable development of enterprises. Internal factors are the enterprise’s life cycle, and the threats faced by the enterprise at different stages. In addition, enterprise strategic objectives, financial ability, and the level of enterprise managers all affect the sustainable development of enterprise finance (Zhao et al., 2020a; Liu et al., 2020; Gao et al., 2020).
Relevant Theories of Corporate Financial Crisis

If an enterprise wants to keep sustainable development, the most important thing is to run smoothly before seeking opportunities for financially sustainable development. Some scholars believe that a financial crisis occurs when an enterprise cannot operate normally. It is a gradual and continuous process for an enterprise to fall into a financial crisis. In China, there is no obvious sign of falling into a financial crisis or going bankrupt (Song et al., 2021; Djuitaningsih & Arifiyantoro, 2020; Liu et al., 2020). According to domestic empirical research, special treatment (St) is regarded as a sign that the company is in a financial crisis. Here, the financial crisis is defined as St.

Causes and Characteristics of Corporate Financial Crisis

Corporate financial crisis has the following characteristics: (1) cumulative: a financial crisis is gradually formed in the production and operation periods. When it does not solve the problems in production and operation, the enterprise may take financial risks. The gradual increase of financial risks will lead to a financial crisis; (2) diversity: it is reflected in the causes, forms, and strategies of corporate financial crises; (3) preventability: there are certain rules for the occurrence of the financial crisis in enterprises. Through the study of the financial and non-financial indexes and conducting all-around enterprise financial analysis, the possibility of a financial crisis can be forecasted (Jiang et al., 2019; Ren, 2020).

Corporate financial crises are caused by internal and external factors. The internal factors involve poor operation, wrong decision-makings of enterprise managers, excessive financing for scale expansion and cash flow, imperfect enterprise management structure, chaotic enterprise financial management, imperfect enterprise supervision mechanism, poor asset liquidity, and unreasonable capital structure. External causes include the changes in national policies, changes in the macro-environment, and possible impacts of affiliated enterprises (Dafermos et al., 2018; Liu, 2020).

Related Theories of DL

Long-short term memory (LSTM) neural networks are used for financial crisis forecast. The LSTM neural network model is compared with the fully connected neural network model to verify its advantages and disadvantages in financial crisis forecast. This section mainly introduces the principles of DL in fully connected neural networks and LSTM neural networks.

Fully Connected Neural Networks

The simplest deep neural networks (DNN) in DL are fully connected neural networks, which have the most network parameters and the largest amount of calculation (Chen et al., 2021; Yu et al., 2021; Liu et al., 2021). The structure of the fully connected neural network is not fixed. The general structure of neural networks include an input layer, a hidden layer, and an output layer. A fully connected neural network has only one input layer and output layer. The hidden layer is between the input layer and the output layer. Each layer of the neural network has several neurons. The neurons between layers are connected, but the neurons in layers are not connected. The neurons in the next layer are connected with all the neurons in the previous layer. Figure 1 shows the structure of fully connected neural networks.

The process of neural networks processing samples is: (1) the training samples are input into the hidden layer by the activation function, and then the data are processed by the hidden layer; (2) the result is output through the nonlinear activation function; (3) the training samples are put in the next hidden layer until the hidden layer transmits the signal to the output layer. For example, DNN comprises $L = \{l_1, l_2, \ldots, l_L\}$ layer, $N = \{n_1, n_2, \ldots, n_m\}$ neurons, $n_1$ features in the input layer, $n_m$ dimensions in the output layer; and activation function $f(\cdot)$. $Z_{i,j}$ of the $j$-th neuron in layer $i$ is calculated by:
In equation (1), $w_i$ is the weight matrix and $b_i$ is the offset vector. The relation between layer $i-1$ and layer $i$ is:

$$Z_{i,j} = f\left(\sum_{k=1}^{n_{i-1}} w_{i,k,j} \cdot z_{i-1,k} + b_{i,j}\right), 1 \leq i \leq l_n, 0 \leq j \leq n_m$$

(1)

The output variables should meet the following condition:

$$\alpha = f\left(w_i \cdot Z_{i-1} + b_i\right)$$

(2)

The model is simplified as:

$$\alpha = f\left(X, \theta\right)$$

(3)

$x$ is the feature of the data, and $\theta$ is the weight parameter.

