A Deep Learning-based Model for Evaluating the Sustainability Performance of Accounting Firms

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***Abstract*—The harmonious and stable development of society is strongly related to the sustainable development of enterprises. In order to better face the challenges of environmental resources, sustainable development must be included in the development focus of accounting enterprises. The research proposes a performance evaluation model based on deep learning, improves RBMs model on the basis of deep belief network (DBN), improves the accuracy of the model through reverse fine-tuning technology, and effectively combines multiple restricted Boltzmann machines (RBMs) and Softmax classifiers to build a modular multi classification model to complete the sustainable development performance evaluation of accounting enterprises. The performance of RBM fine tuning classifier is higher than that of RBM expression and PCA (Principal Component Analysis) expression, which mainly shows the effectiveness and stability of feature extraction. The network output results of test samples are converted into prediction performance evaluation. The model is evaluated by average precision (AP), average recall (AR), and prediction accuracy. The AP, AR, and prediction accuracy of the proposed method are 86.95%, 89.74%, and 88.29% respectively, which are higher than Softmax classifiers, Back Propagation (BP) neural networks, and DBN based Softmax methods, It shows that this method is superior to other algorithms in the application of performance evaluation model for sustainable development of accounting enterprises, and it is feasible and effective, which is of great significance to the establishment of performance evaluation model for the accounting industry.**

Keywords*—*Deep learning; RBM; performance evaluation; classification accuracy; sustainability

I. INTRODUCTION

The sustainable development of enterprises is an important guarantee for a harmonious and stable society [1]. The theory of sustainable development includes equity, commonality, sustainability, coordination, demand, limitation, and inherency [2]. Corporate sustainability can be influenced by resource resources such as corporate culture, human capital, intangible assets and ecological nature [3]. From the perspective of corporate sustainability, its essence is clearly different from the meaning of ecological sustainability, which in depth is the optimal allocation of resources. Enterprise performance evaluation is the basis for measuring the production and operation behaviour of enterprises; therefore, it is positive to construct an enterprise sustainability performance evaluation model [4]. Performance evaluation indicators include the evaluation of non-economic aspects and economic aspects, but the previous economic performance indicators of enterprises are no longer applicable to the concept of accounting standards [5]. Domestic and international research on the evaluation of corporate sustainability performance has gone through four evaluation stages: cost performance, financial evaluation, strategic performance, and multidimensional synthesis [6]. With the advantages of efficient storage capacity, parallel processing capability, and associative memory, deep learning has now been more widely used in natural language processing technology, speech recognition, image recognition and other information retrieval. Common deep learning evaluation models include Deep Belief Network (DBN), Stacked Autoencoder (SAE), CNN, etc., and have positive application value in evaluation. In order to realize the evaluation and prediction of the sustainable development of enterprises with the help of the deep learning algorithm, on this basis, the research introduces the requirements of the harmonious financial theory and the new accounting standards, constructs the performance evaluation system of the sustainable development of accounting enterprises, and constructs the corresponding evaluation model through the deep learning algorithm. The contribution of the research is to propose a new feature extraction method with stronger feature learning ability, improve the RBMs model on the basis of DBN, improve the accuracy of the model through reverse fine-tuning technology, and effectively combine multiple RBMs and Softmax classifiers to build a modular multi classification model to complete the sustainable development performance evaluation of accounting enterprises. The goal and significance of the research is to provide a more scientific theoretical basis for the evaluation of the sustainable development of enterprises, and provide advice and guidance for the long-term development of enterprises. The research makes up for the phenomenon that the subjectivity of traditional evaluation methods is too strong, and the evaluation methods constructed have merit.

II. RELATED WORK

Sokil addressed the issue of information support and practical assumptions for sustainable development policy implementation through accounting analysis and mathematical analysis of the quadratic correlation and regression dependence of corporate value added on social and environmental cost scales [7]. Fu et al. used a multidimensional big data matrix model for optimization analysis to systematically construct a corporate performance evaluation system and two dimensions to construct a systematic model for the use of enterprise performance information. They applied logistic regression methods for empirical research, providing a theoretical and empirical basis for the division of the demand dimensions of the enterprise performance evaluation system [8]. Jana et al. proposed a multi-attribute decision method for enterprise financial performance evaluation, applying the new Dombi hybrid operators, which work on parameters have the advantage of good adaptability to complete financial performance assessment through intuitionistic fuzzy methods [9]. Yan Y et al. researchers analysed the performance appraisal management of manufacturing enterprises based on the Analytic Hierarchy Process (AHP) of fuzzy multi-criteria decision making to establish an enterprise performance management evaluation system, and this This exploration can provide a theoretical basis for improving the management innovation ability of manufacturing enterprises, and also has important reference value for expanding the market competitiveness of manufacturing enterprises [10]. Fang H applied the enterprise value management theory to the performance evaluation of university discipline construction members, established a performance value evaluation model, and applied the AHP method and quantitative research methods to costs and the functions achieved were evaluated [11].

Bao through the analysis of many classical methods such as economic value added, key performance indicators, balanced scorecard and current performance evaluation methods, the application analysis shows that the evaluation model is reasonable and the mathematical method is effective [12]. Yang et al. proposed the design of the enterprise environmental performance evaluation system in the new economic situation, according to the basic laws of the new situation theory and big data technology, the evaluation principles and typical index system were applied to the performance evaluation system as a reference, and the experimental results were of reference value for the application of the performance evaluation system in the field of corporate finance, which substantially improved the overall performance of the enterprise[13]. Qi established an enterprise human resource management performance evaluation system, which combined the relevant features of the opposable theory to provide more effective evaluation of enterprise HRM performance, providing a scalable analytical model for enterprise HRM performance evaluation [14]. Xiong et al. researchers evaluated the performance of food cold chain logistics enterprises based on AHP and entropy method, based on the analysis of the current situation, AHP was used to determine the subjective weights and entropy method was used to obtain experts' own weights. Finally, a comprehensive index fusion weight was performed [15]. Cui et al. researchers designed a multi-objective RBM model for training, and experiments showed that the proposed model could effectively improve the data classification accuracy of the heterogeneous network and reduce the loss in the data fusion process [16]. Sun L et al. proposed a gradient-enhanced Softmax classifier based on Convolutional Neural Networks (CNN), which alleviates the gradient disappearance problem in the Softmax classifier and can achieve better results [17]. Pan et al. proposed a novel deep learning network that performs hierarchical feature learning by limiting RBM machines in parallel, and the results demonstrate that the method is able to extract sensitive features for fault detection [18].

