Design and Application of the DPC-K-Means Clustering Algorithm for Evaluation of English Teaching Proficiency

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***Abstract*—Effective and precise methodologies for evaluating the proficiency in English language instruction are instrumental in enhancing educators' competencies and the effectiveness of educational administrative processes. The objective of this paper is to refine the neutrality and precision of such assessments by introducing a novel approach that leverages an advanced K-means algorithm in conjunction with convolutional neural networks (CNNs). Initially, a thorough examination of the issue at hand leads to the formulation of an assessment framework that integrates both a clustering algorithm and a CNN, with a comprehensive elucidation of the pivotal technical aspects. Subsequently, the paper introduces a data clustering and categorization technique grounded in the DPC-K-means methodology, specifically tailored for indices that measure English teaching proficiency, and employs CNNs to devise a model for evaluating these competencies. The integration of these two components—data clustering and the assessment model—gives rise to an innovative technique. Ultimately, the proposed method is implemented and its practicality is substantiated through an analysis of empirical data from educators' teaching proficiency indices. A comparative analysis with existing algorithms reveals that the proposed method achieves superior clustering performance and the lowest margin of error in predictive assessments.**

***Keywords*—K-Means; density-peak clustering algorithm; ELT competency assessment; convolutional neural network**

I. Introduction

As educational reforms progress and evolve, the caliber of education has emerged as a pivotal topic of societal interest [1]. Proficiency in teaching represents a critical facet of educational quality, reflecting not just the professional acumen of educators but also the trajectory of educational management's advancement [2]. English, being the lingua franca of the modern world, occupies a significant place among the mandatory courses within the academic curricula of higher education institutions [3]. The evaluation of English teaching capabilities is a crucial component in the pedagogical framework of universities and colleges, serving as a vital mechanism for educators to gather feedback, refine their instructional strategies, and uphold educational standards, as well as for students to refine their study approaches, enhance learning techniques, and boost academic performance [4]. In recent years, research into the assessment of English language teaching proficiency has predominantly focused on two key areas: the development of assessment indices and the formulation of algorithms for evaluating teaching proficiency [5]. Existing systems for evaluating English teaching skills are often examined from dual viewpoints—that of the educator and the student—yet they often fall short in terms of being comprehensive, standardized, and providing timely feedback [6]. Current research into algorithms for assessing English teaching skills typically employs the assessment index system as input and the level of proficiency as output, with common methodologies including fuzzy logic [7], hierarchical analysis [8], clustering algorithms [9], and neural networks [10]. However, methods relying on fuzzy logic and hierarchical analysis are limited in their capacity to address intricate and varied mapping relationships and are generally straightforward to compute and implement [11]. On the other hand, clustering-based algorithms for assessing English teaching skills offer a temporal perspective on the assessment challenge, addressing the dynamic nature of teaching data and establishing a big data model for English teaching proficiency through quantitative recursive analysis [12]. Neural network-driven algorithms, meanwhile, are adept at managing the intricate and shifting relationships between the assessment indices and the proficiency levels, offering a degree of generalization [13]. With the advancement of intelligent algorithms, the integration of clustering methodologies with neural networks to cluster and train the indices of English teaching proficiency has become a burgeoning research avenue, aimed at achieving a quantifiable measure of teaching skills [14]. Despite these developments, there remain issues within the algorithms for assessing English teaching skills, including the need for improved generalization and the absence of well-defined quantitative criteria [14].

This paper addresses the aforementioned challenges in the construction of an English teaching proficiency assessment system and the design of its algorithms by integrating a clustering algorithm with a convolutional neural network. It proposes a method for developing an English teaching proficiency system grounded in an enhanced clustering approach and an assessment algorithm based on CNNs. Concentrating on the evaluation of English teaching skills, the paper delves into the conceptualization and resolution of the issue at hand, scrutinizing the critical technical aspects. It utilizes an improved clustering algorithm for the aggregation and synthesis of English teaching proficiency indices and employs a CNN to assimilate and refine the clustered data, ultimately verifying and analyzing the proposed methodology using a test dataset.

II. Programme Research Design

A. Line of Research

To address the problem of assessing English teaching ability, this paper follows the basic research idea of "identifying problems - analysing problems - proposing solutions - verifying solutions" [15] to study the English teaching ability index system (see Fig. 1). The paper follows the basic research idea of "finding the problem - analysing the problem - proposing the solution - verifying the solution" [15] to study the indicator system of English teaching competence, and at the same time, it adopts the data learning model to construct and analyse the model for assessing English teaching competence.

By integrating a clustering methodology with the advanced computational framework of convolutional neural networks (CNNs), a comprehensive scheme for the evaluation of teaching capabilities has been meticulously crafted, as delineated in Fig. 1. As depicted in Fig. 1, this scheme for assessing English teaching proficiency, grounded in both clustering techniques and CNNs, adheres to the foundational principles of assessment system development. It initiates with a thorough examination of the challenges inherent in evaluating English teaching skills, followed by the establishment of pertinent assessment criteria. The data undergoes a rigorous pre-processing phase that includes the mitigation of outliers, the imputation of missing values, normalization to ensure consistency, and a thorough analysis of inter-variable correlations and the reduction of data dimensionality to enhance computational efficiency. Subsequently, the refined indices are aggregated and scrutinized through the application of a clustering algorithm, which facilitates the identification of distinct levels of teaching proficiency. The subsequent phase involves the utilization of a CNN to train a labeled dataset, thereby fostering the development of a robust model capable of accurately assessing English teaching competencies.