The training of neural networks includes the forward propagation of the input signal and the BP of the error signal. BP is to calculate the gradient of the loss function, update the initial weight and offset with the gradient, minimize the value of the loss function or the times of iterations in advance, and calculate the best parameters in the neural network.

**LSTM Neural Networks**

The fully connected neural network performs one-way propagation. If it can circulate in the network, a recurrent neural network (RNN) is obtained. The RNN has a memory mechanism, which can fully analyze the relations between these data when solving the problems related to these sequence data and optimizing the whole neural network (Canizo et al., 2019). Figure 2 shows the structure of RNN. In Figure 2, $x$ is the input at time $h$, $s$ is the state of the immediately hidden node, and $o$ is the output (by RNN). The equations are:
In equation (6), $f$ is the activation function $\text{Sigmoid}$, $U$ and $W$ are the weight matrices between layers, and $b$ and $c$ are offset values. RNN has the advantages of sharing model parameters at different time points and dealing with long-term dependence, but its disadvantages are also obvious. The update of model parameters is unstable, there is a gradient explosion or disappearance, and there is only short-term memory. An improved RNN model and LSMS units are proposed to overcome its disadvantages (Wang et al., 2021). In the structure, a “door” is added, and it can solve the problem caused by long distances, even when the length of the data sequence is different. The neurons of LSTM models are composed of a cell state, an output gate, an input gate, and a forgetting gate. Internal state vector $s$, output vector $h$, state vector $s_{t-1}$ at the previous time, current state vector $s_t$ and variable $f(t)$ control the influence of $s_{t-1}$ on LSTM.

$$g(t) = \tanh \left( X_t W_s + h_{t-1} W_s + b_s \right)$$

$$i(t) = \sigma \left( X_t W_i + h_{t-1} W_i + b_i \right)$$

In equation (7), $b_f$ is the offset parameter of the forgetting gate, $\sigma$ is an activation function, $W_f$ is the weight parameter of the forgetting gate, $W_s$ and $W_i$ are the weight parameters of the input gate, $b_s$ and $b_i$ are the offset parameters of the input gate, and $\text{tanh}$ is a hyperbolic tangent activation function. LSTM updates network state $s_t$ through the forgetting gate and input gate.

$$s_t = f(t) * s_{t-1} + i(t) * g(t)$$

![Figure 2 Structure of RNN](image)
In equation (8), \( f(t) = 1 \) and \( i(t) = 1 \) are turn-on switches of the control door, \( f(t) = 0 \) and \( i(t) = 0 \) are turn-off switches of the control door, \( o(t) \) is the control variable of the output gate, \( b_o \) is the offset parameter of the output gate, and \( W_o \) is the weight parameter of the output gate. LSTM has an output value on each neuron, but only the last output contains the characteristic information of updating memory on all-time axes, which proves that LSTM has advantages in processing time sequence data. However, a corporate financial crisis is a changing process, and the corporate financial data are highly dependent. In response to the problem, LSTM neural networks first store historical information through the circular structure, and then process time sequence data. Theoretically, it has good forecast performance for financial crises.