As can be seen through the research of domestic and international researchers on corporate innovation and development and performance evaluation models in the context of sustainable development, there are currently more studies that use AHP method for performance evaluation. In terms of building evaluation models based on deep learning, some researchers have proposed using RBM for hierarchical feature learning to improve feature extraction, but there are better methods for feature extraction of evaluation indicators. Therefore, the research will propose a new method of feature extraction with stronger feature learning capability, improve the model of Restricted Boltzmann Machine (RBM)s based on DBN, improve the correctness of the model through reverse fine-tuning techniques, and at the same time effectively combine multiple RBMs and Softmax classifiers to construct a modular multi-classification model to complete the sustainability performance evaluation of accounting firms.

III. RBMs Modular Deep Learning Model for Sustainability Performance Evaluation of Accounting Firms

A. RBMs Modular Deep Learning Models

Because the data type of university performance evaluation is sample data with multiple feature modules, deep learning algorithms have outstanding advantages in performance evaluation. RBM, as a new method of feature extraction, has stronger feature learning capability. The study will improve the model of RBMs based on DBN, improve the correct rate of the model through reverse fine-tuning technique, and at the same time effectively combine multiple RBMs and Softmax classifiers to construct a modular DBN is a concept generation model, which consists of multiple RBMs stacked as in Fig. 1.

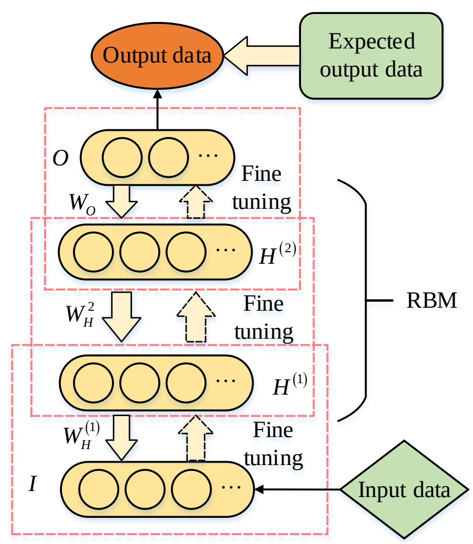


Fig. 1. Classic DBN network structure of two-layer RBM

Fig. 1 shows the structure of a DBN network containing two layers of RBM, which is first trained on the parameters of each layer of RBM by a greedy layer-by-layer unsupervised strategy, and then after confirming that all input data have passed through the full RBM network in order for the me network to obtain useful feature information. Finally, other algorithms such as the Back Propagation (BP) algorithm are used to receive the output data and use it as input data, and the whole network is supervised and adjusted according to the error between the expected and actual output data. At the top is the top layer network for supervised learning, which can become a classifier model such as Softmax depending on the specific practical application.

The RBM is an energy-based model where the visible and hidden layers form a system (v,h) with the energy shown in equation (1).

$$E(v,h) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{j=1}^{n}\sum_{i=1}^{m} h_i w_{ij} v_j \qquad (1)$$

In equation (1), n and m denote the number of neurons in the visual layer and the hidden layer respectively; v denotes the state vector of the visual layer, h denotes the state vector of the hidden layer, a denotes the bias vector of the visual layer, b denotes the bias vector of the hidden layer, and w_{ij} denotes the connection weights of the i neuron in the hidden layer and the j neuron in the visual layer. The writing matrix of equation (1) is shown in equation (2).

$$E(v,h) = -a^T v - b^T h - h^T W v \qquad (2)$$

Equation (2) can be understood as an energy function. This function combined with the RBM corresponding to the state (v,h) yields the expression for the distribution of the expression probability generation model as equation (3).

$$p(v,h) = \frac{1}{Z} e^{-E(v,h)} \qquad (3)$$

In equation (3), Z is the normalisation factor, i.e. it is the accumulation of the states of all visible and hidden layers, as in equation (4).

$$Z = \sum_{v,h} e^{-E(v,h)} \qquad (4)$$

In contrast, for real life and work problems, the RBM network focuses on the marginal fraction of $p(v,h)$, the probability distribution of the input data v $p(v)$, as shown in equation (5).

$$p(v) = \sum_h p(v,h) = \sum_h \frac{1}{Z} e^{-E(v,h)} \qquad (5)$$

Given that there are no neurons that play a connecting role between the visual or hidden layers that are connectionless, the individual neurons are seamlessly connected to each other, as in equation (6).

$$\begin{cases} p(v|h) = \prod_{i=1}^{n} p(v_i|h) \\ p(h|v) = \prod_{j=1}^{m} p(h_j|v) \end{cases} \qquad (6)$$

When given the state of the visual layer v, the probability of finding the hidden layer neuron $h_j = 1$ is given in equation (7).

$$p(h_j = 1|v) = \sigma\left(b_j + \sum_{i=1}^{n} v_i w_{ji}\right) \qquad (7)$$

When given the state of the hidden layer h, the probability of finding the visual layer neuron $v_i = 1$ is given in equation (8).

