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*Research Article*

# An English Diagnostic Intelligence Evaluation Model Based on Organizational Evolutionary Information Entropy

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English is widely used as a universal language in the world, but there are still great limitations in the diagnosis and evaluation of English, which leads to serious errors in the actual use of English. In order to realize the English diagnostic intelligence evaluation, improve the English learning ability, and construct the cognitive framework of English learning, this study proposes an English diagnostic intelligence evaluation model based on the organizational evolution information entropy. Firstly, this study adopts the HRNet text feature extraction model and uses the pretrained model to extract text features from text. Secondly, this study adopts the organizational evolution algorithm to simulate the process of sorting, merging, and cooperating in the evolution of the population and classify and organize the characteristic population. Finally, the information entropy method is used to represent the amount of information contained in each feature for evaluation, and the optimal solution is found. The method proposed in this study has good experimental results in actual testing and comparison and can basically realize the function of English diagnostic intelligence evaluation.

## 1. Preface

As one of the most common languages in the world, the reception and transmission of information in the process of English learning has a special status in practical applications [1, 2]. The English diagnostic test [3, 4] serves as a learning strategy to detect learners' vocabulary mastery and use [5, 6] and the entire process of English learning [7] and is an effective way to learn English. On the one hand, English diagnostic evaluation helps learners to master their own learning status and timely check and fill in gaps [8, 9]; on the other hand, it can help teachers to grasp students' learning loopholes [10, 11], carry out targeted teaching activities, and improve students' learning ability [12, 13]. English diagnostic evaluation is widely used, including self-study [14, 15], classroom teaching [16, 17], practical communication [18], text reading [19], and other scenarios.

With the continuous development and progress of cognitive diagnostic theory, language cognitive diagnostic testing has gradually become the focus of current research. The production of language cognitive diagnosis is mainly composed of the integration of relevant professions and technologies such as cognitive psychology, measurement psychology, modern statistics, and computer science. With the continuous progress of cognition, people are not satisfied with the macroscopic test results provided, but pay more attention to the process of exploring the whole cognitive test, which is more obvious in English diagnosis. With the continuous progress of cognition, people are not satisfied with the macroscopic test results provided, but pay more attention to the process of exploring the whole cognitive test, which is more obvious in English diagnosis.

According to the research status of English diagnostic research at home and abroad, there are certain deficiencies. (1) There is a lack of theoretical test guidance, and it is not updated in principle, but refurbished. The diagnosis in the field of English testing is still in the stage of exploration and small-scale application, and the testing and verification of large-scale examinations has not yet been carried out. Testing researchers lack specific diagnostic testing principles to guide, lack understanding of the steps and principles of English diagnostics, and are easily limited by current testing methods and testing conditions. (2) The definitions of diagnostic attributes are different, and there is great controversy. The factors and attributes of diagnosis have a great influence on the accuracy and rationality of the results of English diagnosis, and different attributes ultimately affect the effect of the experiment. The current related research and technology lack the corresponding English proficiency framework and systematic language theory support; it is difficult to select the corresponding attributes correctly, and it is difficult to guide the determination and classification of attributes. There is a considerable controversy among researchers on the definition and quantity of attributes. At the same time, the granularity of attributes is difficult to control, and the granularity of test attributes included in the diagnosis is too simple and rough, resulting in a wide range of attributes, and it is difficult to determine the role of diagnostic information. On the contrary, the granularity of attribute information included in the research process is too fine and the quantity is too large, which affects the classification accuracy and prediction efficiency of English cognitive diagnosis. (3) The diagnosis object is single, and the group cannot be diagnosed. Most of the diagnosis objects of English diagnosis are individuals, and they are more inclined to find problems from individuals and only focus on individual-level diagnosis, which can effectively provide individual diagnosis information. However, the differences between different testers are relatively large, and the diagnostic information is too fragmented to provide test information for the entire group, and it is difficult to timely feedback group information. The current group diagnosis is still under continuous research, and it is still difficult to perform tests by groups and categories. (4) There are few diagnostic reports, which are out of touch with practical applications. The current English diagnosis is mostly a proficiency test, and the results of the test are difficult to link with the actual use, so many researchers do not pay attention to the diagnosis report. The diagnostic information in the score reports of the current research and literature is very one-sided, with less information, mostly descriptive language, and lack of quantitative methods and operability. In general, there are many problems in the field of English diagnostic intelligence evaluation, and there is a lack of scientific and reasonable methods to quantify and deal with the problems.

