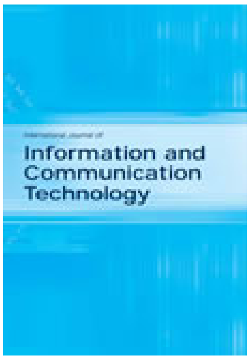


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# Marketing credit evaluation model of B2B e-commerce enterprises based on improved CNN algorithm

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# Marketing credit evaluation model of B2B e-commerce enterprises based on improved CNN algorithm


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**Abstract:** The traditional credit evaluation model has the disadvantages of difficult data mining and low evaluation accuracy. This study constructs an improved convolutional neural network and applies it to the marketing credit assessment technique used by e-commerce businesses. The results showed that the area under the accuracy-recall curve of this study, random forest, and decision tree were 0.83, 0.74, and 0.65, respectively. The area of the convolutional neural network under the curve of number of iterations was 0.65. The convolutional neural network completed the iteration when the iteration number was 198 times. The random forest model completed the iteration when the iteration number was 239 times. The decision tree model completed the iteration when the iteration number was 594. Thus, the suggested method owns better accuracy and robustness.

**Keywords:** neural network; marketing; credit evaluation; convolutional neural network; CNN; model.

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## 1 Introduction

Recently, e-commerce has grown to be a significant force in the world economy. B2B e-commerce enterprises are important, and their marketing activities are significant to the enterprises. Under the current backdrop of emphasising the enhancement of industrial chain resilience, the healthy development of specialised, refined, unique and innovative enterprises, as key links in the industrial chain and an important source of innovation capabilities, is particularly crucial. Market development capability is the core guarantee for supporting specialised, refined, unique and innovative enterprises to resist risks and achieve sustainable growth. In the marketing activities of B2B e-commerce enterprises, credit evaluation is an essential evaluation index, which is associated with the business status and development prospects of enterprises. Especially for specialised, refined, unique and innovative enterprises that adopt the B2B marketing model, their businesses generally have significant characteristics such as large transaction amounts, long decision-making chains, and a high degree of customisation. These characteristics can easily lead to problems such as increased transaction risks, reduced decision-making response speed and poor customer experience in practice. To effectively control transaction risks, reduce bad debt losses, accelerate the decision-making process, enhance customer experience, and ultimately strengthen the market resilience and development capabilities of specialised, refined, unique and innovative enterprises, it is necessary to build a scientific and precise marketing credit assessment model and integrate it into the intelligent marketing decision-making system. Traditional credit evaluation models (CEM) mainly include statistical analysis, logical reasoning, expert judgment and other methods. Although these methods can evaluate the credit status of enterprises to a certain extent, they still have some shortcomings (Prajapati et al., 2022; Zhou et al., 2022a; Rachbini et al., 2021). For example, statistical analysis methods cannot handle complex data, and logical reasoning methods are difficult to handle large amounts of data. Therefore, there is an urgent need for a credit evaluation technology with high accuracy and fast speed to enhance the competitiveness of the B2B e-commerce industry and provide a powerful tool for optimising the cultivation path of specialised, refined, unique and innovative enterprises and strengthening their development resilience. Currently, natural language processing has greatly benefited from deep learning, among which convolutional neural network (CNN) receives a lot of attention due to their processing power and high accuracy for complex data. However, the traditional CNN algorithm still has some problems in the field of credit evaluation, such as overfitting and other problems in the training process (Guo, 2022; Patnaik et al., 2021). In this context, to address the problem of traditional e-commerce enterprise marketing credit models (CEM) being difficult to handle large-scale complex data and slow in processing speed, this study proposes an enhanced CNN and applies it to the marketing CEM of specialised and innovative enterprises in B2B marketing mode. The innovation of the study lies in combining the extreme gradient boosting (XGBoost) algorithm with CNN, which reduces the training time of the model through feature filtering, avoids overfitting, and increases the generalisation ability of the model. The contribution of the study lies in the construction of marketing credit evaluation indicators for e-commerce enterprises and the use of advanced deep learning algorithms for credit evaluation, effectively promoting the progress of e-commerce credit evaluation technology and helping specialised and innovative enterprises to manage risks, optimise decisions, and enhance market competitiveness.

The study consists of six parts. Section 1 introduces the background of marketing credit evaluation of e-commerce enterprises. Section 2 is a review of the study status of marketing credit evaluation of e-commerce enterprises. Section 3 is the construction of B2B e-commerce enterprise marketing CEM based on improved CNN, Subsection 3.1 is the construction of e-commerce enterprise marketing credit model based on CNN, and Subsection 3.2 is the improvement of CNN. Section 4 shows the effect analysis of the designed model, Subsection 4.1 shows the performance test results, and Subsection 4.2 shows the actual application analysis results. Section 5 discusses the results of the study. Section 6 is the conclusion section, where the limitations and future prospects of the study are pointed out, and the impact of the study on the development of the e-commerce industry is given.