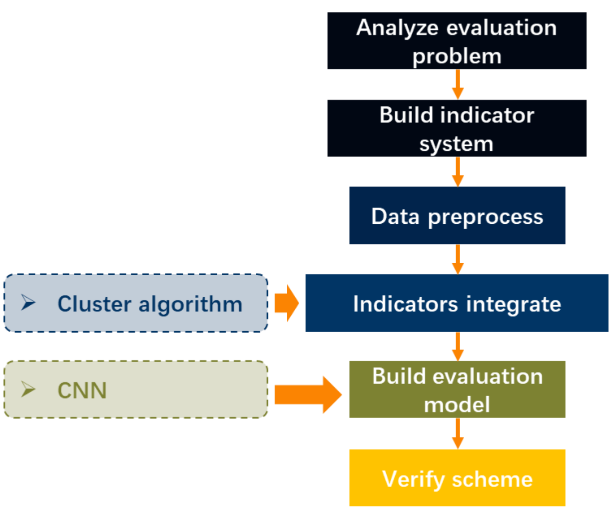


Fig. 1. ELT competency assessment research programme.

B. Analysis of Key Technologies

The system for evaluating English teaching ability, which integrates a clustering algorithm with a convolutional neural network, encompasses several pivotal technological components. These include the development of an assessment framework for English teaching proficiency, the initial handling of gathered data, the organization of data indices through clustering, the assembly of a model for gauging teaching capabilities, and the verification of the system's design, as illustrated in Fig. 2.

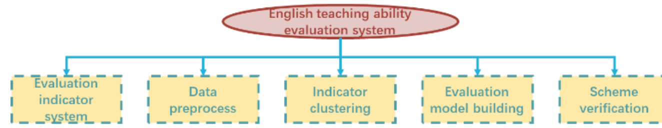


Fig. 2. Key technologies of the EFL assessment system.

1) Establishment of an assessment indicator system: According to the principles of objectivity, orientation, wholeness, operability and English characteristics [16] of the construction of assessment indicators (as shown in Fig. 3), through consultation, investigation and modification, we construct an assessment indicator system of English teaching competence that contains 20 indicators in five aspects, such as the purpose of teaching, the content of teaching, the language of teaching, the method of teaching, and the effect of teaching, as shown in Fig. 4.

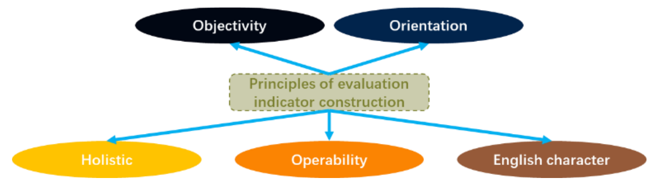


Fig. 3. Principles for selecting assessment indicators.

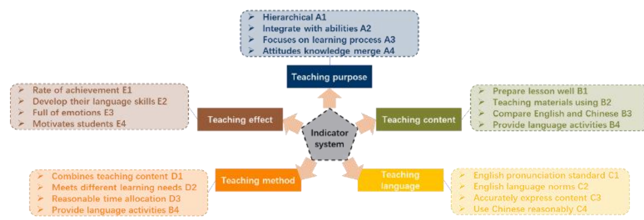


Fig. 4. System of assessment indicators.

2) Data pre-processing: The precision and reliability of the English Language Teaching (ELT) competency evaluation model are often compromised by the absence of comprehensive raw data, the presence of anomalies, discrepancies in scaling, and significant data redundancy, which result in the model's performance falling short of the expected benchmark [17]. To address these issues and enhance the fidelity and exactitude of the assessment model, it is imperative to implement data preprocessing techniques on the collected data. In dealing with anomalies, the paper employs the 3σ rule [18], which designates any data point that lies beyond the mean by more than three standard deviations as an outlier, subsequently eliminating such points. For addressing missing data, the paper utilizes a proximity filling technique [19], which estimates the missing entries based on adjacent data points. To standardize the quantitative index values, the *Z*-score normalization method [20] is applied. Furthermore, to refine the accuracy of the assessment algorithm and mitigate computational overhead, the paper utilizes Pearson's correlation coefficient to assess the interdependencies among the assessment indicators, subsequently employing principal component analysis [21] to streamline the dimensions of the indicators and distill the core variables that capture the most variance in the data.

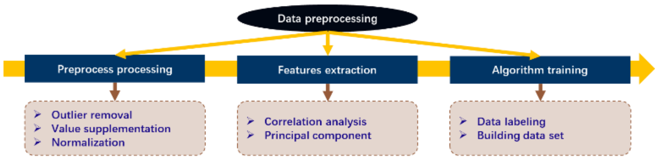


Fig. 5. Flow of data pre-processing technology.

3) Indicator clustering integration: In order to carefully classify the assessment values and grades of English teaching ability, this paper adopts the unsupervised learning method based on clustering algorithm to cluster and analyse the indicator data of English teaching ability assessment. Indicator data clustering integration mainly includes two steps, i.e., indicator data clustering and assessment score labelling division, as demonstrated in Fig. 5.

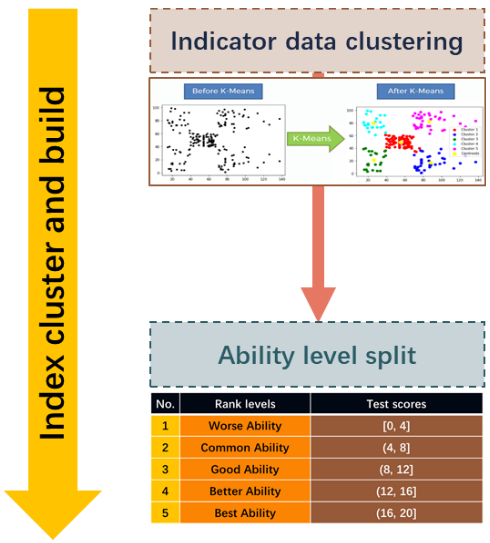


Fig. 6. Flow of indicator clustering integration technique.