English diagnostic evaluation has a very important role, but the effect in actual practice is not optimistic. Usually lack of corresponding evaluation knowledge and ability and evaluation time and energy results in the current English evaluation being still dominated by English dictation. Because the evaluation method is single, it is difficult to evaluate the relationship between actual use and vocabulary storage, and the evaluation effect is not obvious. With the development of science and technology, machine learning methods and deep learning methods are gradually applied in life [20, 21]. In terms of text feature extraction and understanding [22], organizational evolution algorithm [23, 24], information entropy method [25, 26], neural network model [27, 28], and other methods [29, 30] are gradually applied to this task [31, 32], and good experiments have been achieved effectively [33, 34]. At the same time, it provides a good experimental basis for the English diagnostic intelligence evaluation task in this study.

Aiming at the problems of lack of theoretical guidance and inconsistent evaluation standards in traditional English evaluation methods, there is an urgent need for a method to improve the single mode of English learning evaluation methods, enrich English diagnosis methods, and improve evaluation effects. This study proposes an English diagnostic intelligence evaluation model based on organizational evolutionary information entropy, which can evaluate English learning ability from multiple perspectives. In addition, it has a high degree of intelligence, reduces the investment of manpower and capital, and has great advantages in improving English learning important practical significance.

## 2. Related Work

*2.1. Organizational Evolution.* In 1995, Wilcox introduced the concept of organization into the classifier based on genetic algorithm and proposed a classification algorithm of organizational co-evolution. It puts the characteristic data in each organization, realizes the co-evolution between organizations through methods such as division, merger, and cooperation between organizations, and then extracts rules from the evolution process. In the process of continuous evolution, the population structure can use the searched optimal solution and the information of leaders in the organization to guide the model to continuously explore and converge to the vicinity of the optimal solution. In the algorithm of organizational evolution, the entire population is formed through a certain number of organizations. In the process of evolution, these groups continuously interact with each other to increase the diversity and different characteristics of the organization, avoid the situation of the organization falling into the local optimal solution in the process of continuous evolution, and reduce the probability of falling into the local extreme value. Although organizational evolution methods imitate the phenomenon of actual social evolution and show good performance, they do not make full use of the feature information in the organization when dealing with optimization problems and are still difficult to deal with high-dimensional features. Therefore, it is necessary to use other methods to better extract high-latitude features.

*2.2. Information Entropy.* Information entropy is one of the main indicators used to measure the dispersion of the set, and it can also reflect the amount of information contained in different data sequences. It is widely used in tasks such as text classification, text extraction, and image segmentation. Using information entropy, a suitable adaptive scale operator can be constructed so that the network model can classify different types of features, adaptively adjust the scale and scale of the organizational structure, and improve the learning effect of the entire model for texts and populations. Since text features are easily affected by context, this study introduces feature functions into information entropy through references and constructs a new feature information function based on text feature information statistics. Since the main function of the entropy function is to describe the amount of information contained in the organization, it is now introduced into the task of English diagnostic intelligence evaluation to describe the number of text features contained in different organizations, which is equivalent to the evolving organization. Each type of feature value has a corresponding attribute or organization. It can effectively overcome the influence of contextual features, can reduce the influence of irrelevant text feature vectors, noise, and multiword meanings, and has achieved good experimental results in text feature extraction.