**Samples and Evaluation Indexes**

*Sample Selection and the Evaluation System*

All A-share listed companies in China from 2000 to 2020 are selected as the research samples. Among all the listed companies, companies with abnormal financial conditions will be subject to ST. Such companies are called ST companies and taken as a sample of companies with the financial crisis. The financial data of T-2, T-3 to T-2, T-4 to T-2, and T-5 to T-2 from 2000 to 2020 are used to forecast the corporate financial crisis, and they are from the website of the National Bureau. So far, there is no unified standard for index selection in the research of financial crisis forecast. Here, domestic and foreign literature, research results, and data are referred to establish the indexes. The final indexes are shown in Table 1:

| Indexes                  | Roles                                           |
|-------------------------|-------------------------------------------------|
| Solvency Index          | Enterprise’s ability to repay due debts         |
| Operating capacity index| Enterprise capital operation turnover           |
| Profitability index     | Enterprise production and operation profitability|
| Development capacity indexes| Expanding its business scale through the existing foundation |
| Cash flow index         | Visually observing the revenue and expenditure of the enterprise |
| Risk level index        | The financial leverage, operating leverage, and combined leverage |
| Ownership structure index| Determining the enterprise organizational structure and governance structure |
| Corporate governance index| Causing financial crises                        |
| Macroeconomic indexes   | External macro-economy affects the operation of enterprises |
The Evaluation System

Corporate financial crisis forecast has two categories. The commonly used evaluation indexes are the accuracy rate, precision, recall, F-value, G-value, receiver operating characteristic curve (ROC), and area under ROC (AUC) (Zhao et al., 2020b). Here, F-value, the recall rate, ROC, and AUC are employed.

In the binary classification model, ST companies are positive and normal companies are negative samples. According to the actual category and prediction category of the sample, four results are obtained: true negative (TN), false negative (FN), true positive (TP), and false positive (FP). The actual category is consistent with the forecast category, and False indicates inconsistency. The confusion frame is shown in Figure 3.

Figure 3. Confusion frame

Accuracy:

\[ \text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \]  
(9)

Recall:

\[ R = \frac{TP}{TP + FN} \]  
(10)

Specificity:

\[ K = \frac{TN}{TN + FP} \]  
(11)
Precision:

\[ P = \frac{TP}{TP + FP} \]  

(12)

F-Value:

\[ F_\beta = \frac{(1 + \beta^2) \times P \times R}{\left(\beta^2 \times P\right) + R} \]  

(13)

In the corporate financial forecasting system, more attention is paid to the recall rate, which is set in combination with the accuracy rate and recall rate. In equation (14), when the accuracy rate and recall rate are large, \( F_2 \) will have a large value.

\[ F_2 = \frac{5 \times P \times R}{4P + R} \]  

(14)

In signal test theory, ROC is a coordinate pattern analysis tool, which is used to select the best signal detection model and abandon the sub-optimal model, and set the best threshold in the same model (Peterson et al., 2008). The horizontal axis of the ROC coordinate axis is set as the False Positive Rate (FPR), and the vertical axis is set as the True Positive Rate (TPR).

\[ FPR = \frac{FP}{FP + TN} \]

\[ TPR = \frac{TP}{TP + FN} \]  

(15)

The closer ROC is to the upper right corner of the coordinate axis, the better the performance of the classification system is, and ROC cannot be affected by different kinds of samples, which can show the high quality of the classification system. When the curves of two classifiers cross, their ACU can be compared. The closer the AUC value is to 1, the better the classification effect of the system is.

**Construction of Corporate Financial Crisis Prediction System Based on DL**

**Constructing LSTM Neural Networks**

For the missing values in the collected financial data, the mean value of the financial index series is used to fill in to improve the data integrity, and then the maximum and minimum normalization is used for preprocessing.

\[ x_i^n = \frac{x_i^n - \min x_i^n}{\max x_i^n - \min x_i^n} \]  

(16)

Data processing is conducted before model training, and the data are processed into three-dimensional data, which are company samples, time, and characteristics respectively. Then, the
The training set is divided into the verification set and test set of the model according to the time step, and the final number of each dataset is shown in Figure 4.