For the indicator data clustering problem, this paper adopts the improved K-means clustering algorithm based on the assessment of English teaching ability indicator data clustering analysis, through the input of assessment indicator data, to represent the minimum relative distance between the sample point and the data sample point as the optimization goal, after many iterations of search, the output of clustering centre and the assessment of the indicator data division, the specific principle is displayed in Fig. 6 and Fig. 7. The data clustering model is calculated as follows:

$$X_{all-cluster} = f_{DPC-K-means}\left(X\right) \tag{1}$$

where, $X_{all-cluster}$ denotes the data segmentation results, $f_{DPC-K-means}$ denotes the improved K-means clustering algorithm, and X denotes the input indicator data.

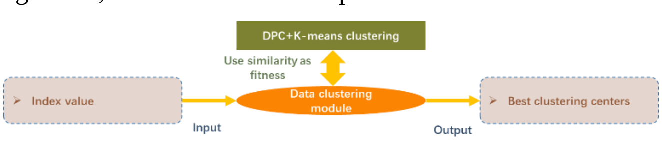


Fig. 7. Data clustering model for assessment indicators.

To address the issues of assessment score labelling and grade division, according to the clustering results, this paper divides the assessment value of English teaching ability into five grades, and the corresponding scores are shown in Table I.

TABLE I. CORRESPONDENCE BETWEEN ENGLISH PROFICIENCY ASSESSMENT SCORES AND CLASSIFICATION LEVELS

No.	Rank Levels	Test Scores
1	Worse	[0,4]
2	Common	(4,8]
3	Good	(8,12]
4	Better	(12,16]
5	Best	(16,20]

$$Y_{rank} = \begin{cases} 5 & Y_{score} \geq 16 \\ 4 & 12 < Y_{score} \leq 16 \\ 3 & 8 < Y_{score} \leq 12 \\ 2 & 4 < Y_{score} \leq 8 \\ 1 & Y_{score} \leq 4 \end{cases} \tag{2}$$

where, Y_{score} denotes the ELT assessment score and Y_{rank} denotes the ELT level.

4) Evaluation model construction: In order to construct the mapping relationship between the index value of English teaching ability and the assessment score, this paper adopts the convolutional neural network to construct the English teaching ability assessment model, as shown in Fig. 8.

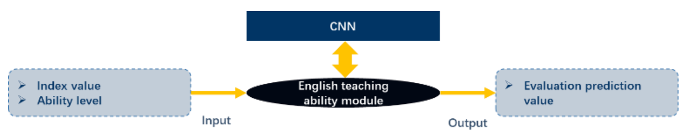


Fig. 8. Schematic diagram of the construction of the EFL assessment model.

$$Y_{score} = f_{CNN}\left(X\right) \tag{3}$$

where, Y_{score} denotes the ELA score, f_{CNN} denotes the convolutional neural network, and X denotes the input indicator data.

5) Programme validation techniques: In order to fairly analyse the performance of each capability assessment model, this paper analyses and compares the clustering delineation capability and assessment prediction capability, and the specific technical ideas are shown in Fig. 9. The clustering delineation ability uses the evaluation indexes such as contour coefficient SI, variance ratio criterion CHI, and Davis-Boulding index DBI to analyse the results [22]. The assessment and prediction ability is used to analyse and compare the results using evaluation indexes such as mean absolute error MAE, root mean square error RMSE, mean absolute percentage error MAPE [23].

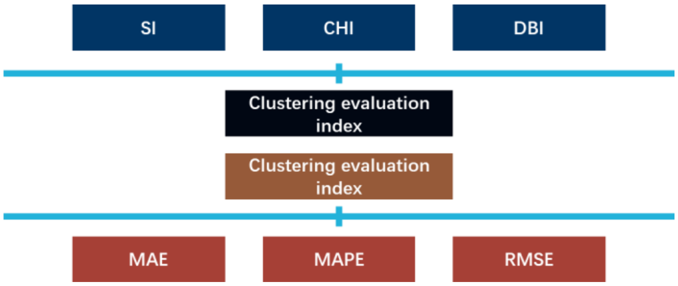


Fig. 9. Programme validation technology roadmap.

III. DATA CLUSTERING AND COMPETENCY ASSESSMENT ALGORITHMS

A. *Clustering of English Teaching Competence Division*

The clustering algorithm's function is pivotal in categorizing the vast and intricate dataset of English Language Teaching (ELT) proficiency indicators into coherent groups based on their inherent characteristics [23]. This process is fundamental to establishing the groundwork for the subsequent development of the ELT proficiency assessment model. The efficacy of the clustering process is paramount, as the accurate segregation of data is directly proportional to the quality of the sample set formation. Consequently, identifying a clustering algorithm with superior performance is of utmost importance to ensure the robustness of the model.

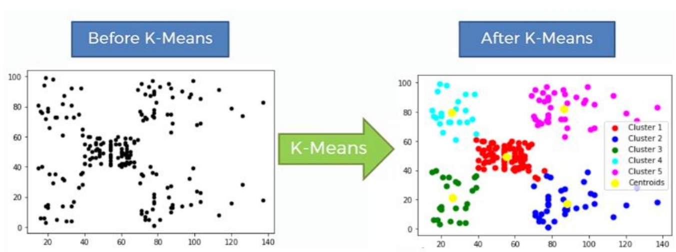


Fig. 10. Principle of K-means clustering algorithm.