*2.3. English Diagnostic Method.* The traditional diagnostic test intelligently reports the total score of the participants, reflecting the overall level of the subjects and their position in the group [35, 36]. There are big problems in the preface research of English intelligent diagnosis at home and abroad, which are mainly divided into several categories [37, 38]. (1) The field of English diagnostics lacks the guidance of evaluation theory to achieve theory-oriented test development. Although many experts and scholars have been doing innovative work at present, the innovation of theory and method cannot be realized. (2) Different cognitive attributes determine different influencing factors, and the choice of factors has a greater impact on the final result. The selection of attributes and factors is now highly controversial. (3) The object of diagnosis and testing is single, and it is more inclined to diagnosing individuals and cannot diagnose and test organizations and groups. (4) The diagnosis report cannot be quantified and is mostly descriptive language, which is out of touch with the actual use environment. Cognitive diagnosis is a combination of psychology and psychometrics, which reflects the tester's mastery of a certain characteristic knowledge point and can describe the tester's proficiency in language knowledge structure and skills in detail [39]. Compared with the previous method, the English diagnostic intelligence evaluation method is based on the previous basis, using the technology to achieve automation and intelligence to more accurately describe the tester's learning status. At the same time, it can intelligently locate the knowledge point loopholes in learning, which is convenient for teaching and learners to check and fill in the gaps and improve continuously.

*2.4. Text Feature Extraction.* Turn text data into vector data, and learn more language features from text data in vector data [40, 41]. In other words, the text is not treated as a string, but as a vector that is more convenient to process mathematically, which is the core problem of text feature extraction [42, 43]. The method based on the neural network model is to create a network model, through continuous iterative learning, and finally obtain the conditional probability of each word based on its context [44, 45]. At the same time, during each iteration, the model can evaluate the error and punish those parameters that cause errors according to certain update rules [46]. Text feature extraction based on neural network tends to be mature, which has established a solid foundation for subsequent tasks. In this study, we will use text feature extraction as the basis for the English diagnostic intelligence evaluation task.

## 3. English Diagnostic Intelligence Evaluation Model

The English diagnostic intelligence assessment is used to diagnose students' reading and writing levels, find their existing problems, provide effective feedback information for students and teachers, and make targeted enhancements and improvements in subsequent learning and teaching. Most of the current studies are mainly English diagnostic tests designed by classification methods, define English assessment methods as English tests under specific conditions, and do not establish a reasonable connection and explanation between the English assessment process and the results. The main problems of English intelligent diagnosis are that the evaluation method is not uniform, the degree of automation and intelligence is low, and it requires a lot of manpower and material resources.

To solve this problem, this study proposes an English diagnostic intelligence evaluation model based on organizational evolutionary information entropy. First, this study introduces the HRNet text feature extraction network and uses the pretrained neural network to extract the feature information corresponding to the English text in Figure 1. Since the HRNet network adopts the fusion of multiscale features and multistage learning, it collects rich text feature information, and at the end of the network, it can output multidimensional text features through multilevel fusion. Secondly, this study inputs the collected text feature information into the organizational evolution module and classifies and organizes different types of feature information through the split operator, merge operator, and cooperation operator. Finally, the difference between the predicted text feature information and the label information is reduced by information entropy, and the entire network model is continuously improved to produce better prediction results. The HRNet text feature extraction network mainly extracts text features, which are multidimensional tensors.

*3.1. HRNet Text Feature Extraction Network.* The HRNet neural network is widely used in image and text feature extraction and other related tasks, focusing on outputting reliable high-resolution representations. The network model maintains high-resolution representations throughout the process, improving the prediction accuracy of various tasks. In this study, we use the HRNet text feature extraction network to extract the text features in the English test images for the subsequent task of English diagnostic intelligence evaluation. There are many kinds of text extraction networks and a wide range of applications. This study mainly adopts the pretraining model obtained in a large dataset in advance and then fine-tunes it in the dataset collected in this study, which is more suitable for the task of English text feature extraction.