Figure 4. Number of samples of various types at different time steps

![Figure 4](image_url)

DL can automatically identify features and train the training set and verification set. After a lot of experiments and debugging, the parameters of the LSTM neural network model are set:

- **Input layer data:** step size, the number of output layer nodes: 1, the number of hidden layers: 2, and the number of neurons in two hidden layers: 32, 16
- **Hidden layer activation function:** the Relu function, the activation function in the output layer, and the sigmoid function

\[
\text{Relu}(x) = \begin{cases} 
  x, & x > 0 \\
  0, & x \leq 0 
\end{cases}
\]

\[
\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}
\]

- **Number of batches:** 256, and times of iterations: 300
- **Cost loss function**
In equation (18), \( n \) is the training data quantity, \( \hat{y} \) is the output value, and \( y \) is the target output.

- The initial learning rate is 0.1, and the threshold is 0.5. If the output value is greater than 0.5, it is forecasted to be positive; if it is less than 0.5, it is forecasted to be negative. The Adadelta optimization algorithm is used to calculate them.

Other Financial Crisis Forecast Models

After debugging, the parameter setting of the fully connected neural network model is consistent with that of the LSTM neural network. However, the number of input layer nodes, namely, the number of characteristic indexes, needs to be set for the fully connected neural network.

The Logistic regression model has the advantages of good interpretation and easy expansion (Kuo et al., 2018). The equation of the probability of financial crisis (\( P \)) is as follows:

\[
\text{logit}(p) = \ln \left( \frac{P}{1 - P} \right) = B_0 + B_1X_1 + B_2X_2 + \cdots + B_iX_i + \varepsilon
\]

\( (19) \)

\[
p = \frac{e^{(B_0 + B_1X_1 + B_2X_2 + \cdots + B_iX_i + \varepsilon)}}{1 + e^{(B_0 + B_1X_1 + B_2X_2 + \cdots + B_iX_i + \varepsilon)}}
\]

\( (20) \)

Figure 5. ROC of LSTM neural networks
In equation (19), $B_i$ is the regression coefficient of $X_i$, $X_i$ is the predictive variable, and $B_0$ is a constant. Similarly, L1 regularization is added to prevent overfitting of the model, and the default parameters are selected for other parameters.

**RESULTS**

**Experimental Results and Analysis of the LSTM Neural Network Model**

*ROC of the Financial Crisis Forecast System Based on LSTM Neural Networks*

The effect of corporate financial crisis forecast obtained by using different time steps is shown in Figure 5:

Figure 5 shows that the ROC of T-3 is closer to the upper left corner, so the classification effect of the T-3 model is the best. It shows that the data of T-3 is the best when the LSTM neural network model is used to forecast corporate financial crises. However, there is randomness in the single prediction effect. The LSTM neural network is used to set the asynchronous length for repeated experiments, and the forecast results of 10 repeated experiments are averaged, as shown in Figure 6.

Figure 6(a) forecast results of LSTM neural networks with different time steps

![Figure 6(a) forecast results of LSTM neural networks with different time steps](image)

Figure 6 (a) shows that the accuracy of the LSTM neural network model reaches more than 93% with different time steps. However, if all the sample forecasts are changed to non-St, the accuracy can reach 94%, and the accuracy evaluation cannot well reflect the performance of the model. The AUC values of different time steps can be compared to avoid the impact of unbalanced positive and negative samples. It is found that in the four different time steps, the AUC of T-3 reaches 93.67%,
which is higher than that of the other three-step models. Figure 6 (b) shows that after SMOTE equilibrium treatment, F2 and the recall rate are improved, and the ability of the model to forecast positive samples is improved.