$$p(v_i = 1|h) = \sigma\left(a_i + \sum_{j=1}^{m} h_j w_{ij}\right) \qquad (8)$$

In equations (7) and (8), $\sigma(x)$ is the Sigmoid function. The essence of the training process of the RBM is the use of learning algorithms to adjust the parameters of $\Theta = (a,b,W)$ through continuous iterative learning, which eventually makes the energy of the entire RBM move towards a gradient that gradually decreases, and finally reaches a state where the energy of the RBM is minimized, i.e., the model reaches a stable state [19]. When the energy of the RBM network is the lowest, it is known that the marginal distribution range of the RBM network is the largest according to the energy conversion formula, and then the parameter Θ needs to be solved for when the value of the marginal distribution is the largest. Based on the expert product system to fit complex high-latitude data, the system can have a more ideal probability distribution in the processing of high-dimensional model data, it can complete the target transformation training of RBM by maximizing the likelihood function, and the calculation expression is equation (9).

$$L(S,\Theta) = \prod_{i=1}^{N} p\left(v^{(i)}\right) \qquad (9)$$

In equation (9) $S = \left\{v^{(1)}, v^{(2)}, \cdots v^{(N)}\right\}$, $v^{(i)}$ denotes the i th training sample and N is the number of samples. Considering that the function $\ln x$ is strictly monotonically increasing and maximizing $L(S,\Theta)$ and maximizing $\ln L(S,\Theta)$ are equivalent, the objective of training the RBM becomes maximizing the log-likelihood function, as in equation (10).

$$\ln L(S,\Theta) = \sum_{i=1}^{N} \ln p\left(v^{i}\right) \qquad (10)$$

The gradient ascent method is the most efficient way to maximise the log-likelihood function and it uses an iterative approach to update the parameters as shown in equation (11) [20].

$$\Theta = \Theta + \eta \frac{\partial \ln L(S,\Theta)}{\partial \Theta} \quad (11)$$

In equation (11), $\eta > 0$ is the learning rate. For the training sample S, Eq. (12) is obtained by derivative calculation.

$$\frac{\partial \ln L(S,\Theta)}{\partial \Theta} = \sum_{i=1}^{N} \left(-\left\langle \frac{\partial E(v^{(i)},h)}{\partial \Theta} \right\rangle_{p(h|v^{(i)})} + \left\langle \frac{\partial E(v,h)}{\partial \Theta} \right\rangle_{p(v,h)} \right) \quad (12)$$

In equation (12) $\langle \cdot \rangle_{p(h|v^{(i)})}$ denotes the mathematical expectation based on the training samples and $\langle \cdot \rangle_{p(v,h)}$ denotes the mathematical expectation based on the model reconstruction data.

The study constructs a modular multi-classification model by combining multiple RBMs and Softmax classifiers. The model structure is shown in Fig. 2.