1) K-means clustering algorithm: The K-means methodology stands as a prevalent technique for partitioning datasets into distinct clusters, particularly adept at classifying extensive volumes of data [24]. This algorithm operates by identifying the optimal positions for cluster centroids and assigning data points to the nearest of these, thereby minimizing an objective function that is predicated on the sum of squared differences. The objective is to maximize the distance between centroids while ensuring that each data point is linked to the closest centroid. Within the K-means framework, the Euclidean distance serves as the standard metric for gauging the similarity between data points, where a shorter distance signifies a higher degree of resemblance and a longer one suggests dissimilarity, as depicted in Fig. 10.

The objective function of the K-means algorithm is defined as follows:

$$J=\sum_{i=1}^{K}\left(\sum_{k}\left\|x_k-c_i\right\|^2\right) \tag{4}$$

where, K is the number of clusters, c_i is the centre of the cluster, and x_k is the k th data point in the i th cluster.

The algorithm proceeds as follows (see Fig. 11):

- Step 1: Determine the total number of categories K and randomly select K cluster category centres $C=(c_1,c_1,\cdots,c_K)$.
- Step 2: Compute the partition matrix. A data point belongs to the cluster whose centre is closest to that data point. Therefore, the clusters are represented by the binary division matrix U . U The elements in it are determined as follows:

$$u_{ij}=\begin{cases}1 & if\ \left\|x_j-c_i\right\|^2\le\left\|x_j-c_t\right\|^2, \forall t\neq i\\ 0 & otherwise\end{cases} \tag{5}$$

where u_{ij} indicates whether the j th data point belongs to the i th cluster class.

- Step 3: Update the cluster centres. Define each cluster class centre c_i that minimizes the objective function as follows:

$$c_i=\frac{\sum_{j=1}^{N}u_{ij}x_j}{\sum_{j=1}^{N}u_{ij}} \tag{6}$$

where, N denotes the number of samples.

- Step 4: Compute the objective function using equation (4). Verify that the function converges or the difference between two neighbouring values of the objective function is less than a given threshold and stop; otherwise repeat step 2.

2) DPC-K-means clustering algorithm: Given that the initial selection of cluster centroids in the K-means algorithm is arbitrary, there is a propensity for the algorithm to converge on a local rather than global optimum, potentially resulting in erroneous classification outcomes [25]. To counteract this, the present study introduces an enhanced version of the K-means algorithm, aimed at elevating the precision of the clustering results. This enhancement is achieved by integrating the Density Peaks Clustering (DPC) approach [26], which facilitates the identification of more accurate initial centroids for the K-means clustering process.

a) Peak density clustering algorithm: The Density Peak Clustering (DPC) algorithm is based on two assumptions: 1) The local density of the cluster centre is higher than that of its neighbourhood samples. 2) The cluster centre is farther away from other high local density samples. According to the above assumptions, given a dataset $X=\left[x_1,x_2,\cdots,x_N\right]$ with a sample size of N ,the attribute (dimension) of each sample x_i is D , the DPC process is shown in Fig. 12. The clustering process of the standard DPC algorithm is divided into three main steps:

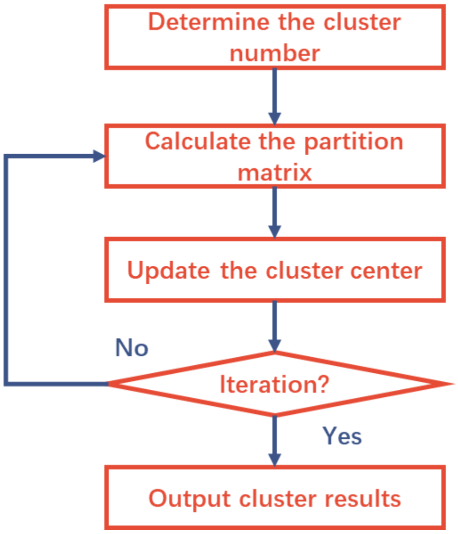


Fig. 11. K-means clustering algorithm.

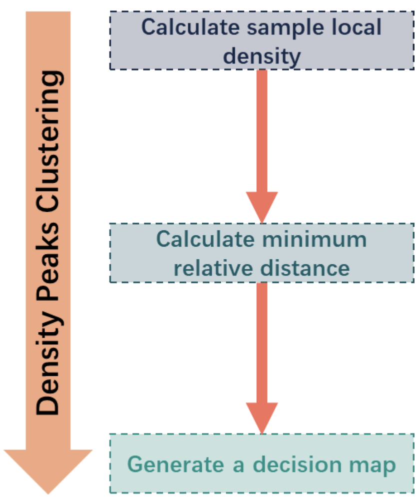


Fig. 12. DPC flowchart.

- Step 1: Calculate the local density of the sample point. For the sample point x_i , the local density ρ_i is described as follows:

$$\rho_i = \sum_j \chi(d_{ij} - d_c) \tag{7}$$

where, $\chi(x) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases}$. d_{ij} denotes the Euclidean distance between x_i and x_j . d_c denotes the stage distance, the exact value of which needs to be set manually.

- Step 2: Calculate the minimum relative distance. The minimum relative distance between the sample point x_i and any other sample point δ_i that has a higher local density than it is calculated as follows:

$$\delta_i = \begin{cases} \min(d_{ij}), & \rho_j > \rho_i \\ \max(d_{ij}), & \rho_j < \rho_i \end{cases} \tag{8}$$

where, if x_i is a sample point with a local or global maximum in the density, its relative distance δ_i is much larger than the relative distance of the neighbouring sample points.