Figure 6(b) forecast results of LSTM neural networks after Synthetic Minority Oversampling Technique (SMOTE) equilibrium treatment

Figure 7. AUC of the financial crisis forecast system based on LSTM neural networks before and after equilibrium treatment
Figure 8(a) forecast results of the fully connected neural network structure with different time steps

Figure 8(b) forecast results of fully connected neural networks after SMOTE equilibrium treatment

Accuracy
Recall
True negative category rate
Precision
F2
AUC
Figure 7 shows that the AUC values of 10 repeated training experiments are compared. Figure 7 shows that AUC of the model with step T-3 is significantly higher than that of others. After 10 repeated experiments, the neural network model using T-3 data still has the best classification effect. Experiments show that in the financial crisis forecast model based on the LSTM neural network model, using T-3 year data can make the forecast effect of the prediction system the best. When Figures 6 and 7 are compared, it is found that the forecast effect of using the data in T-3 is better than that in T-2, but AUC in T-4 and T-5 decrease, indicating that the forecast effect does not change linearly with time, and the data are timely.

Other Financial Crisis Forecast Models

Analysis of Experimental Results of The Financial Crisis Forecast Model Based On Fully Connected Neural Networks

Figure 8 shows the forecast effect of the fully connected neural network model after 10 repeated experiments. Figure 8 (a) shows that the accuracy of the fully connected neural network model with different time steps can reach more than 93%. It is because of the unbalanced positive and negative samples, and the accuracy cannot reflect the performance of the model. After the AUC of different time steps is compared, it is found that in the four different time steps, the AUC value of T-2 reaches 93.01%, T-3 reaches 93.43%, T-4 reaches 93.32%, T-5 reaches 93.26%, and the AUC value is the highest when the time step is T-3. Figure 8 (b) shows that after SMOTE equilibrium treatment, F2 and the recall rate increase, and the forecast ability of the system for positive samples is improved.
Analysis of Experimental Results of The Logistic Regression Model And Financial Crisis Forecast Model

Figure 9 shows the forecast effect of repeated experiments of the logistic regression model 10 times. Figure 9 shows that the accuracy of the logistic regression model with different time steps can also reach more than 93%. Due to the unbalanced positive and negative samples, the accuracy evaluation cannot well reflect the performance of the model. After the AUC values of different time steps are compared, it is found that in the four different time steps, the AUC value of T-2 reaches 88.90%, T-3 reaches 91.43%, T-4 reaches 90.32%, and T-5 reaches 90.98%, and the AUC value is the highest when the time step is T-3.

Comparative Analysis of Experimental Results Between The LSTM Neural Network Model And Different Models

Figure 10 shows the comparison of the AUC values between the LSTM neural network model and different models. Figure 10 shows that among all the forecast models, the highest AUC value of the forecast model based on LSTM neural networks is 93.67%, that of the fully connected neural network model is 93.43%, and that of the logistic regression model is 91.43%. The AUC value of each model is the highest when the time step is T-3, which shows that the data with the time step of T-3 can achieve the best effect in different models. According to the data analysis, the AUC value of the LSTM neural network model is the highest and that of the logistic regression model is the lowest. Therefore, the LSTM neural network model can achieve a good forecast effect in corporate financial crises.
CONCLUSIONS

The sustainable reuse strategy of corporate financial management modes based on DL is discussed. If enterprises want to maintain financially sustainable development, they must adopt an efficient financial management mode and keep smooth operation. Sustainable financial development should be based on good operation, so a corporate financial crisis forecast system is established based on LSTM neural networks. First, the influencing factors and related theories of corporate sustainable financial development are analyzed. Second, the LSTM neural network model is implemented based on DL. Finally, different models are used to experiment with the unbalanced sample data and processed sample data, including the LSTM neural network model, fully connected neural network model, and logistic regression model. The experimental results show that the forecast model can achieve the best effect by using the financial data with the time step of T-3. Compared with the other two models, the accuracy of the LSTM neural network model can reach more than 93%, and the highest AUC value is 93.67%. The LSTM neural network model can achieve a good effect in the financial crisis forecast. There are still some shortcomings. For example, when companies are distinguished by financial states, the categories are simply financial normality and financial crisis. In practice, this should be detailed. In the future, more researches will be conducted on the corporate sustainable financial development strategy to improve the model.

FUNDING AGENCY

Open Access Funding for this article has been covered by the authors of this manuscript.

