Acta Technica 62 (2017), No. 7A, 1283–1296

CNN assessment research of procedural mode for college course education based on big data source

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Abstract. An assessment research method of convolutional neural network for the procedural mode of college course education based on the big data source was proposed so as to increase the procedural research effectiveness of college course education. Firstly, the evaluation index system of core competence recognition for colleges was obtained through the processes of principal component analysis, correlation analysis and quantitative analysis of discrimination based on pinpointing the core competence components for colleges; secondly, the mapping input form of two-dimension array feature for core competence assessment for colleges was constructed and all mappings were indicated as MFSC coefficient features containing static data, the first-order derivative and the second-order derivative; the convolutional neural network learning algorithm of finite partial weight was constructed pertinent to the partial features of core competence assessment feature for colleges so as to increase the identification degree of core competence assessment for colleges and reduce the algorithm complexity; finally, the algorithm effectiveness was verified through the simulation experiment.

Key words. Big data, College course, Convolutional neural network, Partial weight.

1. Introduction

The first twenty years of this century is the important strategic period for Chinese development and the brand-new historic mission of Chinese higher education is attached to the national strategies of developing the country through science and education and strengthening the country through talents. The college is the base of talent cultivation, the main body of knowledge innovation system and one of the foot-stones to support China to construct an innovative country. The international advanced level and world class university are needed to construct an innovative country and it has become an important objective to construct world class universities

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for Chinese higher education. Chinese higher education development will be fused to the world to greater extent so as to participate in international competition and meet new challenges in the new trend of economic and scientific globalization. Whether Chinese colleges can grasp the opportunity, conduct scientific positioning, choose the objective and school-running mode following their development and increase their core competence in the fierce competition or not is the strategic problem related to the sustainable development of Chinese higher education.

The international competition of higher education is increasingly dramatic along with the overall openness of Chinese education market including higher education deeply in multi angles. On one hand, the economic competition and the overall national strength competition among nations and regions are fundamentally decided by the competition of talents and technology along with the rapid development of science and technology, quick production change and increasingly fierce international competition and new requirements are proposed on Chinese higher education in aspects of quantity, quality, profit and level, etc worldwide. On the other hand, the college development is exposed to the world scope along with economic and technological globalization and further requirements are proposed to Chinese colleges so as to obtain high-quality resources of a certain quantity in the world market of global resource configuration. Great changes took place in the social and economic environments of colleges after China joined the WTO and foreign advanced education brands flooded into China in a large number, thus the Chinese education market competition is increasingly intensified. However, there is great gap prominently embodied in aspects such as education resource configuration, insufficient national education input and weak capacity for colleges to raise funds by themselves, etc between Chinese colleges and world class universities. These problems will be especially outstanding along with global technological advance and economic globalization development. Chinese colleges can only obtain the initiative of resource configuration optimization and realize beneficial existence and development by increasing the competence in the face of competition and challenge in the world scope.

To sum up, it has become the important strategy for Chinese college development to increase the college competence in the face of opportunity and challenge; the key to increasing Chinese college competence lies in cultivating and increasing the core competence for colleges to be in the favorable status in the market competition, which is also the historical background to research the core competence problem for Chinese colleges.

2. Determination of evaluation index system for core competence recognition of colleges

The following evaluation index system of core competence recognition for colleges was obtained through the processes of principal component analysis, correlation analysis and quantitative analysis of discrimination in combination with the data accessibility based on pinpointing the core competence components for colleges, as shown in the Table 7.2. Four first-grade indexes, 11 second-grade indexes and 37 third-grade indexes are included in the evaluation index system. The first-grade indexes include: talent cultivation. research ability, subject construction and subject team; the first-grade index of talent cultivation is composed of four second-grade indexes such as postgraduate, college students, higher adult education students and foreign students; research ability is composed of three second-grade indexes such as researcher input, research expense input and research output; subject construction is composed of two second-grade indexes such as subject and laboratory; subject team is composed of two second-grade indexes such as academician and faculty.