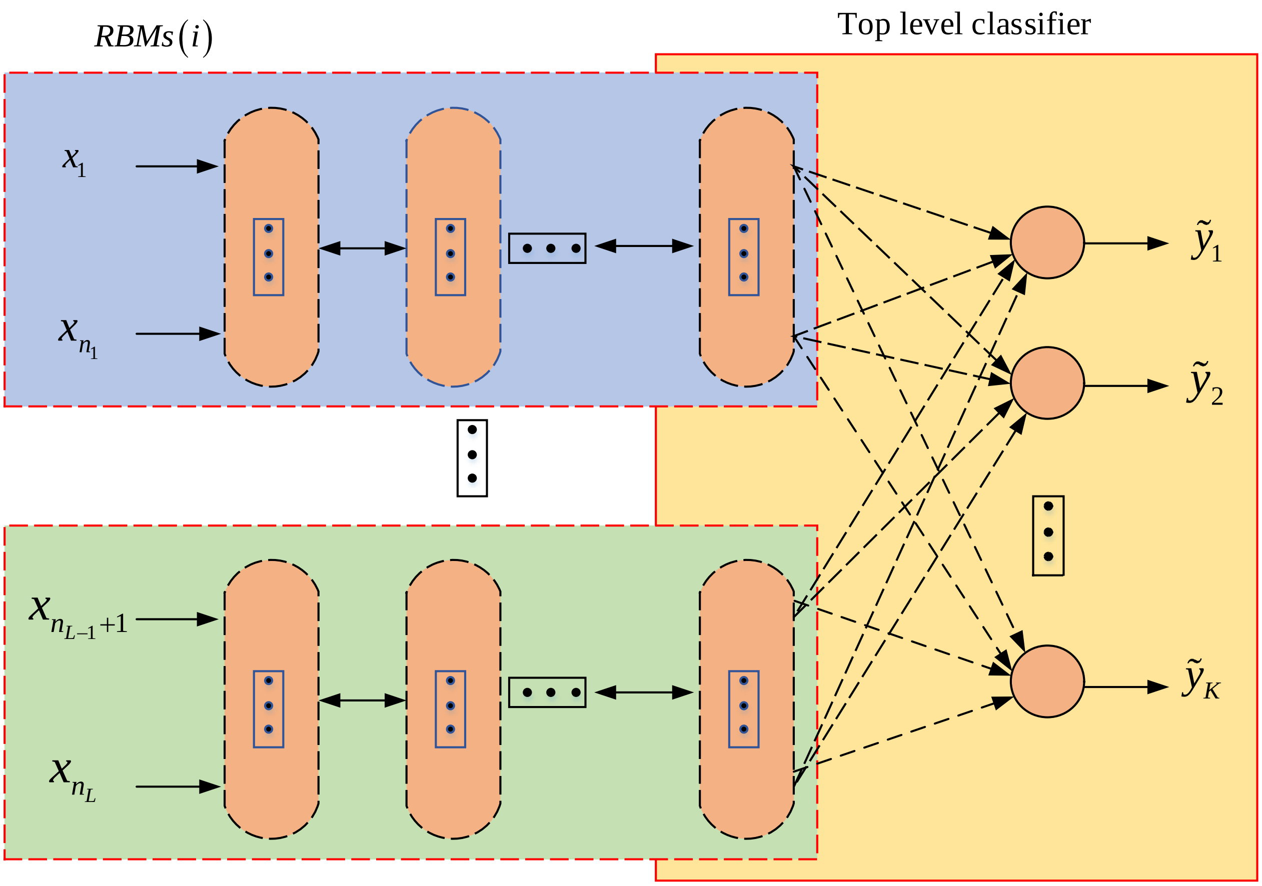


Fig. 2. Structural diagram of RBMs based modular deep learning model

The deep learning model designed in the study is a multiple RBMs feature extractor and a top-level classifier. The deep model first extracts different feature module samples using RBMs features, and then classifies various different types of data by the top-level classifier. The structure of the RBMs is contained in dashed lines, which is a modular feature extractor composed of RBMs, where $RBMs(i)$ is the i th RBM and $i = 1,2,\cdots,L$. Set the input features set to $(x_1, x_2, \cdots, x_n)$, divide them into L feature modules according to the sample characteristics, without considering the sequential nature, the feature modules are noted as $(x_1,\cdots,x_{n_1})$, $(x_{n_1+1},\cdots,x_{n_2})$, $\cdots$, $(x_{n_{L-1}+1},\cdots,x_{n_L})$, then the input layer of $n_L = n, i$ feature module is equivalent to the visual layer of the first RBMs of $RBMs(i)$. The hidden layer of the last RBM is the new feature data, then the input of the top-level classifier is the output reconstruction result of each RBMs. The solid line included in the figure shows one of the network structures of the top-level classifier, with the classifier's first j network output value being $\tilde{y}_j$, where $j = 1,2,\cdots,K$.

The top layer of the deep learning model requires the addition of a classifier, and the study uses the Softmax classifier. The Softmax classifier is used as a non-linear model for classification, and it has a high correct classification rate when combined with a deep neural network. The Softmax classifier performs model training through a cost function, and it solves for the optimal parameters of the model through a parametric gradient method [21].

Given the training sample dataset $S=\left\{\left(X^{(1)},y^{(1)}\right),\left(X^{(2)},y^{(2)}\right),\cdots,\left(X^{(N)},y^{(N)}\right)\right\}$, where $X^{(i)}$ is the i sample, the category output values of $X^{(i)}$ are referred to by $y^{(i)}$ and the number of samples is referred to by N. Assuming that the output data contains K categories, the probabilistic classification values are calculated using the hypothesis function approach for $y^{(i)}\in\{1,2,\cdots,K\}$, and $\phi_j=p\left(y=j\middle|X\right)$, which defines the hypothesis function of the form shown in (13).

$$h_\theta\left(X^{(i)}\right)=\begin{bmatrix} p\left(y^{(i)}=1\middle|X^{(i)},\theta\right) \\ p\left(y^{(i)}=2\middle|X^{(i)},\theta\right) \\ \vdots \\ p\left(y^{(i)}=K\middle|X^{(i)},\theta\right) \end{bmatrix}=\frac{1}{\sum_{j=1}^{K}e^{\theta_j^T x^{(i)}}}\begin{bmatrix} e^{\theta_1^T X^{(i)}} \\ e^{\theta_2^T X^{(i)}} \\ \vdots \\ e^{\theta_K^T X^{(i)}} \end{bmatrix} \tag{13}$$

In equation (13), $\theta=\left[\theta_1,\theta_2,\cdots,\theta_K\right]^T$ is the Softmax classifier model parameter; the expression for the probability value of the sample $X^{(i)}$ being classified as the j class is $p\left(y^{(i)}=j\middle|X^{(i)}\right)$, the value normalized to the model output value is $\sum_{i=1}^{K}e^{\theta_j^T X^{(i)}}$, and the sum of the output values of all classes is 1. The cost function of the Softmax classifier is shown in equation (14).

$$C(\theta)=-\frac{1}{N}\left(\sum_{i=1}^{N}\sum_{j=1}^{K}I\left\{y^{(i)}==j\right\}\log\frac{e^{\theta_j^T X^{(i)}}}{\sum_{s=1}^{K}e^{\theta_s^T X^{(i)}}}\right) \tag{14}$$

In equation (14) I is the indicator function, when the expression is false, $I=0$; otherwise, $I=1$. The cost function of the partial derivative processing Softmax classifier yields the gradient expression of the parameters, which is calculated as shown in equation (15).

$$\nabla_{\theta_j}C(\theta)=-\frac{1}{N}\sum_{i=1}^{N}\left[X^{(i)}\left(I\left\{y^{(i)}==j\right\}-p\left(y^{(i)}=j\middle|X^{(i)};\theta\right)\right)\right] \tag{15}$$

B. Sustainability Performance Evaluation Model for Accounting Firms

After obtaining the enterprise performance evaluation data, the modular deep learning model combined with RBMs constructed by the institute is shown in Fig. 3. S I_1 I_2 The RBM training algorithm is used to obtain the output values of the first layer of RBMs u^2 and $\overline{u}^2$ connection weights, and the input data of the second RBM are the output values of RBMs u^2 and $\overline{u}^2$. The output values and connection weights of each layer are obtained through continuous iteration using the RBM training algorithm and a greedy layer-by-layer unsupervised pre-training strategy, and are used as the initial parameters of the network. After reconstructing the last output values u^{L1} and $\overline{u}^{L2}$, they are fed directly into the top layer Softmax classifier as input data, and the desired output data is used to obtain the initial parameters θ. A deep learning network model with classification function is formed by connecting the pre-trained RBMs(1), RBMs(2) and Softmax classifiers, and the parameters of the network are adjusted using the BP algorithm, and if the number of iterations meets the maximum number of iterations or the classification accuracy does not meet the requirements, the learning is terminated, otherwise the iteration step is repeated.