- Step 3: Generate decision diagram. Select the sample points where local density ρ_i is large while the minimum distance δ_i is large as the cluster centre and generate a decision diagram with ρ_i as the x coordinates and δ_i as the y coordinates. After selecting the cluster centres in the decision diagram, the remaining sample points are assigned to different cluster classes based on the minimum distance.

b) Improvement strategies: To address the issue of clustering inaccuracies in the K-means algorithm that arise from the suboptimal identification of cluster centroids, the paper presents a novel adaptation of the K-means algorithm, underpinned by the Density Peaks Clustering (DPC) strategy, termed DPC-K-means. This refined algorithm is structured into two distinct phases: initially, the DPC algorithm is deployed to pinpoint the precise locations of cluster centroids within the raw dataset; subsequently, these centroids are integrated into the K-means algorithm, which then proceeds through iterative refinements to achieve a more nuanced clustering resolution.

Stage 1 is the prerequisite basis for ensuring the clustering accuracy. In order to confirm the initial clustering centre more accurately, the DPC algorithm is improved in this paper. The standard DPC algorithm is very subjective about the selection of d_c . And different d_c often leads to a large variability in the final results of clustering. Since the standard deviation can reflect the degree of dispersion of the data set, d_c is redefined as:

$$d_c = \omega \frac{\sqrt{\sum_{j=1}^{m} (\sigma_j / \mu_j) \sum_{j=1}^{m} \mu_j (m-1)}}{2m^2} \tag{9}$$

where, σ_j and μ_j are the standard deviation and mean of attribute j, respectively. $\omega \in (0,1]$ is the weight parameter that controls the size of the cutoff distance. d_c Approaching the 2-parameter of the standard deviation vector, which represents the standard deviation of all attributes, the cut-off distance is computed under the same mean criterion.

Facing multi-dimensional data, the metric error of standard Euclidean distance is large. Aiming at this problem, this paper designs a dynamic weight to correct the Euclidean distance in order to improve the final clustering accuracy. The basic design idea is: according to the magnitude of the difference between the corresponding attributes between two different data, matching different size weights. When the values of two attributes are more similar, the greater the proportion of in the overall similarity measure should be, and the greater the weights of should be assigned accordingly. The more distant the values of the two attributes are, the less weight should be assigned to the overall similarity measure, and therefore the less weight should be assigned accordingly. Dynamic Weight Correction Euclidean The exact form of the distance is as follows:

$$d_{ij} = \sqrt{\sum_{m=0}^{D} \frac{w_m}{W} \left(x_{im} - x_{jm} \right)^2} \tag{10}$$

where, $W = \sum_m w_m$ is the normalisation factor. w_m is the dynamic weights and its expression is

$$w_j = e^{-\left(\frac{R_m - R_{MIN}}{R_{MAX} - R_{MIN}} \right)} \tag{11}$$

In the Eq. (11), $R_m = \left| x_{im} - x_{jm} \right|$, $R_{MAX} = \max \sum_{m=0}^{D} \left(x_{im} - x_{jm} \right)$, $R_{MIN} = \min \sum_{m=0}^{D} \left(x_{im} - x_{jm} \right)$.

c) Algorithm flow: In summary, the flowchart of the DPC-K-means algorithm is shown in Fig. 13 and the overall process is:

- Step 1: Calculate the dynamic weight-corrected Euclidean distance d_{ij} ;
- Step 2: Calculate the stage distance d_c ;
- Step 3: Calculate the local density ρ_i and the relative minimum distance δ_i ;
- Step 4: Generate a decision diagram to identify the clustering centres K ;
- Step 5: Calculate the division matrix U ;
- Step 6: Update the clustering centre c_i ;
- Step 7: Compute the objective function. Verify that the function converges and no longer changes, then stop; otherwise repeat step 2.

3) Algorithmic applications: To enhance the precision of the model assessing English teaching capabilities, this study employs a clustering approach that segments the indicators of English teaching proficiency using the DPC-K-means methodology. The algorithm processes the input values representing the indicators of English teaching ability and yields both the categorized indicator data and the determined centroids of the clusters.

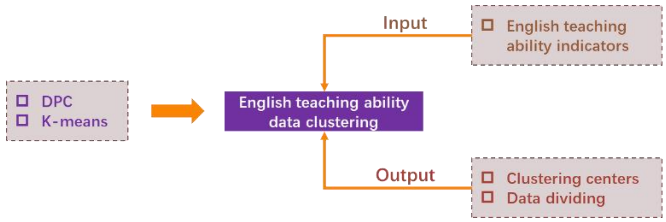


Fig. 13. Application of DPC-K-means clustering algorithm.

B. *Algorithm for Assessing Competence in Teaching English*

The assessment of English teaching ability is inherently a factual representation of the intrinsic laws governing teaching proficiency. To achieve autonomous capability evaluation, this study integrates convolutional neural networks to formulate a model for assessing English teaching ability.

1) Convolutional neural network: A CNN is an artificial neural network (structure as in Fig. 14) that consists of one or more convolution layers (convolution layer) [27], including two most important operations: convolution and pooling. The convolution layer uses the convolution operation instead of the matrix multiplication operation, which serves to detect the local connectivity of the features in the previous layer; the pooling layer serves to merge similar features [27].The features of a CNN include 1) sparse connectivity, 2) weight sharing, and 3) pooling. The convolution operation of the convolution layer is defined as follows:

$$z_j^{(l)} = \sum_{i=1}^{I} w_i^{(l)} a_{i+j-1}^{(l-1)} + b^{(l)} \tag{12}$$

In this context, *i* signifies the identifier for the convolutional kernel, while l serves as a marker for the active convolutional layer, with $l-1$ representing its preceding layer. The dimension of the convolutional kernel is denoted by I . Post-convolution operations, the resultant feature map is referred to as $z_j^{(l)}$, which is derived from the shared weights $w_i^{(l)}$, the activation outputs of the preceding layer $a_{i+j-1}^{(l-1)}$, and adjusted by the bias term $b^{(l)}$ associated with the convolutional layer

2) Algorithm application: In order to portray the mapping relationship between the constructed ELT competence assessment indicators and the assessment scores, this paper adopts CNN to construct the ELT competence assessment model, as shown in Fig. 18. The algorithm applies the input as the value of English teaching ability index and the output as the assessment score and ability level.