The postgraduate index is reflected through the two third-grade indexes such as doctoral student ratio and postgraduate ratio in colleges and the doctoral student ratio in colleges refers to the ratio of total doctoral amount to the overall student amount in the college; the sum of postgraduate amount (including doctoral students) in the college, college student amount in the college, student amount of higher adult education and foreign students in the college is adopted as the overall student amount in the college in this paper and the equation of doctoral student ratio in the college is: doctoral student ratio in the college of a certain year = doctoral student amount in the college/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college); the calculation method of postgraduate ratio in the college is basically the same as that of doctoral student ratio, namely postgraduate ratio in the college of a certain year = postgraduate amount in the college/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college).

The second-grade index of college students is reflected through the college student ratio in the college and employment ratio for college students and the calculation method of the college student ratio in the college is the same as the doctoral student ratio, namely the college student ratio in the college = the college student amount in the college/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college); employment ratio for college students refers to the ratio of the amount of employed college students to the overall amount of college students for a certain college in a certain year, namely employment ratio for college students in a certain year = the amount of employed college students / the overall amount of college students in a certain year.

The second-grade index of higher adult education students is reflected through the three third-grade indexes such as correspondence student ratio, night university student ratio and the ratio of adult student temporarily released from their regular work and the calculation of three indexes such as correspondence student ratio, night university student ratio and the ratio of adult student temporarily released from their regular work is the same as the that of doctoral student ratio, namely: correspondence student ratio in a certain year = correspondence student amount in a certain year/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college); night university student ratio in a certain year = night university student amount in a certain year/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college);

the ratio of adult student temporarily released from their regular work in a certain year = the amount of adult student temporarily released from their regular work in a certain year/ (postgraduate amount in the college + college student amount in the college + student amount of higher adult education + foreign students in the college).

The second-grade index of foreign students is reflected through the three third-grade indexes such as postgraduate ratio, college student ratio and training ratio in the foreign students. Postgraduate ratio in the foreign students refers to the ratio of postgraduates to foreign students and training personnel in a college of a year and college student ratio is similar to the training ratio, but the personnel training of foreign companies, governments or other departments is included. The calculation equation of the above three indexes is: ratio of postgraduates to foreign students = postgraduates amount in foreign students/ (total foreign student amount+ foreign training personnel amount); ratio of college students to foreign students = college student amount in foreign students/ (total foreign student amount+ foreign training personnel amount); foreign training ratio = total foreign training personnel amount/ (total foreign student amount+ foreign training personnel amount).

The second-grade index of researcher input is reflected through the research activity personnel ratio, research and development personnel ratio and full-time research and development personnel ratio and the research activity personnel ratio in a year refers to the ratio of research activity personnel amount to the total amount of research activity personnel, research and development personnel and full-time research and development personnel; the calculation method of research and development personnel ratio and full-time research and development personnel ratio is the same as above. The calculation equation of above indexes is: research activity personnel ratio in a year = research activity personnel / (research activity personnel+ research and development personnel + full-time research and development personnel); research and development personnel ratio in a year = research and development personnel/ (research activity personnel+ research and development personnel + full-time research and development personnel); full-time research and development personnel ratio in a year = full-time research and development personnel/ (research activity personnel+ research and development personnel + full-time research and development personnel).

3. Automatic speech recognition of convolutional neural network

3.1. Network mapping construction

Input data needs to be expressed into the form of feature mapping in the mode recognition algorithm based on CNN network. Input data is expressed into two-dimension array input presented in the forms of horizontal x and vertical y pixels. CNN network is operated in the small window of input image in the phases of training and testing so as to make the network weight observe the speech features from the input data through this window. The detailed process is shown in Fig. 1.