In Figure 2, the HRNet neural network starts from the high-resolution subnetwork as the first stage and gradually

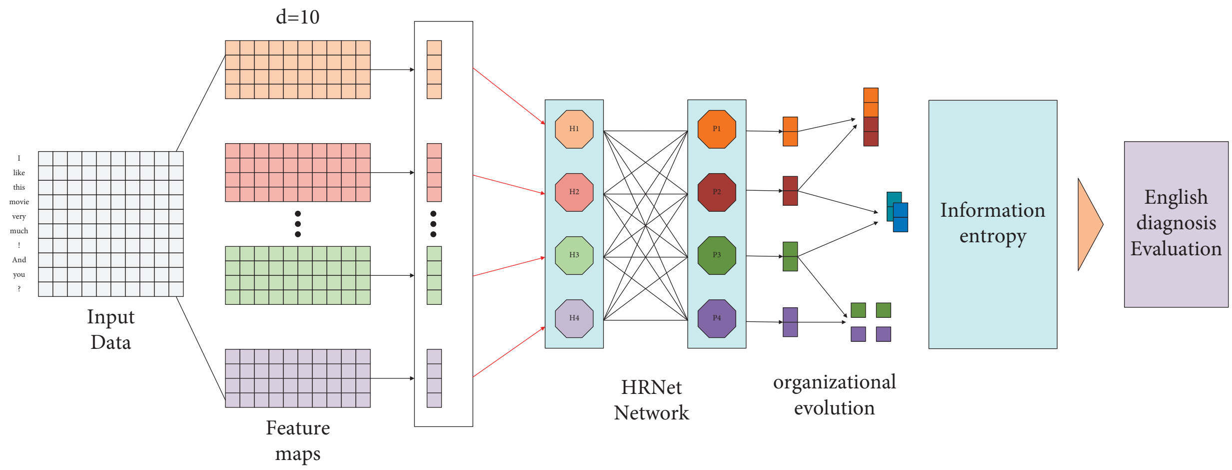


Figure 1: Structure diagram of the English diagnostic intelligence evaluation model.

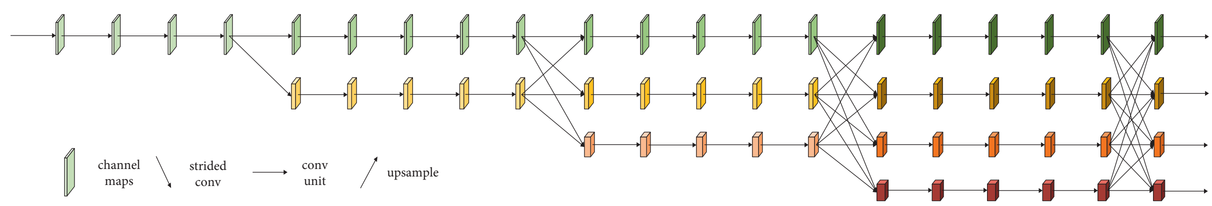


Figure 2: HRNet text feature extraction network.

increases the subnetworks from high resolution to low resolution to form more stages and connects parallel subnetworks of multiple resolutions. In stages 2, 3, and 4 of the network structure, multiple multiscale feature fusion modules are used to fuse multiscale features so that features of each resolution can repeatedly receive feature information from representations of other resolutions. Get rich high-resolution features:

$$N_{11} \longrightarrow N_{22} \longrightarrow N_{33} \longrightarrow N_{44}. \tag{1}$$

The current text feature extraction network in the image is to connect high-resolution to low-resolution self-networks in series. Each subnetwork forms a stage, which is composed of a series of convolution modules. The adjacent self-network modules are downsampling connect. As shown in formula (1), it represents the four stages of HRNet neural network:

$$\begin{array}{ccccccccccc} C_{31}^{1} & \searrow & & \nearrow & 2 & \searrow & & \nearrow & C_{31}^{3} & \searrow & \\ C_{32}^{1} & \longrightarrow & \varepsilon_3^1 & \longrightarrow & C_{32}^{2} & \longrightarrow & \varepsilon_3^2 & \longrightarrow & C_{32}^{3} & \longrightarrow & \varepsilon_3^3 \\ C_{33}^{1} & \nearrow & & \searrow & C_{33}^{2} & \nearrow & & \searrow & C_{33}^{3} & \nearrow & \end{array} \tag{2}$$