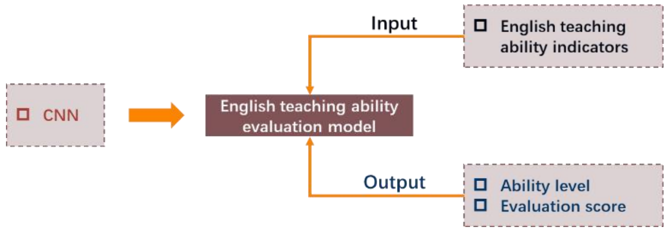


Fig. 14. CNN network application.

IV. Algorithmic Application Process Methodology

This manuscript introduces an innovative approach to evaluating the proficiency in English language instruction by fusing the DPC-K-means clustering technique with convolutional neural networks (CNNs), as depicted in Fig. 15. The methodology for appraising English teaching skills is delineated through the following sequential stages:

- Step 1: A thorough analysis of the English teaching proficiency assessment is conducted, identifying key features across five dimensions—objectives, content, language, methodology, and outcomes—to forge a comprehensive indicator system for evaluation purposes;
- Step 2: Data pertaining to English Language Teaching competencies are sourced through expert deliberation, literature synthesis, and surveys, followed by a meticulous preprocessing regimen involving the 3σ criterion, imputation of missing data via proximity methods, standardization through Z-score normalization, and dimensionality reduction via principal component analysis;
- Step 3: The DPC-K-means algorithm is harnessed to perform clustering on the meticulously preprocessed indicator data, thereby categorizing the data into distinct groups;
- Step 4: The CNN framework is then engaged to cultivate the correlation between the quantified indicators of English teaching proficiency and their corresponding assessment scores, effectively mapping the data to defined scoring echelons;
- Step 5: Validation analysis of the proposed ELT competency assessment method using the test set.

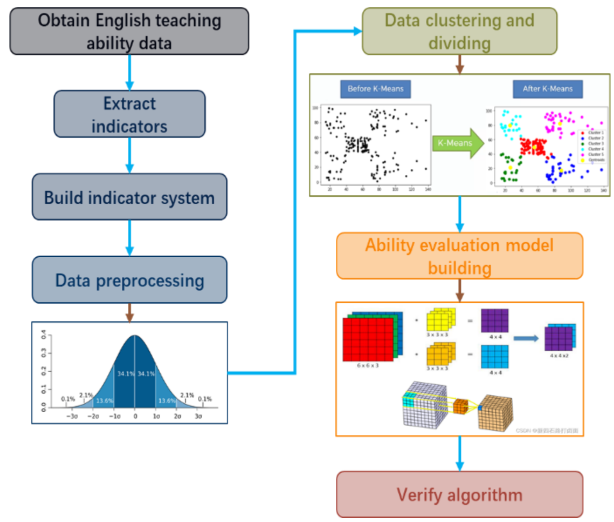


Fig. 15. Flowchart of algorithm application.

V. Experimental Analysis

A. Experimental Environment Design

To substantiate the practicality of the English teaching ability assessment method that integrates DPC-K-means and CNN algorithms, this study scrutinizes the data collected from English teaching index measurements. In this evaluation, a quintet of algorithms has been selected for comparative analysis. Table II enumerates the configuration parameters for these comparative algorithms, with the DPC-K-means-CNN being the algorithm posited by this paper, alongside others for comparative purposes.

TABLE II. Parameter Settings of Clustering Algorithm

Name	Composition method	Parameterisation
DPC-K-means-SVR	DPC-K-means SVR	SVR regularisation factor 1, kernel function is radial basis kernel function The number of K-means clusters is 5
DPC-K-means-RBM	DPC-K-means RBM	RBM with a learning rate of $10e^{-3}$ K-means clusters set to 5
DPC-K-means-ELM	DPC-K-means ELM	ELM featuring 50 nodes in the hidden layer K-means clusters set to 5
DPC-K-means-BP	DPC-K-means BP	Backpropagation (BP) training with 60 hidden layer nodes K-means clusters set to 5
K-means-CNN	K-means CNN	CNN with 100 nodes in the hidden layer network is 100, utilizing Adam's optimization K-means clusters set to 5
DPC-K-means-CNN	DPC-K-means CNN	CNN with 100 nodes in the hidden layer network is 100, employing Adam's method K-means clusters set to 5

The experimental simulation environment uses Matlab programming language and the system is Win10.

B. Parametric Analysis

The determination of clustering precision is significantly influenced by the selection of the number of cluster centers. With the aim of enhancing the accuracy of the model and accelerating the efficiency of the assessment process, this study delves into the impact of varying the number of clusters from two to ten on the model's accuracy, with the outcomes graphically represented in Fig. 16. A visual analysis of the figure reveals that at the threshold of five clusters, the DPC-K-means-CNN algorithm achieves the optimal precision in evaluating the capabilities of English language instruction Fig. 17 gives the results of the principal component analysis of the indicators of English proficiency assessment based on PCA technique. From

Fig. 17, when the indicator reaches 15, the cumulative contribution reaches 90 per cent.