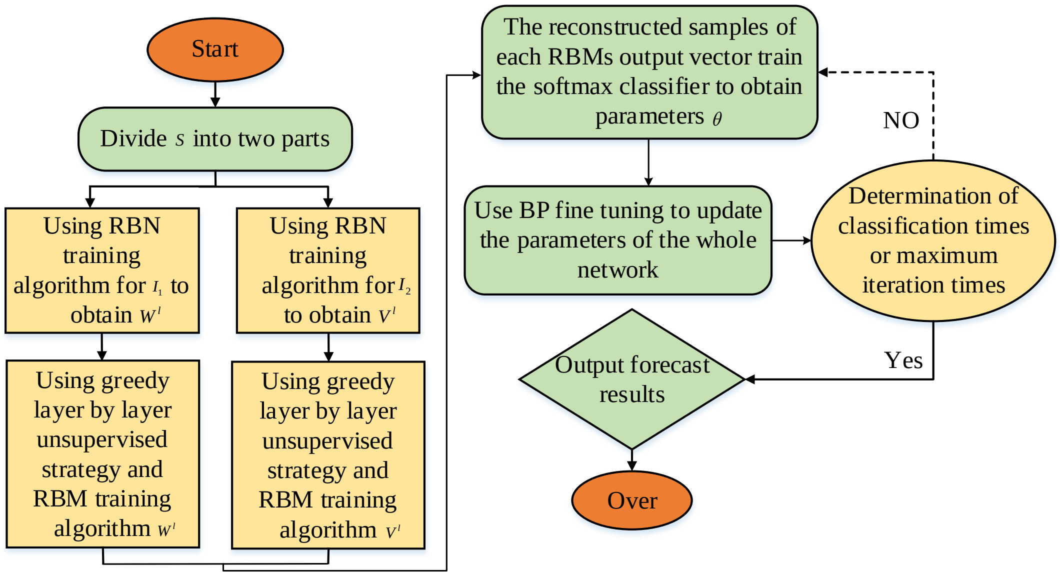


Fig. 3. Flow chart of modular deep learning algorithm based on two RBMs

The sustainable development of accounting enterprises depends on the optimal allocation of resources. Based on the experience of previous studies, the principles to be followed in the evaluation system for sustainable development of accounting enterprises are multiple evaluation subjects, multiple evaluation objectives, multiple evaluation contents and multiple evaluation methods, and the performance evaluation index system includes three aspects: social, resource and economic. According to the basic characteristics, completeness and reliability of the economic performance evaluation system, the study sets five secondary indicators, including cash flow, development capacity, profitability and quality, asset operation capacity and debt servicing capacity. Moreover, there are 15 tertiary indicators, including net asset cash return rate, net asset additional economic value rate, unit asset cash flow from operating activities, capital preservation growth rate, operating income growth rate, net asset additional economic value rate and net operating profit index. The 15 level 3 indicators are cash return on net assets, economic value added to net assets, cash flow from operating activities per unit of asset, capital preservation growth rate, operating income growth rate, economic value added to net assets, operating net profit index, return on total assets, return on net assets, total assets turnover, inventory turnover, accounts receivable turnover, quick ratio, interest earned multiple and gearing ratio.

According to the characteristics of human resources of the resource performance evaluation system, four secondary indicators are constructed including human resources output capacity, human resources utilization capacity, human resources input situation and basic human resources situation. 15 tertiary indicators include the adoption rate of rationalized suggestions, market share of new products, number of patents per capita, new technology development capacity, employees' profit generating capacity, staff turnover rate, employees' satisfaction rate, employees' career development level, staff training expenditure, human resources maintenance capacity, human resources investment level, professional work experience level of technical staff, proportion of technical staff, average age of staff, and education level of staff. Based on the definition of corporate social responsibility, the three secondary indicators of the social performance evaluation system selected for the study are the fulfillment of responsibility to the community, the fulfillment of responsibility to the government and the fulfillment of responsibility to consumers. After-sales service rate, return or repair rate, consumer complaint rate, and customer satisfaction. Table I refers to secondary and tertiary indicators at the social level.

TABLE I. SECONDARY AND TERTIARY INDICATORS OF SOCIETY, RESOURCES AND ECONOMY

Evaluation level	Evaluating indicator
Fulfillment of community responsibilities	Proportion of public service advertising expenditure
	Contribution rate of community activities
	Donation income ratio
Performance of government responsibilities	Employment rate of the disabled
	Employment ratio
	Social contribution rate
	Asset tax rate
Performance of consumer responsibilities	After sales service rate per unit income
	Return or repair rate
	Consumer complaint rate
	Customer satisfaction

The dataset selected for the study was data related to 83 accounting firms for the period 2017-2021, with a total sample data of 415 entries. Given the low relevance of the data sample data to the performance evaluation indicators, missing feature data and most of the data values being zero, the study cleared some of the indicator data. The raw values of the study performance were taken as 56-100, and the performance of the sample data was taken as the output variable, and the performance values were discretized into four category labels with values of 1, 2, 3 and 4 according to K mean clustering, with larger category labels indicating better performance, while the performance single output was discrete into a multiple output form. Given the variation in input feature magnitudes and magnitude units, the study utilises minmax normalisation for sample data processing. Assuming that x_i is the input feature and $x_i^{'}$ is the normalised feature, the normalisation formula can be expressed as equation (16).

$$x_i^{'} = x_i - \min\left(x_i\right) / \left(\max\left(x_i\right) - \min\left(x_i\right)\right)$$

In equation (16), the maximum and minimum values of the x_i feature are $\min\left(x_i\right)$ and $\max\left(x_i\right)$, respectively.