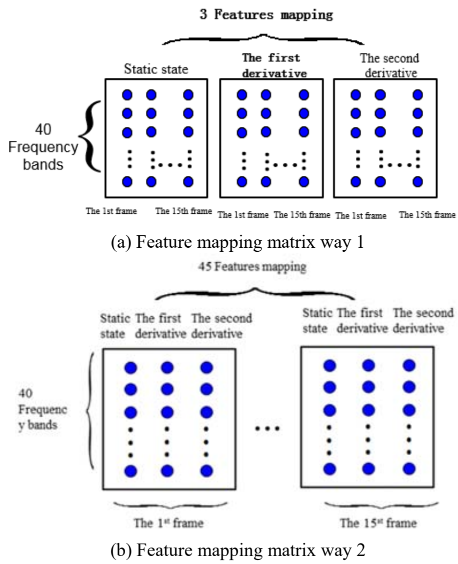

Fig. 1. Different speech matrix form inputs

There are many types of DNN matrix input forms currently and the two common types of them are offered in Fig. 1. Firstly, as shown in the Fig. 1(a), input speech matrix can be set as three two-dimension feature mappings indicated as Mel spectral frequency coefficient features (static state, the first derivative and the second derivative) along the distribution forms of frequency (frequency wave band index) and time (data frame). The two-dimension convolutional operation can be conducted in this circumstance to conduct normalization operation on frequency and time at the same time. Or the frequency normalization is only considered.

The same MFSC feature is combined as one-dimension feature mapping (along the frequency band index) in this circumstance, as shown in Fig. 1 (b). For example, the one-dimension feature matrix of 45 features mapping can be constructed if 15 frames are included in the speech window and 40 filters are included in each frame. The result is that one-dimension convolution can be exerted along the frequency coordinate axis. The one-dimension convolution with the latter one used along the frequency is mainly considered in this paper, as shown in Fig. 1(b). Activation operation can be respectively conducted in convolutional and convergence layers to construct input feature vectors. Similar to the input layer, the convolutional and convergence layers of the unit can also be expressed into the form of mapping matrix. The convolutional and convergence layers can be indicated as one CNN layer in the CNN term.

3.2. CNN convolutional layer

It is assumed that I is total mapping quantity, $O_i (i = 1, \cdots, I)$ and all input feature mappings are connected to multiple feature mappings (if the total number is J); the convolu-tional layer is $I \times J$, $\mathbf{w}_{i,j}(1,\cdots,I;j=1,\cdots,J)$ based on partial weight matrix. The mapping can be indicated as the convolutional operation in the signal handling. The feature mapping of all neuron convolution layers can be calculated as fol-lows if the input feature mapping is one-dimensional:

$$q_{j,rm} = \sigma\left(\sum_{i=l}^{I}\sum_{n=1}^{F} O_{i,n+m-1}w_{i,j,n} + w_{o,j}\right), (j=1,\cdots,J)\,. \tag{1}$$

Where, $o_{i,m}$ is the ith input of the feature mapping O_i of the neuron m; $q_{j,m}$ is the jth input of the neuron m for feature mapping O_j of convolutional layer; $w_{i,j,n}$ is the nth element of weight vector $\mathbf{w}_{i,j}$; F is the filter size and the input frequency band quantity of feature mapping of all convolutional layers is decided by its value. These feature mappings are limited in the frequency scope of core competence assessment for colleges for definition due to the locality of the selected MFSC feature mappings. Simplification in the form of matrix can be conducted on the Equation (1) based on convolutional operators:

$$Q_j = \sigma(\sum_{i=1}^{I} O_i * \mathbf{w}_{i,j}), (j=1,\cdots,J)\,. \tag{2}$$

Where, the ith input feature mapping is indicated by O_i and partial weight matrix is indicated by $\mathbf{w}_{i,j}$. O_i and $\mathbf{w}_{i,j}$ are both vectors when it is based on one-dimensional feature mapping and O_i and $\mathbf{w}_{i,j}$ are both matrixes when it is based on two-dimensional feature mapping.