ACKNOWLEDGEMENTS

The authors would like to thank the National Social Science Foundation of China (Grant no. 20CZZ017).
REFERENCES

Ahmed, Z., Zhang, B., & Cary, M. (2021). Linking economic globalization, economic growth, financial development, and ecological footprint: Evidence from symmetric and asymmetric ARDL. *Ecological Indicators, 121*, 107060. doi:10.1016/j.ecolind.2020.107060

Canizo, M., Triguero, I., Conde, A., & Onieva, E. (2019). Multi-head CNN–RNN for multi-time series anomaly detection: An industrial case study. *Neurocomputing, 363*, 246–260. doi:10.1016/j.neucom.2019.07.034

Cao, M. (2020). Merging game theory and control theory in the era of AI and autonomy. *National Science Review, 7*(7), 1122–1124. doi:10.1093/nsr/nwaa046 PMID:34692134

Cheah, J., Amran, A., & Yahya, S. (2019). Internal oriented resources and social enterprises’ performance: How can social enterprises help themselves before helping others? *Journal of Cleaner Production, 211*, 607–619. doi:10.1016/j.jclepro.2018.11.203

Chen, J., Zheng, H., Xiong, H., Chen, R., Du, T., Hong, Z., & Ji, S. (2021). FineFool: A novel DNN object contour attack on image recognition based on the attention perturbation adversarial technique. *Computers & Security, 104*, 102220. doi:10.1016/j.cose.2021.102220

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics, 152*, 219–234. doi:10.1016/j.ecolecon.2018.05.011

Djuitaningsih, T., & Arifianto, D. (2020). Individual And Organizational Impacts: Information And System Quality Inflence On Attitude Towards Use And User Satisfaction Of Agency-Level Financial Application System. *Acta Informatica Malaysia, 4*(1), 10–18. doi:10.26480/aim.01.2020.10.18

Gao, H., Hsu, P. H., Li, K., & Zhang, J. (2020). The real effect of smoking bans: Evidence from corporate innovation. *Journal of Financial and Quantitative Analysis, 55*(2), 387–427. doi:10.1017/S0022109018001564

Jiang, L., Tong, A., Hu, Z., & Wang, Y. (2019). The impact of the inclusive financial development index on farmer entrepreneurship. *PLoS One, 14*(5), e0216466. doi:10.1371/journal.pone.0216466 PMID:31063505

Kuo, C. L., Duan, Y., & Grady, J. (2018). Unconditional or conditional logistic regression model for age-matched case–control data? *Frontiers in Public Health, 6*, 57. doi:10.3389/fpubh.2018.00057 PMID:29552553

Liu, F., Zhang, G., & Lu, J. (2020). Multisource heterogeneous unsupervised domain adaptation via fuzzy relation neural networks. *IEEE Transactions on Fuzzy Systems, 29*(11), 3308–3322. doi:10.1109/TFUZZ.2020.3018191

Liu, Y. (2020). Design of Port Enterprise Financial Shared Service Center Based on Nested Logit Model. *Journal of Coastal Research, 103*(1), 29–32. doi:10.2112/SI103-007.1

Liu, Z., Lang, L., Li, L., Zhao, Y., & Shi, L. (2021). Evolutionary game analysis on the recycling strategy of household medical device enterprises under government dynamic rewards and punishments. *Mathematical Biosciences and Engineering, 18*(5), 6434–6451. PMID:34517540

Llerena Caña, J. P., García Herrero, J., & Molina López, J. M. (2021). Forecasting Nonlinear Systems with LSTM: Analysis and Comparison with EKF. *Sensors (Basel), 21*(5), 1805. doi:10.3390/s21051805 PMID:33807681

Peterson, A. T., Papeş, M., & Soberón, J. (2008). Rethinking receiver operating characteristic analysis applications in ecological niche modeling. *Ecological Modelling, 213*(1), 63–72. doi:10.1016/j.ecolmodel.2007.11.008