C. Contribution of Indicators

An evaluation was conducted on the models DPC-K-means-SVR, DPC-K-means-RBM, DPC-K-means-ELM, DPC-K-means-BP, K-means-CNN, and DPC-K-means-CNN using a dataset comprising the profiles of 30 educators. The findings are detailed in Fig. 18 (a)-(f) and Tables III and IV. A review of Fig. 18 indicates that the method underpinned by the DPC-K-means-CNN algorithm outperforms others in terms of precision, with its assessment of English teaching proficiency closely mirroring the actual levels of competence.

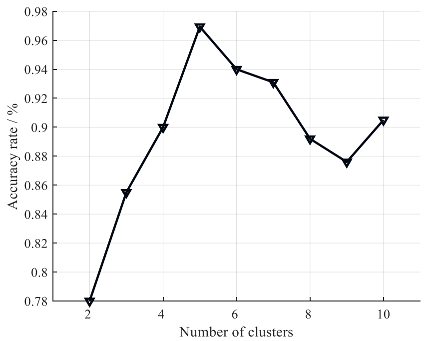


Fig. 16. Accuracy with different number of clustering centres.

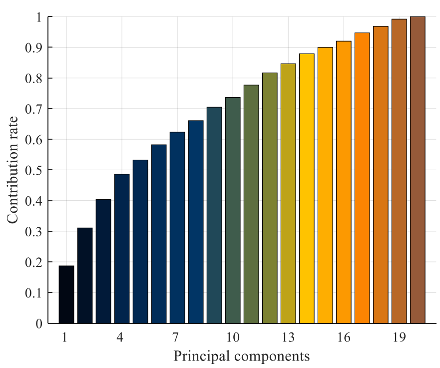
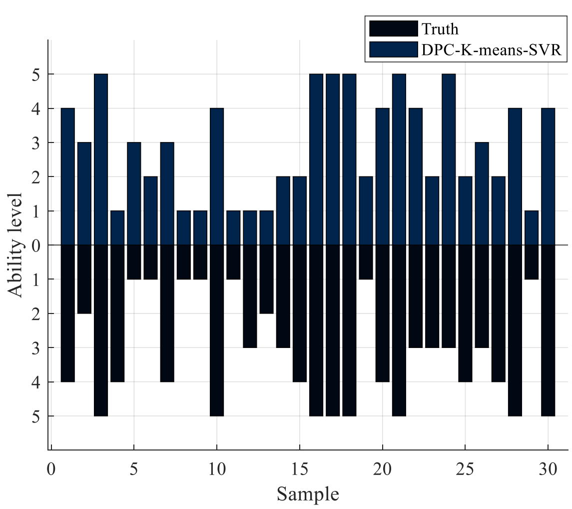
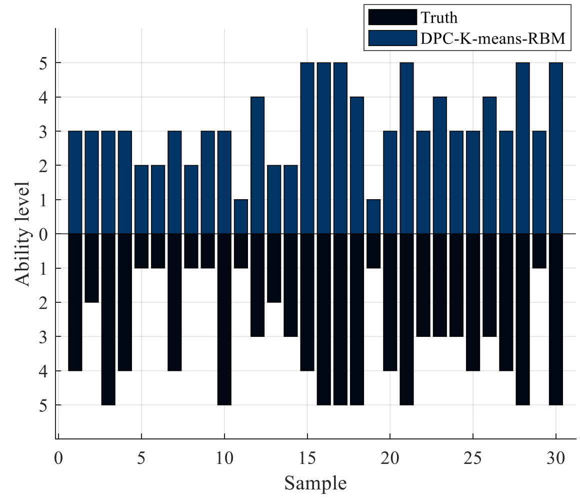


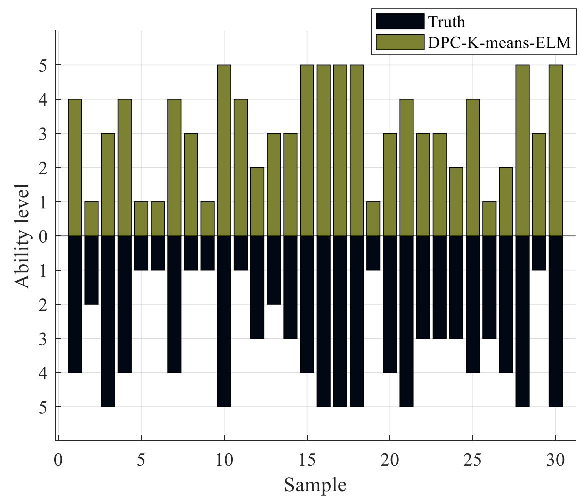
Fig. 17. Contribution of indicators.



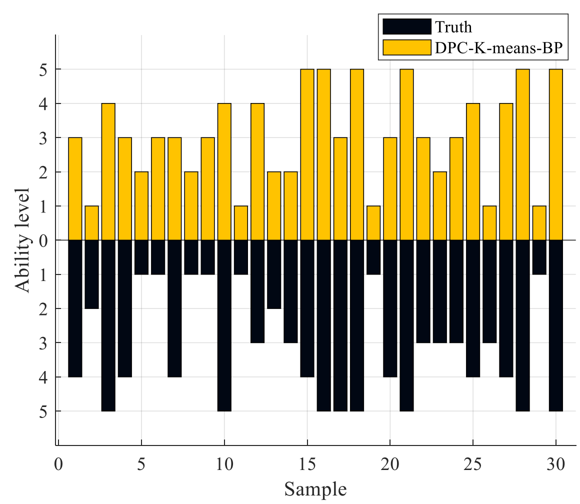
(a) DPC-K-means-SVR.