3.3. CNN convergence layer

The corresponding convergence layer can be generated through exerting convergence operation on CNN convolutional layer. Convergence function is independently applied to all convolutional feature mappings. CNN convergence layer can be defined as follows [14] when the maximum convergence function is used:

$$p_{i,m} = \max_{n=1}^{G} q_{i,(m-1)\times s+n}\,. \tag{3}$$

Where, G is the convergence layer scale and s is the displacement size to determine the overlap ratio of neighboring convergence windows. Similarly, the input can be calculated as follows if the average function is used:

$$p_{i,m} = r\sum_{n=1}^{G} q_{i,(rm-1)\times s+n}\,. \tag{4}$$

Where, r is the scale factor which can be learnt. There is no gap between them and the maximum convergence feature mapping performance is better than average convergence feature mapping performance in this circumstance in the graphic recognition application commonly under the constraint $G = s$ on condition that the convergence windows are not overlapped. The way of independently adjusting G and s is adopted in this paper. Besides, the non-linear activation function is adopted to generate the final output. All convergence layer units accept the input of three convolutional layer neurons in the same feature mapping. The size of the convergence layer will be one third of that of the convolutioanl layer if $G = s$.

4. Shared learning algorithm of finite weights for CNN network

4.1. Finite weights sharing

The weight sharing scheme shown in Fig. 2 is the fully weights sharing (FWS). This is the standard application form of CNN network in the graphic handling because this mode can appear in any partial positions in the image. However, its sound features on different frequency bands are different and the effect is not ideal to apply the fully weights sharing to the speech recognition for detailed assessment features of core competence for colleges. The use of different weight sets is more applicable to the situation that the sound signal is equipped with different assessment features of core competence for colleges under different frequency band features. The weights need to be shared by these convolutional units so that the calculation can be compared with speech features and these features will be converged to the convergence layer. It can be explained that all frequency bands can be regarded as independent sub-networks equipped with the independent shared convolutional weight. Some feature mappings in the convolutional layer are included in all sub-networks. All the input dimensions are scanned by these feature mappings through weight vectors to determine whether the feature exists or not. The use amount of the weight vector in the neighboring position of the input space is decided by the size of the convergence layer, namely that the size of all feature mappings is equal to that of the convergence layer in the convolutional layer. The complete convolutional features of all convergence neutrons are gathered as a feature with the convergence function in the paper. The activation function of the convolutional layer can be calculated as:

$$q_{k,j,m} = \sigma\left(\sum_{i}\sum_{n=1}^{F} O_{i,(k-1)\times s+n+rm-1} \cdot w_{k,i,j,n} + w_{k,0,j}\right). \tag{5}$$

Where, $w_{k,i,j,n}$ is the nth convolutional weight that the ith input feature maps to the jth convolutional mapping in the sub-network k; the value scope of m is $1 \sim G$. The activation function form of convergence layer is as follows in this circumstance:

$$p_{k,j} = \sum_{m=1}^{G} q_{k,j,m}. \tag{6}$$

Similarly, above LWS convolutional layer can also be indicated as the multiplication form of the large-scale sparse matrix, but the construction way of $\hat{\mathbf{o}}$ and $\hat{\mathbf{w}}$

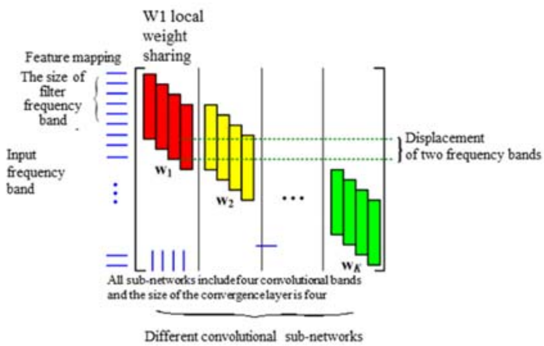

Fig. 2. CNN network calculation process of local weight sharing

is different from that of FWS convolutional layer. Firstly, the sparse matrix $\hat{\mathbf{w}}$ is constructed according to Fig. 2 and each $\hat{\mathbf{w}}$ is constructed accord-ing to local weight $w_{k,i,j,n}$; the form is:

$$\mathbf{W}_k = \begin{bmatrix} w_{k,1,1,1} & w_{k,1,2,1} & \cdots & w_{k,1,J,1} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,I,1,1} & w_{k,I,2,1} & \cdots & w_{k,I,J,1} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,I,1,2} & w_{k,I,2,2} & \cdots & w_{k,I,J,2} \\ \vdots & \vdots & \ddots & \vdots \\ w_{k,I,1,F} & w_{k,I,2,F} & \cdots & w_{k,I,J,F} \end{bmatrix}. \tag{7}$$