Qi, S., Jin, K., Li, B., & Qian, Y. (2020). The exploration of internet finance by using neural network. *Journal of Computational and Applied Mathematics, 369*, 112630. doi:10.1016/j.cam.2019.112630

Ren, H. (2020). Design of Port Enterprise Logistics Vehicle Location Tracking System Based on Big Data. *Journal of Coastal Research, 103*(1), 873–876. doi:10.2112/SI103-181.1

Shin, H., & Lee, K. (2019). Impact of financialization and financial development on inequality: Panel cointegration results using OECD data. *Asian Economic Papers, 18*(1), 69–90. doi:10.1162/asep_a_00659

Song, J., Zhang, Z., & So, M. K. (2021). On the predictive power of network statistics for financial risk indicators. *Journal of International Financial Markets, Institutions and Money, 75*, 101420. doi:10.1016/j.intfin.2021.101420
Waheed, A., & Zhang, Q. (2020). Effect of CSR and ethical practices on sustainable competitive performance: A case of emerging markets from stakeholder theory perspective. *Journal of Business Ethics*, 1–19.

Wang, W., Li, W., Zhang, N., & Liu, K. (2020). Portfolio formation with preselection using deep learning from long-term financial data. *Expert Systems with Applications, 143*, 113042. doi:10.1016/j.eswa.2019.113042

Wang, Z., Zhang, T., Shao, Y., & Ding, B. (2021). LSTM-convolutional-BLSTM encoder-decoder network for minimum mean-square error approach to speech enhancement. *Applied Acoustics, 172*, 107647. doi:10.1016/j.apacoust.2020.107647

Wu, B., Wang, Q., Fang, C. H., Tsai, F. S., & Xia, Y. (2022). Capital flight for family? Exploring the moderating effects of social connections on capital outflow of family business. *Journal of International Financial Markets, Institutions and Money, 77*, 101491. doi:10.1016/j.intfin.2021.101491

Xu, X. L., Shen, T., Zhang, X., & Chen, H. H. (2020). The role of innovation investment and executive incentive on financial sustainability in tech-capital-labor intensive energy company: Moderate effect. *Energy Reports, 6*, 2667–2675. doi:10.1016/j.egyr.2020.09.011

Yang, L., Qin, H., Xia, W., Gan, Q., Li, L., Su, J., & Yu, X. (2021). Resource slack, environmental management maturity and enterprise environmental protection investment: An enterprise life cycle adjustment perspective. *Journal of Cleaner Production, 309*, 127339. doi:10.1016/j.jclepro.2021.127339

Yu, H., Zhao, Y., Liu, Z., Liu, W., Zhang, S., Wang, F., & Shi, L. (2021). Research on the financing income of supply chains based on an E-commerce platform. *Technological Forecasting and Social Change, 169*, 120820. doi:10.1016/j.techfore.2021.120820

Zhang, P., Guo, Q., Zhang, S., & Wang, H. H. (2019). Pattern mining model based on improved neural network and modified genetic algorithm for cloud mobile networks. *Cluster Computing, 22*(4), 9651–9660. doi:10.1007/s10586-017-1334-1

Zhang, Y., Chu, G., & Shen, D. (2021). The role of investor attention in predicting stock prices: The long short-term memory networks perspective. *Finance Research Letters, 38*, 101484. doi:10.1016/j.frl.2020.101484

Zhao, J., Xue, R., Dong, Z., Tang, D., & Wei, W. (2020a). Evaluating the reliability of sources of evidence with a two-perspective approach in classification problems based on evidence theory. *Information Sciences, 507*, 313–338. doi:10.1016/j.ins.2019.08.033

Zhao, Y., Zhang, W., Wang, P., & Shen, D. (2020b). Borrower platform choice: The influencing factors on herding. *International Journal of Financial Engineering, 7*(01), 2050002. doi:10.1142/S2424786320500024