## 2 Related work

CED refers to the model of evaluating the credit of enterprises by using mathematical and statistical methods. This model is mainly split into two types, one is a statistical analysis model based on credit history data, and the other is a model based on machine learning algorithms. Lee and Chang explored business ethics and organisational performance through study, integrating them with corporate cognition and management. The study used a model to explore whether enterprises with good credit can create better organisational benefits, which helped to quantify business ethics (Lee and Chang, 2021). Andersen et al., focusing on the concept of enterprise marketing, conducted a study on the basis of this thesis. The experiment explored the promoting role of users and brands in cultural transmission through the construction of marketing models. This study supported business marketing by emphasising the challenge of corporate centrality (Andersen and Johansen, 2021). Through study on the internal and external environment of enterprises, Zonya et al. built a model based on enterprise credit risk assessment, and provided relevant suggestions on frameworks for managing danger. The model was classified systematically from economy, marketing, finance and so on. The results showed that this model could make use of extra stage risk to build a model and provide the quality of enterprise risk management (Косова et al., 2021). Karimi and Hojati designed an inference machine and constructed a new enterprise CEM based on the output of the inference machine. In this paper, rough theory was used to cross the models, then clustering was applied to combine the same near, and finally the conditional attributes were reduced. The model could have high accuracy in credit evaluation (Karimi and Hojati, 2022). Li et al. built a CEM based on numerisation through the study of business audit. This study applied hybrid extreme gradients to promote multi-layer perceptrons to evaluate the credit risk of financial firms. The results showed that this model performed well in credit evaluation (Li et al., 2022).

Chu et al. built a new fuzzy comprehensive evaluation model based on medium-sized enterprises and selected different indicators for evaluation of small- and medium-sized businesses' credit risks. The coefficient of variation was used as the calculation index, and the results showed that the accuracy of SME had been improved, which could provide guidance for the development of SMEs (Chu et al., 2021). Based on the XGBoost, Cheng developed a multi-indicator scoring model for SME credit evaluation. In the experiment, the credit rating was divided first, the data features were extracted, and then the assessment index was built. This approach could accurately account for the impact of unforeseen circumstances and timely modify SMEs' financing strategies (Cheng, 2021). Li studied the difficulties in credit control in C2C online transactions and found that most credit evaluation algorithms of C2C e-commerce are too simple. The study constructed a new method for credit evaluation based on transaction history data and iteration principle. Firstly, the iterative algorithm was used for calculation, and then the transaction data was extracted. This algorithm could significantly enhance the credit security and improve the security of C2C e-commerce (Li, 2021).

To sum up, credit assessment plays a crucial role in enhancing the resilience of the industrial chain and supporting the healthy growth of specialised, refined, unique and innovative enterprises, but there are still some shortcomings such as large amount of data processing, uncertain factors and difficult model training in the evaluation process. Using a summary of the available technologies, this study constructs an e-commerce CEM based on the improved CNN, aiming to provide technical support for optimising the market expansion path of specialised, refined, unique and innovative enterprises, enhancing their development resilience and the stability of the industrial chain they are in.

## 3 Construction of B2B e-commerce enterprise CEM by integrating and improving CNN algorithm

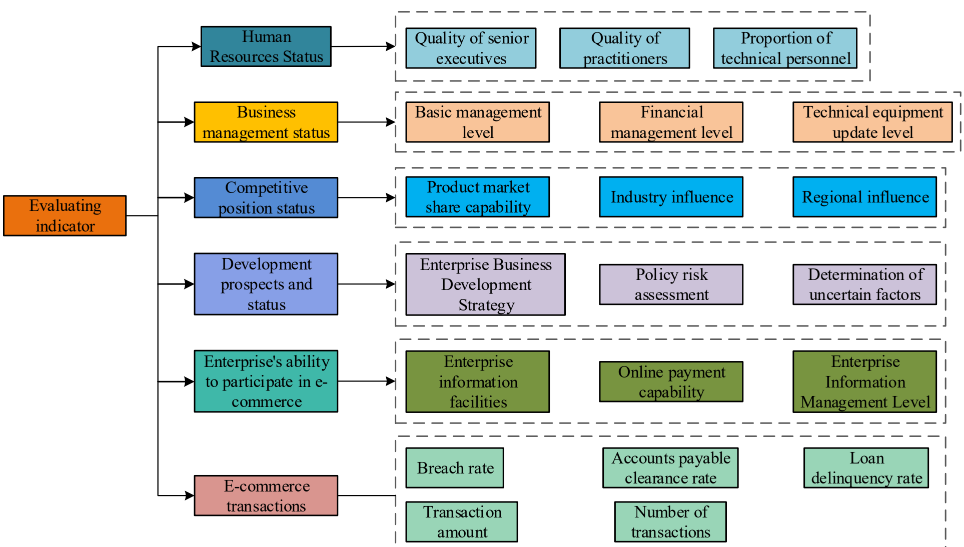
CEM of e-commerce business refers to the process of evaluating the credit status of e-commerce enterprises, fulfilling legal obligations and social responsibilities, and announcing the evaluation results. The CEM of e-commerce enterprises is to evaluate the credit status, performance ability and obligation performance of e-commerce business in the process of operation, so as to reflect the credit status and market competitiveness of enterprises.