Where, $k = (1, 2, \cdots, K)$ and the same weight for all sub-networks is repeatedly used, while weight of different sub-networks is different. Secondly, the calcu-lation form of feature mapping can be indicated in the form of a large-scale vector:

$$\hat{\mathbf{q}} = [|\mathbf{v}_{1,1}| \cdots |\mathbf{v}_{1,G} \cdots |\mathbf{v}_{K,1}| \cdots |\mathbf{v}_{K,G}|]. \tag{8}$$

Where, K is the total number of sub-network and G is the size of the convergence layer; $\mathbf{v}_{k,m}$ is the output row vector of k sub-network neuron of m frequency bands in the feature mapping.

$$\hat{\mathbf{q}}_{kmrm} = [q_{k,1,m}, q_{k,2,m}, \cdots, q_{k,J,m}]. \tag{9}$$

Where, I is the total amount of input feature mapping in each sub-network. Then the weight learning way based on LWS is as follows:

$$\begin{cases} \hat{\mathbf{q}} = \sigma(\hat{\mathbf{o}}\hat{\mathbf{W}}) \\ \Delta\hat{\mathbf{W}} = \varepsilon\hat{\mathbf{o}}'\mathbf{e} \end{cases} \tag{10}$$

Meanwhile, the error vector is spread as follows through the maximum convergence function:

$$e_{k,i,n}^{\text{low}} = e_{k,i} \cdot \delta(u_{k,i} - n)\,. \tag{11}$$

Where

$$u_{k,i} = \arg\max_{m=1}^{G} q_{k,i,m}\,. \tag{12}$$

Because different weights are used in all frequency bands and it is only needed to consider the frequency band scope of the speech mode, so LWS way helps to reduce the total neuron amount in the convergence layer. One frequency band should be enough for the feature mapping of a small quantity. On the other hand, it is not allowed to exert the convolutional layer on the convergence layer for LWS scheme because the features of LWS among different convergence layers are unrelated.

4.2. LWS-CNN network training

Modified LWS-CNN training form based on limited convolutional Boltzman machine is proposed by us in this section. We need to define the state condition probability of hidden layer neurons so as to learn CRBM model parameters. The activation condition probability $h_{k,j,m}$ of the hidden neuron can be defined as:

$$P(h_{k,j,rm} = 1|\mathbf{v}) = \frac{\exp(I(h_{k,j,rm}))}{\sum_{n=1}^{p} \exp(I(h_{k,j,n}))}\,. \tag{13}$$

Where, $I(h_{k,j,rm})$ is the weighted signal sum of reachable neuron signal in the input layer, which can be defined as follows:

$$I(h_{k,j,rm}) = \sum_{i} \sum_{n=1}^{f} v_{i,(k-1)\times s+n+rm-1} w_{k,i,j,n} + w_{k,i,j,0}\,. \tag{14}$$

Then the calculation form of the conditional probability distribution $v_{i,n}$ of the feature mapping i for frequency band n of the explicit neurons in the state of hidden layer satisfies Gaussian feature distribution:

$$P(v_{i,n}|\mathbf{h}) = N\left(v_{i,n};\ \sum_{j,(k,m)\in\mathbf{C}(i,n)} h_{k,j,m} w_{k,i,j,f(n,k,m)}, \sigma\right)\,. \tag{15}$$

Where, $c(i,n)$ indicates that the input convolutioanl frequency band and the link index of sub-networks are received from the neuron in explicit layer and $w_{k,i,j,f(n,k,m)}$ is the link weight from the frequency band m of input feature map-ping to the frequency band m of feature mapping j for the kth convolutional sub-network; $f(n,k,m)$ is the mapping function from the link node index to corresponding filter component index and σ^2 indicates the Gaussian distribution variance of fixed model parameters.