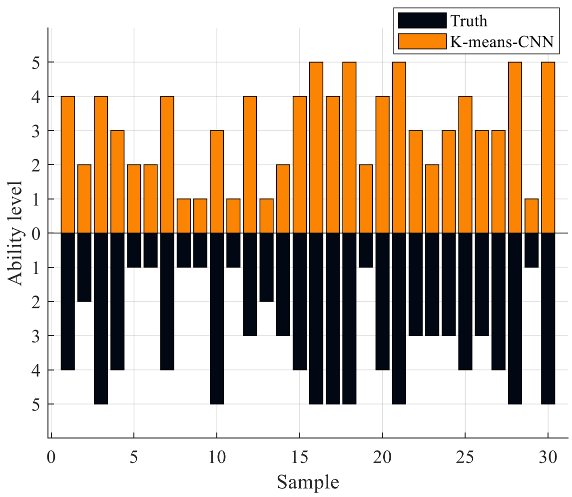
(b) DPC-K-means-RBM.



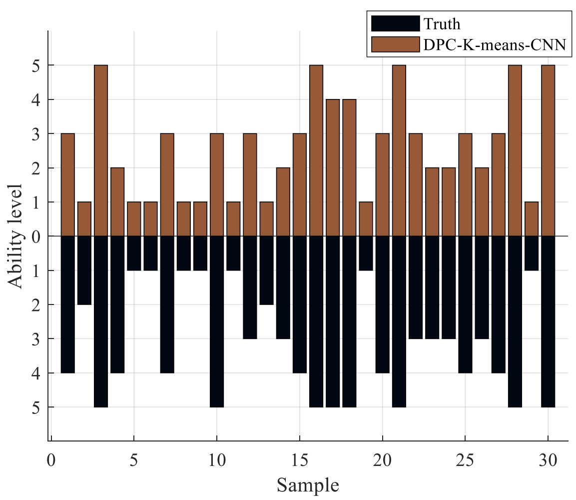
(c) DPC-K-means-ELM.



(d) DPC-K-means-BP.



(e) K-means-CNN.



(f) DPC-K-means-CNN.

Fig. 18. Comparison of assessment level results for different fusion assessment algorithms.

Upon examination of Table III, it is evident that the clustering of teaching ability data utilizing the DPC-K-means-CNN model yields the highest Silhouette Index (SI) value, with K-means-CNN, DPC-K-means-BP, DPC-K-means-RBM, DPC-K-means-ELM, and DPC-K-means-SVR trailing in sequence; concerning the CHI value, the DPC-K-means-CNN model demonstrates the most substantial ratio of inter-cluster to intra-cluster distance, peaking at 81.4, ahead of the DPC-K-means-BP, K-means-CNN, DPC-K-means-RBM, DPC-K-means-ELM, and DPC-K-means-SVR algorithms; regarding the Davies-Bouldin Index (DBI), the DPC-K-means-CNN algorithm exhibits the lowest average similarity score of 0.79 when comparing each cluster to its nearest cluster, outperforming alternative methodologies. A holistic assessment confirms that the DPC-K-means-CNN algorithm achieves superior clustering performance.

From Table IV, it can be seen that the DPC-K-means-CNN evaluates the best score prediction performance when analysed in terms of MAE, MAPE, and RMSE, with values of 0.0108, $2.7053e^{-04}$, and 0.0122, respectively.

TABLE III. DATA CLUSTERING RESULTS

Arithmetic	SI	CHI	DBI
DPC-K-means-SVR	0.12	34.2	1.18
DPC-K-means-RBM	0.29	56.1	1.41
DPC-K-means-ELM	0.28	37.3	1.23
DPC-K-means-BP	0.31	78.3	1.21
K-means-CNN	0.37	76.1	0.83
DPC-K-means-CNN	0.40	81.4	0.79

TABLE IV. RESULTS OF THE CAPACITY ASSESSMENT

Arithmetic	MAE	MAPE	RMSE
DPC-K-means-SVR	0.0506	1.2650e-03	0.0589
DPC-K-means-RBM	0.0323	8.0814e-04	0.0388
DPC-K-means-ELM	0.0492	1.2300e-03	0.0590
DPC-K-means-BP	0.0390	9.7548e-04	0.0447
K-means-CNN	0.0248	6.2057e-04	0.0291
DPC-K-means-CNN	0.0108	2.7053e-04	0.0122

VI. CONCLUDING REMARKS

The pursuit of an intelligent and precise system for evaluating English teaching skills stands as a pivotal aspect of the reform in English education, with the dual benefit of elevating the instructional proficiency of teachers and solidifying the neutrality of the criteria used in educational administrative decisions. This paper advances an assessment methodology that integrates clustering algorithms with advanced recognition techniques, thereby enhancing both the precision and the objectivity of the evaluation process. By dissecting the complexities inherent in assessing English teaching capabilities, the paper formulates a strategy that leverages the strengths of data clustering and optimized training routines. It presents a scheme for evaluating English teaching ability that synergizes the DPC-K-means clustering approach with the analytical prowess of convolutional neural networks (CNNs), scrutinizing the critical technologies underpinning this method. The paper introduces a novel clustering and categorization technique grounded in the DPC-K-means algorithm, complemented by an assessment methodology that harnesses the predictive capabilities of CNNs for English teaching proficiency indicators. Utilizing a dataset comprising the teaching ability indicators of 30 educators, the paper validates the proposed method's feasibility and scrutinizes its performance through established clustering and predictive metrics. The analysis affirms the proposed method's preeminence in clustering efficacy, reflected in the superior values of SI, CHI, and DBI—0.40, 81.4, and 0.79 respectively. Furthermore, the method demonstrates the minutest error in predictive assessment, with MAE, MAPE, and RMSE values recorded at 0.0108, 2.7053e-04, and 0.0122 respectively.

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