### *3.1 Construction of enterprise marketing CEM based on CNN algorithm*

CEM is a method of quantitative evaluation of enterprise credit status, it through the enterprise credit history, credit record, credit performance and other information analysis and evaluation, so as to obtain a comprehensive evaluation result. The CEM is widely used and can be used in many different industries and fields. The application of CEM depends on the characteristics of the objects and data to be evaluated. If the object is human, then the CEM may be suitable for financial institutions, financial leasing companies, etc. to evaluate the credit of customers. If the data is text, image, etc. then the

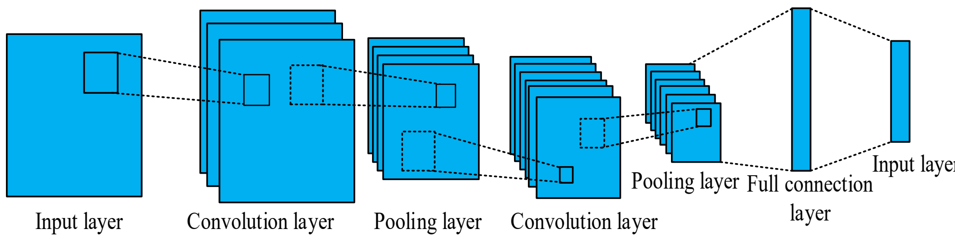
CEM may be suitable for e-commerce enterprises and Internet enterprises to conduct credit evaluation on users (Kvainauskaitė et al., 2025; Sharma et al., 2021; Veeramanikandan and Jeyakarthic, 2021). In practical application, the CEM needs to be selected and adjusted according to the specific situation. Common CEM include credit score based on statistical analysis, credit evaluation based on machine learning, credit evaluation based on neural network, etc. Different models have different advantages and scope of application. Among them, the CEM based on neural network can improve the prediction accuracy through nonlinear processing and classification tasks. Therefore, this study first constructs a B2B e-commerce credit evaluation index system based on commonly used indicators of corporate credit, combined with the characteristics of B2B e-commerce enterprises. Then, a CEM is established through CNN algorithm. The study constructs a B2B e-commerce enterprise credit evaluation index system from five aspects: human resources status, business management status, competitive position status, development prospects status, and enterprise participation in e-commerce ability, as shown in Figure 1.

**Figure 1** Basic credit evaluation index system (see online version for colours)




In Figure 1, the credit evaluation index system for B2B e-commerce enterprises includes the quality of senior management personnel, the quality of employees, and the proportion of technical personnel in terms of resource status. The operational management status includes basic management level, financial management level, and technological equipment update level. The competitive position status includes the ability to level market share, industry influence, and regional influence. The development prospects include the enterprise’s business development strategy, policy risk assessment, and uncertainty factor assessment. The ability of enterprises to participate in e-commerce includes enterprise information facilities, online payment capabilities, and enterprise information management level. E-commerce transactions include breach rate, accounts payable clearance rate, loan delinquency rate, transaction amount, and transaction frequency. Then, a CNN is used to construct an enterprise marketing CEM, which learns and trains a large amount of data to achieve the evaluation and prediction of enterprise marketing credit. CNN consists of two parts: forward extraction topology and backward propagation optimisation, which is essentially a multi-layer perceptron. It can improve the prediction accuracy by learning a large amount of sales data, and meanwhile, it can mine local features to achieve training and classification, with strong adaptability (Zhou et al., 2022b; Kang, 2021; John et al., 2023; Alsaad et al., 2021). The CNN structure is shown in Figure 2.

**Figure 2** CNN structure diagram (see online version for colours)




CNN owns the advantages of weight sharing, local connection and space pooling, which reduce training parameters and computational costs, and further reduce computational costs by sharing parameters. CNN mainly realises pattern recognition through convolution, pooling and full connection. The convolution layer consists of multiple convolution nuclei. The step length and the side length of convolution nuclei are set in advance, and different results can be obtained by moving the convolution nuclei. The larger the step size, the less repeatability, and the entire feature set will be obtained when the convolution kernel movement is complete. The output equation of one-dimensional convolution is shown as equation (1).

$$C_{cn} = f\left(X * W_{cn} + b_{cn}\right) \tag{1}$$

In equation (1), $f$ is the activation function. $X$ denotes the input data. $W_{cn}$ denotes the weight of the convolution kernel. $b_{cn}$ denotes the offset of the convolution kernel. Pooling layer is mainly to partition the obtained feature set to achieve dimensionality reduction, so as to reduce the computation and the size of the model and enhance the robustness. Generally, the pooling layer consists of two methods: maximum pooling and mean pooling. The fully connected layer can be regarded as a feature classifier, usually a softmax classifier, which can map the output to a normalised probability distribution and output confidence.

$$p(x)i\tau_i = \frac{e^{\tau i}}{\sum_k e^{\tau i}}, i = 1, 2, \ldots, k^{\tau i} \tag{2}$$

In equation (2), $k$ is the classification quantity. $\tau_i$ represents the unactivated output value of the last layer of neurons. After the model is built, it is required to be trained to optimise the network parameters. Meanwhile, to prevent the phenomenon of underfitting or overfitting, it is required to set the learning rate, iteration times and other parameters reasonably. Sales data forecasting is a multi-classification problem, and the optimisation goal is to minimise or maximise the objective function. The cost function is a measure of error between the predicted result and the actual classification, commonly known as the cross entropy loss function. If the target distribution is defined as $p(x)$ and the prediction distribution is defined as $q(x)$, then the cross entropy can be expressed by equation (3).

$$H(p, q) = -\sum_{x} p(x) \log q(x) \tag{3}$$

The key of neural network parameter optimisation is the backpropagation algorithm. The principle is to update the optimisation algorithm after obtaining the partial derivation of the objective function, basically the discrepancy between the production and the desired. That is, the sensitivity of the error relative to the parameter, and the error is calculated as shown in equation (4).

$$\delta^{l-1} = \frac{\partial J}{\partial \tau^{l-1}} = \frac{\partial J}{\partial \tau^{l}} \frac{\partial \tau^{l}}{\partial \tau^{l-1}} = \delta^{l} \frac{\partial \tau^{l}}{\partial \tau^{l-1}} \frac{\partial a^{l-1}}{\partial \tau^{l-1}} \tag{4}$$

In equation (4), $\delta^l$ is the error of objective function $J$ to $\tau^l$.