Iterated estimation can be conducted on all above link weights of CRBM models with the regular ramification based on the above two conditional probabilities. The weight training value of CRBM models can be the initial value of LWS convolutional layer scheme. The output of the convolutional and convergence layers is calculated based on Equations (12-13) after the learning training is conducted on the first convolutional layer weight. The convergence layer output will be continuously as the training input of deep layer network of the next layer until the algorithm is convergent.

5. Experimental analyses

5.1. Experimental environment

We divide the colleges directly subordinated to the Ministry of Education into five levels based on the college level analysis and DEA analysis of 72 colleges directly subordinated to the Ministry of Education. It is difficult to find out the same rule between them and other colleges due to the strong expertise of the four colleges including Central Academy of Drama, Central Academy of Fine Arts, Central Conservatory of Music and Beijing Broadcasting University. So the four colleges of especially obvious expertise including Central Academy of Drama, Central Academy of Fine Arts, Central Conservatory of Music and Beijing Broadcasting University are deleted in this chapter to increase the comparability, namely that the analysis will be conducted on the rest 68 colleges. The core competence of different colleges is different, as shown in the following Table 1-2.

Table 1. The first-grade index weight comparison of colleges at various levels

The first-grade index	The college in the first layer	The college in the second layer	The college in the third layer	The college in the fourth layer	The college in the fifth layer
Talent cultivation	0.21537582	0.24126583	0.27709062	0.25562545	0.3424160
Scientific research	0.47750820	0.45423611	0.39560693	0.41240745	0.3744861
Subject construction	0.14567516	0.14725291	0.14604803	0.13513355	0.1345976
Subject team	0.16992791	0.15724515	0.18125442	0.16961988	0.1485003

It can be found from the Table 1 that the main component of core competence for colleges is scientific research, but colleges at different levels are focused on different points. The colleges in the first layer have obvious advantages in the aspect of scientific research to concentrate most scientific results of colleges; the colleges in the second layer have advantages in the aspect of subject construction to master the development trend of college subject construction; the colleges in the third layer and the fourth layer are in the middle link to have certain relative advantages in the two aspects of talent cultivation and subject construction and it is difficult to explain that they have especially obvious advantages in which aspects for the two levels due to the different development direction and possible future obvious level deviation for the colleges at these two levels; the colleges at the fifth level are focused on training college students, so they have obvious advantages in the aspect of talent training.

Table 2. The second-grade index weight table of colleges at various levels

The second-grade indexes	The college in the first layer	The college in the second layer	The college in the third layer	The college in the fourth layer	The college in the fifth layer
Postgraduate	0.0661	0.0312	0.0326	0.0349	0.0454
College students	0.0788	0.0701	0.0921	0.0624	0.0855
Adult education students	0.0419	0.0661	0.0819	0.0476	0.1022
Foreign students	0.0297	0.0839	0.0706	0.1108	0.1093
Input of scientific researchers	0.0265	0.4363	0.0429	0.0416	0.0509
Input of scientific research funds	0.2509	0.2475	0.1886	0.2468	0.1658
Output of scientific research	0.1621	0.1704	0.1641	0.1241	0.1578
Subject situation	0.0658	0.0620	0.0621	0.0534	0.0596
Laboratory	0.0799	0.0653	0.0840	0.0815	0.0750
Academician	0.0554	0.0388	0.0838	0.0964	0.0756
Faculty team	0.1045	0.1085	0.0975	0:0732	0.0729