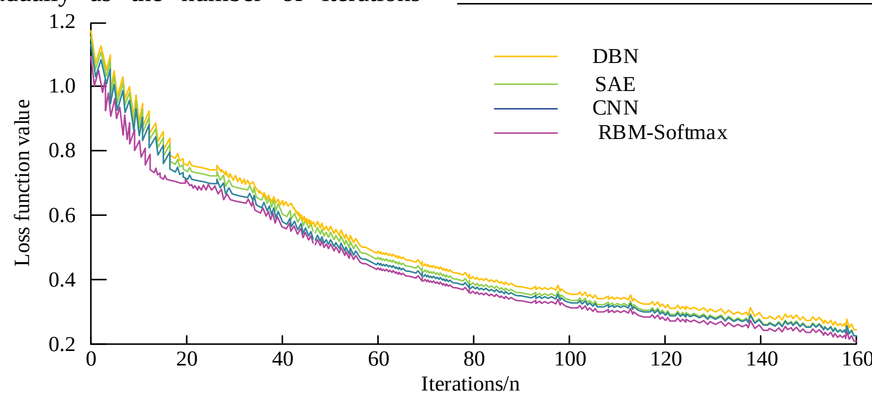
IV. Analysis of the Effectiveness of the Application of the Sustainable Development Performance Evaluation Model for Accounting Firms

The study used the 348 samples close to the centre of clustering as the training sample and the remaining samples as the test sample. Table II shows the results of the mean clustering referred to K. The four centres of performance clustering were 62.7, 68.5, 75.7 and 89.6.

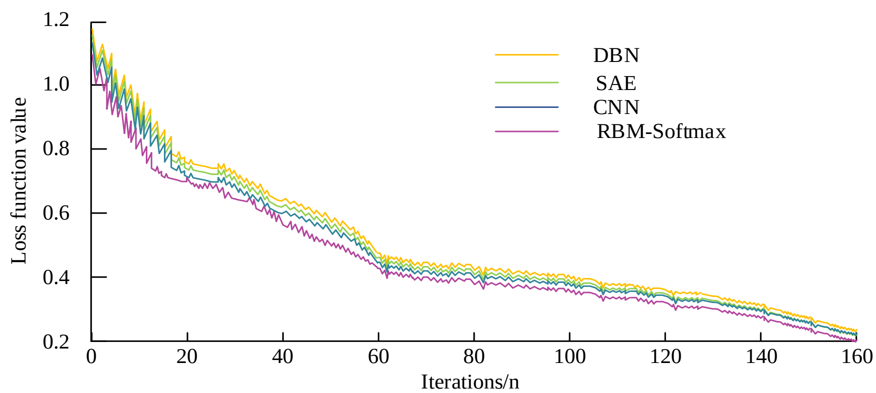
The loss function values of the four different deep learning algorithms for both the training and test sets are shown in Fig. 4(a) and 4(b). From the figures, it can be seen that the RBM-Softmax deep learning algorithm has the lowest value of loss for both the training and test sets, and the reduced value of loss decreases gradually as the number of iterations increases. The results for both the training and test sets show that the minimum loss value is achieved at 160 iterations, with corresponding values of 0.213 and 0.202, respectively.

TABLE II. Results of Mean Clustering K

Performance clustering centre	Category label	Multiple output form	Total samples	Number of training samples	Number of test samples
62.7	1	[1,0,0,0]	168	143	25
68.5	2	[0,1,0,0]	123	103	20
75.7	3	[0,0,1,0]	96	82	14
89.6	4	[0,0,0,1]	28	20	8



(a)Training set results of different depth learning algorithms



(b)Results of different depth learning algorithms

Fig. 4. Loss function values of four different depth learning algorithms in training set and test set

Setting the dimensionality of the input features and the dimensionality of the new features to 4 and 53, respectively, the changes of RBM fine-tuning, PCA (Principal Component Analysis) expression, and RBM expression on the performance of the Softmax classifier were analyzed, and the results are shown in Fig. 5. PCA expression and RBM expression refer to the method of classifying feature data through the Softmax classifier after the extraction of PCA and RBM features, respectively, while RBM fine-tuning refers to parameter tuning of the network based on the RBM expression (Ye F X et al. 2019) [22]. The study set each feature dimension to be run 10 times, and their average result was taken as the final result. Along with the gradual increase in the number of feature dimensions, the RBM expression Softmax classifier performed better compared to the PCA expression, and the RBM expression Softmax classifier extracted features with a correct rate of up to 75%. This is due to the fact that PCA as a linear feature extraction method decreases significantly when the number of feature dimensions increases, while the performance of the RBM fine-tuned Softmax classifier is higher than that of both PCA and RBM expression. There is no significant fluctuation in the performance of the classifier at different dimensions, with accuracy varying within a certain range. This indicates that the data features extracted by RBM fine-tuning are highly effective and stable, which in turn improves the accuracy of the model with a high probability.