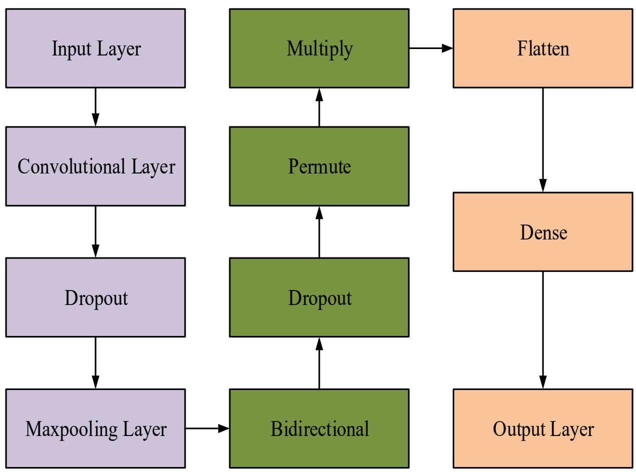
## *3.2 Construction of B2B e-commerce enterprise CEM based on improved CNN algorithm*

Although the enterprise marketing CEM integrated with CNN algorithm has certain advantages, it needs a lot of computing resources and computing time during operation, which is usually difficult to meet the real-time requirements of enterprise marketing credit evaluation. Meanwhile, since the e-commerce marketing dataset has a lot of characteristic variable indicators, and it also involve assets and other information with strong privacy. In addition, in the process of selling, there will be some interference problems, or useless information. However, this information is not obvious, so it cannot be judged on the basis of subjective factors such as meaning. These underlying data attributes or characteristics are of little significance in building a credit rating classification model. Even the inclusion of these irrelevant attributes in the use of the predictor may adversely affect the resulting model. Therefore, the CNN algorithm is improved on the basis of 2.1. In this study, the XGBoost algorithm is integrated with the CNN algorithm to get the improved CNN algorithm, and it is used to build the CEM of B2B e-commerce business. XGBoost's feature screening, variable selection, is a process used during modelling to reduce features or narrow down a subset of attributes. By feature screening, the overall training time can be reduced, overfitting can be prevented to a certain extent, and the model's capacity for generalisation may be improved. Figure 3 illustrates the neural network diagram after the fusion of the two algorithms.

There are two sections to the XGBoost algorithm's goal function during training, namely, the loss function of gradient lifting algorithm and the regularisation term. In the process of data feature extraction, the advantage of XGBoost is that it not only adopts first-order partial derivation in the loss function, but also adopts Taylor expansion to obtain second-order differential. This method can accelerate the gradient descent speed and improve the accuracy of the descent direction by using second-order deflection. In addition, the second order expansion loss function is used to calculate the optimal blade splitting only according to the input data when the specific form of the loss function is uncertain. XGBoost algorithm expands the loss function in the second order, in essence, it distinguishes the selection of loss function, the optimisation of model algorithm and the selection of model parameters. This approach enhances XGBoost's ability to generalise by allowing you to select loss functions as needed, rather than using only specified functions. This method is applicable not only to classification problems, but also to regression problems. XGBoost uses the greedy algorithm to traverse all feature segmentation points for all data features. The core idea is to learn a new function by constantly adding trees, and to grow a tree by unlimited feature splitting. After that, the residual of the last prediction is fitted. When the score of a sample is predicted, it is placed into the corresponding leaf node according to its data characteristics. The scores assigned to each leaf node are summed together to provide the anticipated value for the sample. The predicted value can be calculated by equation (5).

$$\hat{y}_i = \varnothing(x_i) = \sum^{K} f_k(x_i),\ f_k \in \Im \tag{5}$$

**Figure 3** Structure diagram of the fused neural network (see online version for colours)




In equation (5), $x_i$ represents the value of $y$ of the $i$ data. $K$ represents an addition function. $f_k$ denotes the weight value. The loss function in XGBoost's objective function can reflect the bias in the training process. As a function of the complexity of the tree structure, the regularisation term can significantly reduce the variation of the model, making the training process of the model simpler, and have lower computational complexity and better generalisation performance. The objective function of XGBoost can be defined by equation (6).

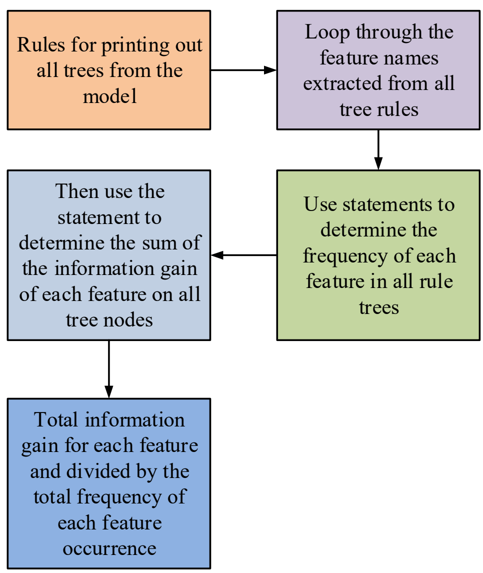
$$L(\varnothing) = \sum_i l(\hat{y}_i - y_i) + \sum_K \Omega(f_k) \tag{6}$$

In equation (6), $y_i$ represents the value of $x$ of the $i$ data. $\sum_K \Omega(f_k)$ represents the regularisation term. $\sum_K \Omega(f_k)$ can be calculated by equation (7).