Colleges of level 1 have obvious advantages in the aspect of scientific research funding due to more scientific research operating expenses and national funds and also have obvious advantages in the aspect of laboratory construction and academician, which is corresponding to the realistic requirement that colleges of level 1 are positioned to scientific research and training core competitiveness; Colleges of level 2 have obvious advantages in the aspect of disciplines as it is located in intermediate stage that teaching strives forward to scientific research and they increase input in the aspect of scientific research invisibly at the same time of striving forward to scientific research. Therefore, input proportion of these colleges in the aspect of scientific researchers is relatively great, but as scientific research operating expenses and national funds are less relative to colleges of level 1, special funds of other central departments and local special funds are more in order to increase scientific research funds. Colleges of level 3 and level 4 are located in imitative intermediate level. Some colleges strive forward to scientific research of colleges of level 1, but some colleges utilize current resources realistically and improve its teaching level. Therefore colleges of these two levels pay more attention to teaching staff, which is advantage of its core competitiveness. Relative to colleges of level 4, colleges of level 3 have more local special funds, but they are at a disadvantage in the aspect of self-financing; main task of colleges of level 4 and 5 is to improve teaching level and serve local economy. Therefore, proportion of universities and colleges is higher and entrusted funds of organizations are more in the aspect of scientific funds. There are many professional colleges among colleges of this level, such as foreign language school and so on. Therefore, there are more overseas students. The proportion of teaches of 36-50 years old in full-time teachers of teaching staff is larger, but doctors' proportion of full-time teachers is lower.

5.2. Contrast experiment

In order to verify effectiveness of algorithm, selected contrast algorithms are Naive Bayes algorithm, decision tree algorithm and random prediction algorithm. Experimental results are shown in Table 3.

Table 3. Experimental results contrast

College level	Index	Bayes	Decision tree	Random prediction	Algorithm in the paper
Level 1	Precision	96.82	97.52	91.26	98.32
	Recall	95.21	96.13	90.58	97.64
	Stability	92.68	93.84	89.64	94.56
Level 2	Precision	48.76	47.53	41.62	82.16
	Recall	50.76	51.69	48.75	81.28
	Stability	51.26	52.76	46.21	79.46
Level 3	Precision	33.21	34.27	30.69	83.64
	Recall	36.38	35.19	32.84	82.93
	Stability	33.27	34.68	30.42	81.69
Level 4	Precision	23.16	29.16	28.94	72.59
	Recall	23.82	30.67	27.63	73.64
	Stability	25.39	28.91	24.18	71.82

It can be known from experimental data in Table 3 that prediction accuracy, recall rate index and stability index of these algorithms are higher in core competitiveness assessment of colleges and can reach above 90%, which reflects simplicity of core competitiveness assessment prediction of colleges. Algorithm of the paper is superior to contrast methods selected in the above indexes. Contrast situations of training convergence time of several selected algorithms are shown in Table 3.

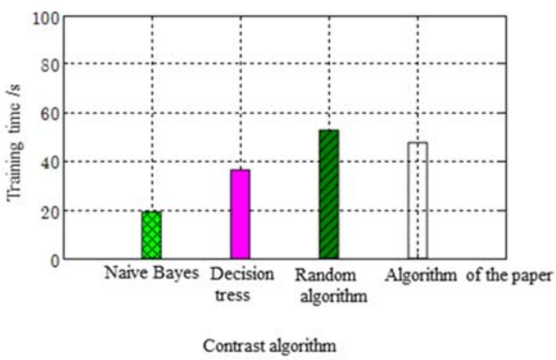

Fig. 3. Algorithm running time contrast

It is shown according to results of Fig. 3 that running time of algorithm of the paper is longer than Naive Bayes algorithm and decision tree algorithm but less than random prediction algorithm for running time index. Because offline training method is adopted for the above algorithms at the time of attack prediction, difference of running time is within acceptable range.

6. Conclusions

On the basis of college level positioning analysis in the preamble based on DEA, core competitiveness of colleges is recognized in the chapter. Firstly, the method of combining principal component analysis, correlation analysis and discrimination analysis is adopted to construct index system for core competitiveness of colleges based on selection principle of indexes; on this basis, core competitiveness recognition model of colleges for limited local weight sharing convolutional neural networks learning algorithm is constructed. 72 colleges directly under Ministry of Education are adopted as sample in the paper. According to statistic data in 2004, empirical analysis on core competitiveness of colleges is implemented, which provides thought and methods for core competitiveness recognition of colleges based on level positioning.

Acknowledgement

Henan province soft science research project in 2018 "Research on the integration of innovation and entrepreneurship education in Henan universities and the 2 construction of intelligent city".

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Received May 7, 2017