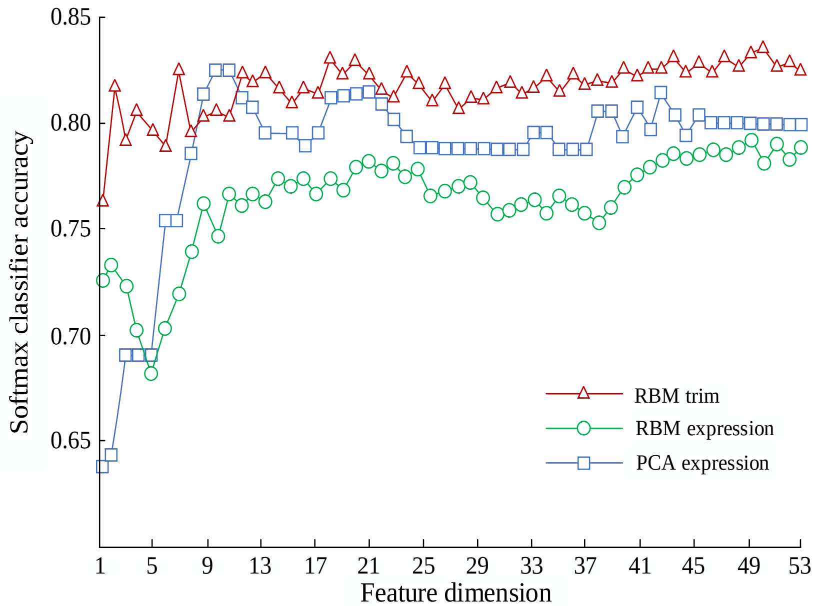


Fig. 5. Curve of accuracy with feature dimension

The study fed test samples into the already trained network and the corresponding classification results for each sample were obtained by classifying them with the top layer Softmax classifier. The input data of five randomly selected samples and the output values of the RBMs at each layer of the RBM were used as data for the performance analysis of the RBMs feature extractor, as shown in Fig. 6. For sample 1, sample 2, sample 3, sample 4 and sample 5 respectively, each dash in Fig. 6 indicates the input data value or RBM output value of a sample. As can be seen from the figure, the samples have high input data complexity and low correlation, which results in poorly differentiated and distinguishable samples. Each dash in Fig. 6 represents a sample's input data value or RBM output value. The output values of the input data after the two-layer RBM action are shown in Fig. 7.

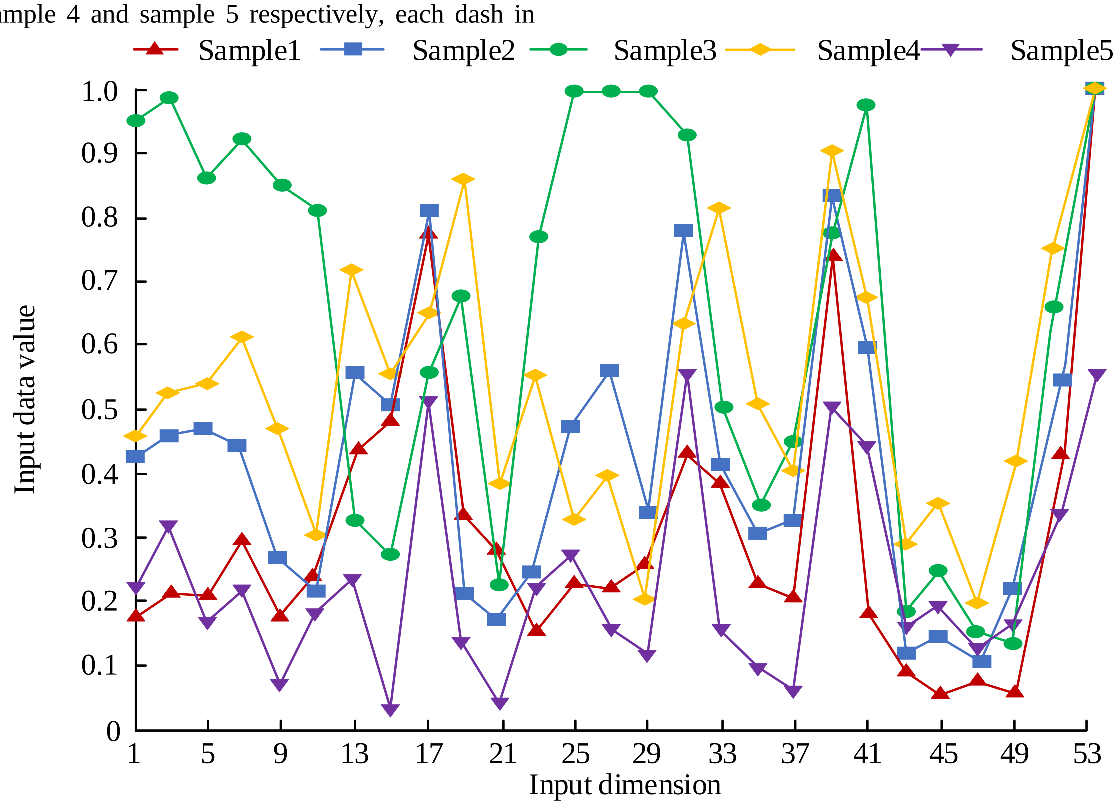


Fig. 6. Input value of sample

As can be seen in Fig. 7, after the extraction of data features by the two-layer RBM network, each sample presents an extremely clear data distribution, and the test samples are highly differentiable between different features. The feature results of the five samples show that the node output values of samples 3 and 4 are all greater than 0.7. The node output values of sample 2 are all relatively intermediate; and the number of nodes of samples 1 and 5 is close to 90% of the Therefore, the study divided the test samples into three categories, namely sample 3 and sample 4, sample 2, sample 1 and sample 5. The longitudinal comparison shows that the relationship between the magnitude of the second layer RBM output values of the samples is, sample 4 > sample 3 > sample 2 > sample 1 > sample 5. The cross-sectional comparison of the samples illustrates the characteristic of differentiability of the sample features.