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2 \tag{7}$$

In equation (7), $\gamma$ represents the factor determining how many leaf nodes there are. $T$ represents the quantity of leaf nodes. $\lambda$ represents the coefficient controlling the fraction of leaf nodes. $\omega$ represents the leaf node score. A very essential application of XGBoost is to determine the importance of eigenvalues by importance. Considering the increase in the structural score, which feature is chosen as the segmentation point is calculated. The total number of times a characteristic appears in all trees determines its significance. To solve the above problems, XGBoost algorithm has also made some improvements in the implementation process: First, based on the greedy algorithm, all possible segmentation points are counted for each feature. However, since the search efficiency is too high, XGBoost algorithm solves the optimal segmentation point and obtains the optimal segmentation point. Second, when the sample is sparse, XGBoost algorithm can give a default branching direction to the missing or given sample, which greatly improves the computational efficiency of the algorithm. Figure 4 illustrates the flowchart of XGBoost algorithm feature screening.

**Figure 4** XGBoost algorithm feature screening process (see online version for colours)




After the successful construction of the model, it is necessary to use the index system to evaluate the model. In this index system, the dimension of each index is different, which causes the difficulty of evaluation. Therefore, it is necessary to convert the evaluation indicators of different dimensions into dimensionless standardised indicators through appropriate transformations (such as vector normalisation, linear proportional transformation, range transformation, etc.), so as to achieve the standardisation of evaluation indicators. The standardisation of indicators is divided into quantitative indicators and qualitative indicators, in which quantitative indicators are specified in the evaluation of quantitative indicators. Indicators are split into positive indicators and negative indicators. The forward index has the property that the bigger the better, and the reverse index has the property that the smaller the better. The quantitative index includes linear proportion transformation, step difference transformation and vector normalisation. The positive indicator can be represented by equation (8).

$$Y_{ij} = \frac{e_{ij}}{E_j^+} \tag{8}$$

In equation (8), $e_{ij}$ represents the index value. $i$ denotes the number of regions. $j$ denotes the number of indicators in the region. $E_j^+$ indicates a positive value. The inverse index can be expressed by equation (9).

$$Y_{ij} = \frac{e_{ij}}{E_j^-} \tag{9}$$

In equation (9), $E_j^-$ represents the inverse value. To ensure the accuracy of the forward index, the half-ascending trapezoidal fuzzy membership function of the forward index can be quantified by using step difference transformation, which is expressed by equation (10).

$$Y_{ij} = \frac{e_{ij} - m_{ij}}{M_{ij} - m_{ij}} = \begin{cases} 1 & e_{ij} > M_{ij} \\ \dfrac{e_{ij} - m_{ij}}{M_{ij} - m_{ij}} & m_{ij} < e_{ij} < M_{ij} \\ 0 & e_{ij} \leq M_{ij} \end{cases} \tag{10}$$

In equation (10), $M_{ij}$ represents the maximum value of the attribute value of $i$ indicator between different regions in a certain period of time. $m_{ij}$ represents the minimum value of the attribute value of $i$ of the indicator in different intervals during the same period. In the same way, the difference transformation of the reverse index is carried out, which is expressed by equation (11).

$$Y_{ij} = \frac{M_{ij} - e_{ij}}{M_{ij} - m_{ij}} = \begin{cases} 1 & e_{ij} > M_{ij} \\ \dfrac{M_{ij} - e_{ij}}{M_{ij} - m_{ij}} & m_{ij} < e_{ij} < M_{ij} \\ 0 & e_{ij} \leq M_{ij} \end{cases} \tag{11}$$

In equation (11), after $e_{ij}$ range exchange, $0 < y_{ij} < 1$. Finally, the vector in the indicator is normalised, and the forward indicator vector can be expressed by equation (12) after normalisation.

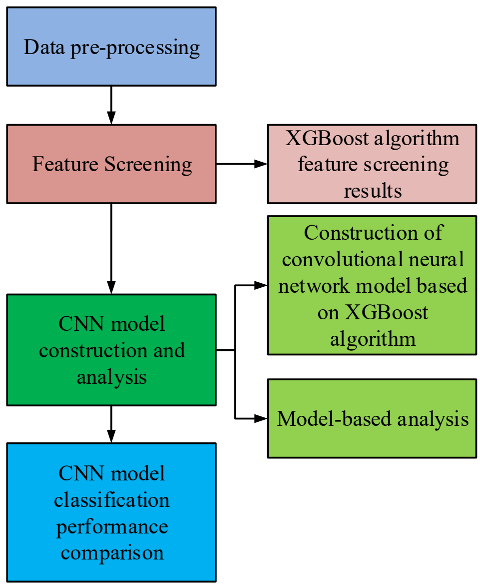
$$C_{ij} = \frac{V_{ij}}{\sum_{k=1}^{m} V_{ik}} \tag{12}$$

In equation (12), $V_{ij}$ represents a normalised vector; $V_{ik}$ represents a positive predicted value. The inverse index vector can be expressed by equation (13) after normalisation.

$$C_{ij} = \frac{1}{V_{ij} \sum_{k=1}^{m} V_{ik}^{-1}} \tag{13}$$

In equation (13), $V_{ik}^{-1}$ represents the inverse predicted value. Combined with the above analysis, the flowchart of the B2B e-commerce enterprise marketing CEM is shown in Figure 5.

**Figure 5** Process of model evaluation (see online version for colours)




## 4 Performance analysis of CEM based on improved CNN algorithm

To verify the performance of the constructed model in the marketing credit evaluation of B2B e-commerce enterprises, this study chose decision tree and random forest for comparative verification.

### *4.1 Performance analysis of B2B enterprise CEM based on improved CNN algorithm*

To determine the result of feature extraction of marketing credit data of e-commerce enterprises by model method, the fitness distribution of parameter space was analysed by model, and the result of feature extraction was analysed.

From Figure 6, with the increase of ln2c logarithmic function, the fitness of the model changed regularly, unlike the chaos at the beginning. The accuracy of model fitness played an active role in model training, prediction and application scenarios. In other words, the higher the fitness accuracy of the model, the stronger its generalisation ability, and the better the training effect. Meanwhile, it could also fit more data characteristics for predicting different types of data, and could also adapt to a variety of application scenarios. To make the model better fit the actual data and possess improved generalisation and prediction skills, it was required to optimise the training and prediction methods reasonably. To test the effectiveness, the study used the model method to compare with the decision tree model and the random forest model. The results of PR curve and iterative training error are shown in Figure 7.

**Figure 6** Moderate distribution of parameter space (see online version for colours)

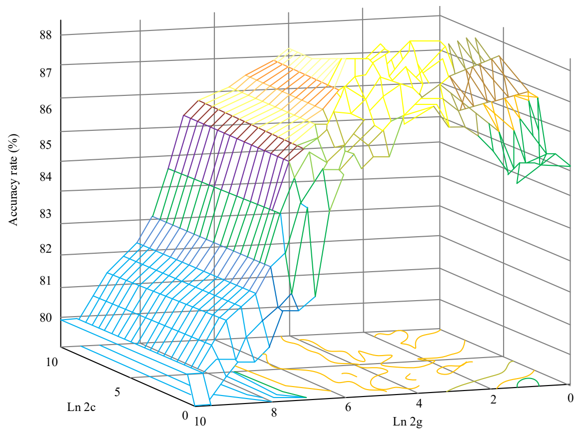
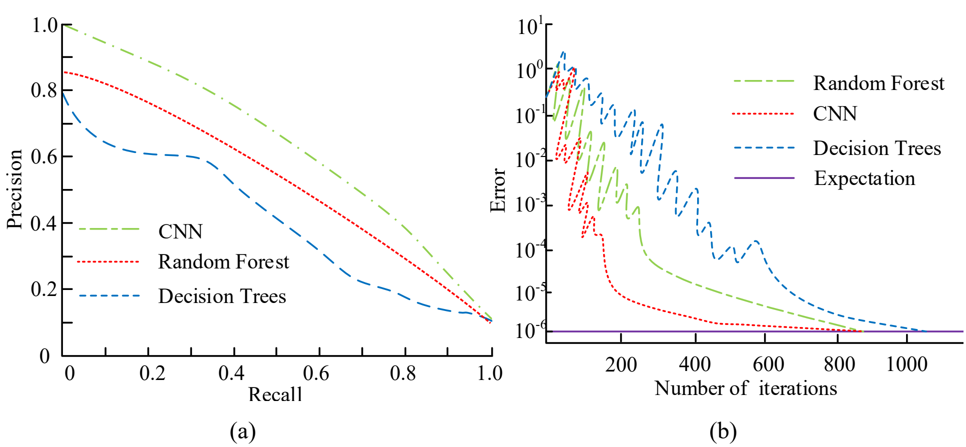



**Figure 7** PR curves and iteration error rates for the three models, (a) PR curve (b) number if iterations and training error (see online version for colours)




From Figure 7 that the PR curves of the three models all showed a downward trend. The area under the PR curve of the CNN was 0.83. The random forest was 0.74. The decision tree model was 0.65. In comparison to the random forest model and the decision tree model, the area value of the model technique was 0.09 and 0.18 greater, respectively, indicating that the CNN algorithm used in the model was more reliable. From Figure 7(b), with the increase of iterations, the error rates of the three models all showed a downward trend. Among them, CNN completed the iteration when the number of iterations was 198. The random forest model completed the iteration when the iteration number was 239 times. The decision tree model completed the iteration when the iteration number was 594, indicating that the model had better accuracy. To verify the evaluation stability, the training set and test set were used in the study to apply the model. The results are shown in Figure 8.