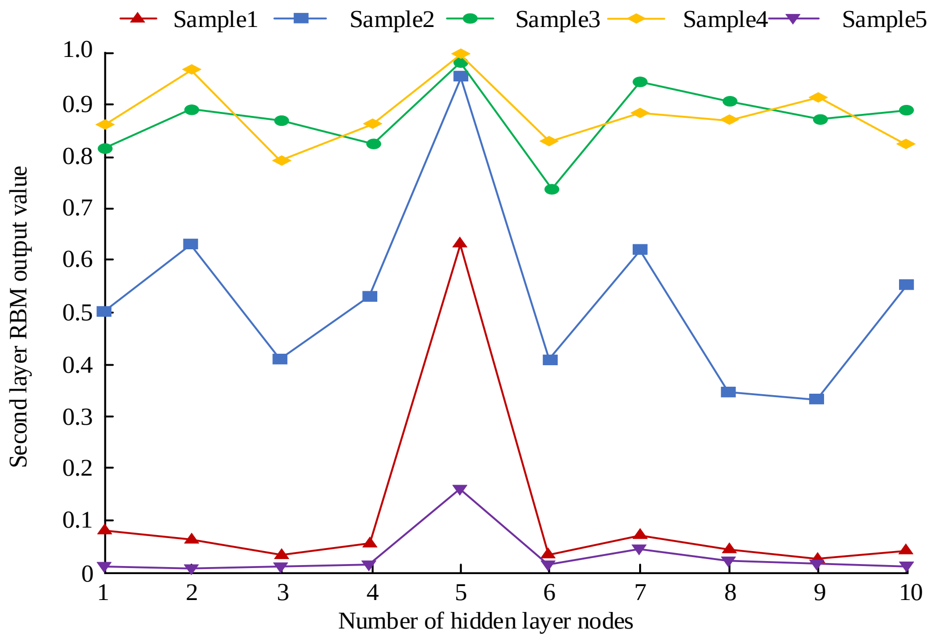


Fig. 7. Output value of the sample in the second layer RBM

The input samples indicate that the data distributions for sample 5 and sample 1 are indeed at a much lower position. The network outputs of the partial test sample data in the Softmax classifier are shown in Table III, where the sum of the probability values of each sample belonging to the four categories is 1. A higher probability value of a sample belonging to a category indicates that the sample belongs to that type. The categories for samples 1 - sample 10 are 2, 2, 3, 1, 2, 1, 2, 4, 4, and 3 in that order. This further validates that the deep learning model, after obtaining abstract feature representations through a multi-layer RBM network structure, the higher the differentiability of the features, which in turn allows for more accurate classification.

TABLE III. PARTIAL TEST SAMPLE DATA OUTPUT VALUE

Sample	Category 1	Category 2	Category 3	Category 4
1	0.0426	0.9402	0.0086	0.0086
2	0.0303	0.9514	0.0151	0.0032
3	0.0016	0.0715	0.8948	0.0320
4	0.9403	0.0423	0.0088	0.0086
5	0.2406	0.7315	0.0188	0.0091
6	0.9388	0.0435	0.0090	0.0087
7	0.0952	0.8816	0.0172	0.0060
8	0.0005	0.0032	0.0460	0.9504
9	0.0030	0.0004	0.0442	0.9524
10	0.0214	0.0006	0.9602	0.0179

The model is evaluated by average precision (AP), average recall (AR) and prediction accuracy, as shown in Fig. 8. It can be seen from the table that the AP of the proposed method is 86.95%, AR is 89.74%, and the prediction accuracy is 88.29%. The three evaluation indicators of the proposed method are greater than Softmax classifier, BP neural network and DBN Softmax. BP neural network algorithm is likely to fall into local extreme value, making training failure. The approximation and generalization ability of networks are closely related to the typicality of learning samples. For the Softmax classifier, the exponential Softmax function can be used to extend the numerical distance with large difference. Therefore, the proposed performance evaluation model for sustainable development of enterprises is more practical than other evaluation models.

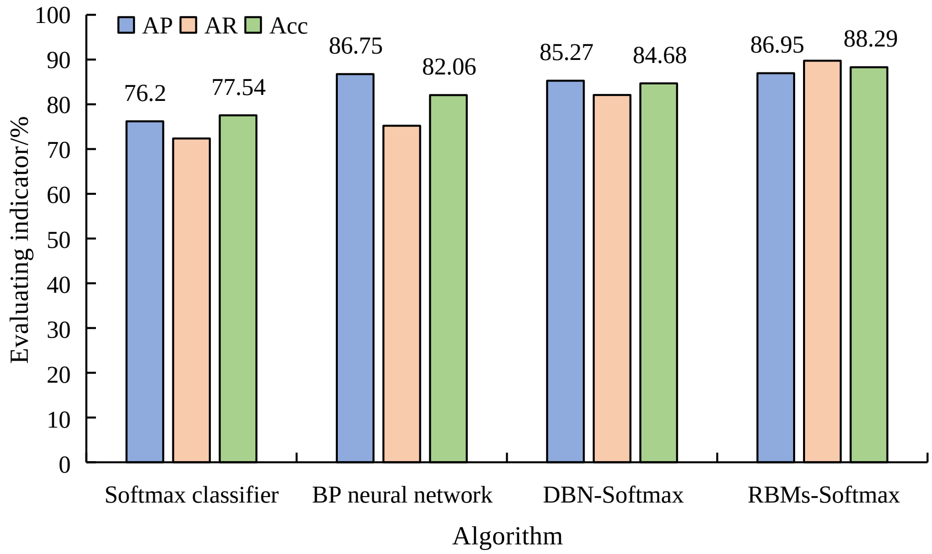


Fig. 8. Comparison of evaluation indexes of each algorithm

V. Conclusion

On the basis of analyzing the sustainable development evaluation system of accounting enterprises, the research constructs a sustainable development performance evaluation model combining multiple RBMs and Softmax classifiers. The results of training set and test set show that the minimum loss value is obtained when the number of iterations is 160 and the corresponding values are 0.213 and 0.202, respectively. The model is evaluated by AP, AR and prediction accuracy. The AP, AR and prediction accuracy of the proposed method are 86.95%, 89.74% and 88.29% respectively, which are higher than the Softmax classifier, BP neural network and DBN based Softmax method. This method is superior to other algorithms in the application of accounting enterprise sustainable development performance evaluation model. Embed sustainable development into the theory of enterprise performance evaluation, realize the comprehensive combination of sustainable development and enterprise performance evaluation theory, theoretically solve the problem of disconnection between enterprise performance evaluation and sustainable development, and enhance the scientificity, integrity and systematicness of performance evaluation theory. In the context of sustainable development, the model has important reference value and significance in the application of accounting enterprise performance evaluation. Although the proposed model has effectively improved the accuracy, the network initialization parameter color setting of this model refers to the empirical value and previous research results, and the training algorithm needs to be further studied in the future. The methods given need to be applied to empirical analysis in the future, and the follow-up research is expected to provide referential ideas and methods for the implementation of the concept of sustainable development at all social levels.

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