**Figure 8** Convergence of the model in the training and test sets, (a) training set (b) test set (see online version for colours)

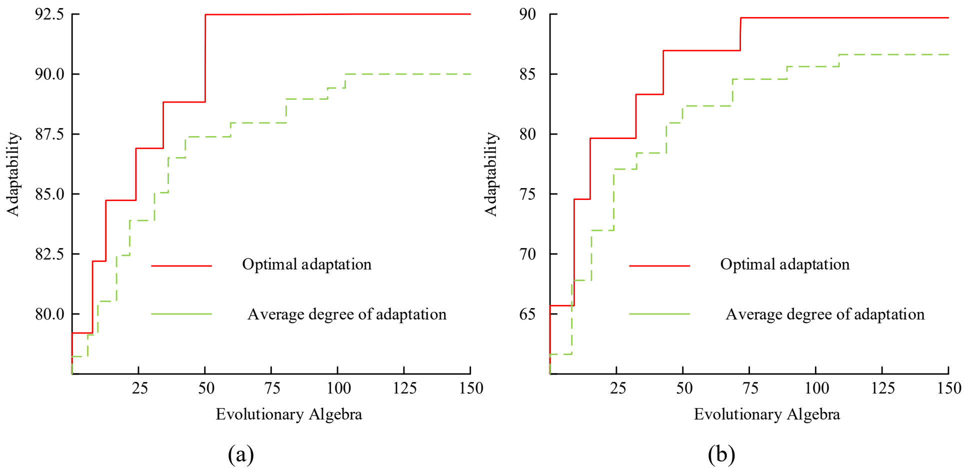
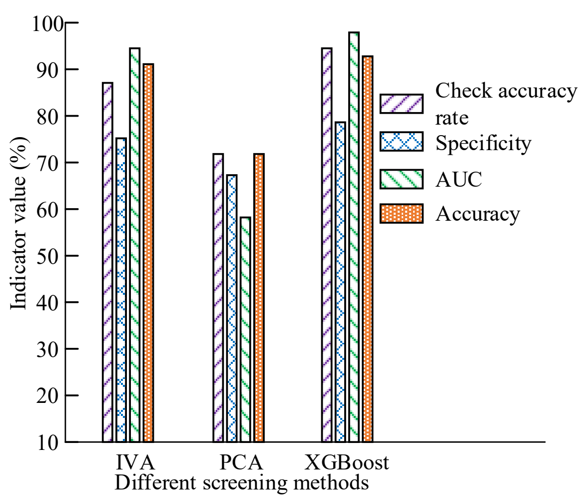



**Figure 9** CNN network model evaluation metrics (see online version for colours)



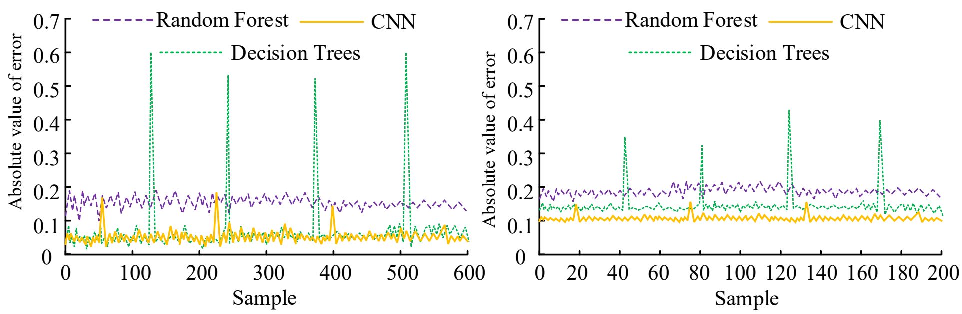

In Figure 8, in the training set, the optimal fitness of the model algorithm converged in the 53rd generation, which indicated that the model algorithm had a good effect in the training set. In Figure 8(b), in the test set, the optimal fitness of the model algorithm converged in the 76th generation. Compared to 53 generations of the test set, the number of iterations increased by 23. However, the test set's findings were still within an acceptable range and met the requirements of the pattern design. To verify the feature screening and extraction capability of the CNN model with XGBoost algorithm, the study compared CNN with principal component analysis (PCA) and information value analysis (IVA). The comparison indexes included precision, specificity, AUC value and accuracy. The results are shown in Figure 9.

In Figure 9, the accuracy, specificity, AUC value and accuracy of IVA analysis were 87.61%, 76.23%, 93.26% and 91.08%, respectively. The accuracy, specificity, AUC value and accuracy of PCA analysis were 72.03%, 68.13%, 57.92% and 71.93%, respectively. The accuracy, specificity, AUC value and accuracy of CNN model were 96.27%, 79.83%, 98.73% and 93.42%, respectively. The model integrated with XGBoost algorithm had better extraction and screening ability in feature screening, and could effectively ensure the model's analysis of credit data.

## 4.2 *Application effect analysis of CEM*

To evaluate the model's impact on B2B e-commerce businesses' marketing credit, the constructed model, decision tree and random forest were applied to the test set and training set. Figure 10 displays the outcomes using the evaluation index of the error's absolute value.

**Figure 10** Absolute values of the errors of the three models in the training and test sets, (a) training set (b) test set (see online version for colours)




(a) (b)

From Figure 10, the absolute errors of the three models in the training set all showed a fluctuating trend. The absolute error value of CNN was the lowest, and its average absolute error value was 0.095. The decision tree had an average absolute error of 0.396, whereas the random forest had an average absolute error of 0.186. In Figure 10(b), CNN possessed the lowest absolute error, with a mean absolute error of 0.13. The absolute error on average of decision tree was 0.38. The mean absolute error of random forest was 0.19, showing that CNN model had a high predictive ability in CEM. To verify the distinguishing ability of CNN model, the study reflected the KS curve of the model through false alarm rate and hit rate. The results are shown in Figure 11.

From Figure 11, the peak value of KS curve of CNN model was 0.62, and the peak value of KS curve could represent the differentiation ability of the model. When the peak value of KS curve of the model was greater than 0.75, the model was abnormal. When the maximum value fell between 0.4 and 0.65, the model had a strong ability to distinguish data. The peak value of the model constructed in this study was 0.62, indicating the model had a strong ability to distinguish marketing credit evaluation data. The running time of the constructed model was studied and validated, and the decision tree and random forest models were compared. To prevent accidental errors, the study conducted three repeated experiments for the three kinds of operation time. Table 1 displays the results.

**Figure 11** KS curve for the model approach (see online version for colours)

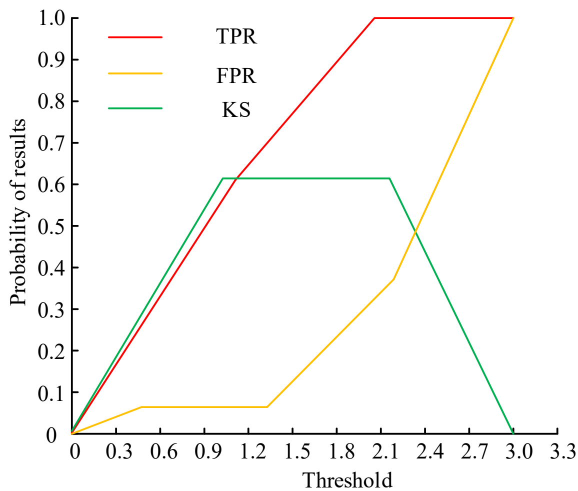



**Table 1** Comparison of the running time of the three models

| *Number of experiments* | *Algorithm* | *Running time (s)* |
|---|---|---|
| First comparative experiment | CNN | 198 |
| | Random forest | 231 |
| | Decision trees | 256 |
| Second comparative experiment | CNN | 201 |
| | Random forest | 239 |
| | Decision trees | 248 |
| Third comparative experiment | CNN | 195 |
| | Random forest | 261 |
| | Decision trees | 251 |

From Table 1, the operation time of CNN model was the lowest, followed by random forest model, and decision tree model was the longest. Therefore, from the running time dimension, the performance of the suggested model was superior to the comparison model, indicating that the model had a high application effect.

## 5 Discussion

To establish a reasonable credit evaluation system to solve the problem of B2B e-commerce credit, this paper constructs an enterprise marketing CEM based on CNN, and introduces XGBoost to improve CNN to improve the performance of the model. The results showed that the area under the PR curve of the improved model was 0.83, which was significantly higher than the area under the PR curve of other algorithms. Compared with the B2B e-commerce CEM based on BP neural network proposed by Tuo (2024), the designed model was significantly better. This was because the improved CNN had automatic extraction ability and can automatically learn useful features from the original data, while BP neural network needed to manually design feature extraction algorithm, which may lead to inaccurate or incomplete feature extraction. The average absolute error of the designed improved model was 0.095, which was lower than the average absolute error of other models. Compared with the dynamic CEM based on sensitivity optimisation weight proposed by Zhang et al. (2023), the evaluation accuracy of the designed improved model was significantly higher, indicating that the dynamic CEM based on sensitivity optimisation weight was only for e-commerce SMEs and could not cover all e-commerce enterprises, which had a certain impact on the results and reduces the evaluation accuracy. The peak KS curve of the designed model was 0.62, and there was no anomaly, and its discrimination ability was significantly stronger than that of the other two models. Compared with the CEM based on dynamic ensemble selection algorithm proposed by Zheng et al. (2023), the recognition rate of the design method in the identification of users with credit problems was higher. This was because CNN could deal with large-scale data sets well, and it could extract local features, thus effectively improving the recognition accuracy. In short, the design model for e-commerce credit evaluation can build a healthy e-commerce trading market environment, provide a reliable reference for consumers and businesses, and also provide an important guarantee for the healthy development of e-commerce.

## 6 Conclusions

With the rapid development of e-commerce business, the marketing credit evaluation requirements are getting higher. This paper constructs a marketing CEM of B2B e-commerce business on the basis of improved CNN algorithm. It was verified that the accuracy, specificity, AUC value and accuracy of the CNN method CEM were 96.27%, 79.83%, 98.73% and 93.42%, respectively. Meanwhile, the peak value of KS curve of CNN model was 0.62, and the absolute error value of CNN was the lowest, and the average absolute error value was 0.13. The absolute error on average of the decision tree was 0.38. The mean absolute error of random forest was 0.19. The accuracy and robustness of the designed model have been demonstrated, providing a comprehensive and accurate credit evaluation method for B2B e-commerce enterprises. At the same time, when dealing with specialised, refined, unique and innovative enterprises with large transaction amounts, long decision-making chains and high degrees of customisation, the proposed model can effectively identify credit risks, optimise customer management, accelerate transaction decisions, significantly enhance their risk prevention and control capabilities and market response efficiency, thereby providing strong support for enhancing the resilience of the enterprises themselves and the overall stability of the industrial chain they are in.

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## Declarations

The authors declare that they have no conflict of interest.

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