A switching unit across parallel subnets is introduced in HRNet neural network so that each subnet repeatedly accepts feature information from other parallel subnets. As shown in equation (2) and Figure 3, we take the third stage as an example. HRNet divides the third stage into several exchange modules, each of which consists of three parallel convolutional units and one exchange unit. The image features of the three parallel subnetworks are fused and learned through the exchange unit module. In the HRNet network, a $3 \times 3$ convolution is used for downsampling and a $1 \times 1$ convolution is used for upsampling. The images of the same resolution do not perform any operations, and the images are directly fused.

As shown in Figure 4, a represents the feature selection of HRNet V1, and only the feature image with the highest resolution is selected. B shows the feature selection of HRNet V2, which links and fuses feature images of all resolutions, mainly for semantic segmentation and monitoring tasks of key points in images. C represents the feature selection of HRNet V2p. Based on HRNet V2, a feature pyramid is used. In order to get a better effect of the network model on text extraction, we adopt the C network structure to improve the feature extraction ability of the network model.

### 3.2. Organizational Evolution Model

*3.2.1. Split Operator.* The main function of the split operator is to classify a large number of organizations into smaller ones in Figure 5. Different types of tiles in Figure 5 represent different types of data features. A threshold is designed in the algorithm. If the size or number of the tissue exceeds the corresponding threshold, it will be decomposed, and the split tissue will be put into the next generation of the population for subsequent tasks. For an organization *orG*, if *orG*> *orG* > max_os, split it into zero child organizations $orG_1$ and $orG_2$, where max_os is the threshold. The main function of the split operator is to balance the distribution of individuals in the organization which cannot achieve new solutions. However, it can prevent individuals from tending to the sameness in the organization and avoid the situation that the whole

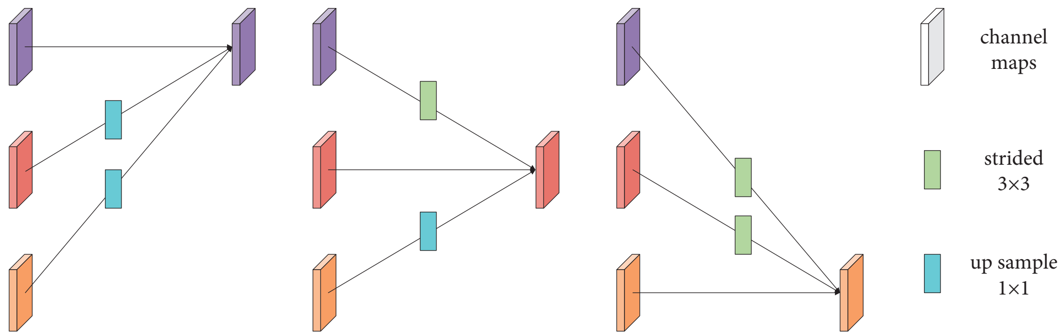


FIGURE 3: Multiscale text feature fusion.

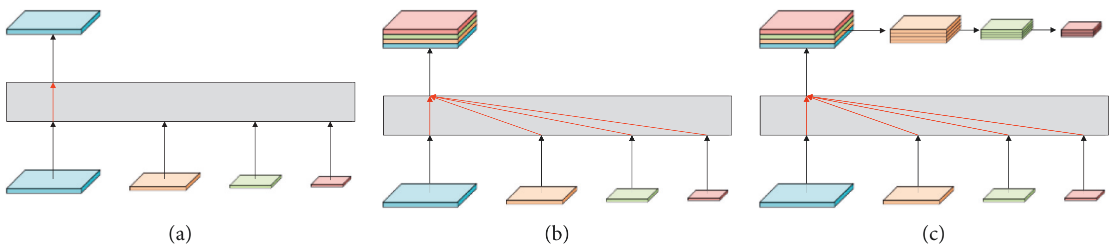


FIGURE 4: The last layer of the text feature extraction method.

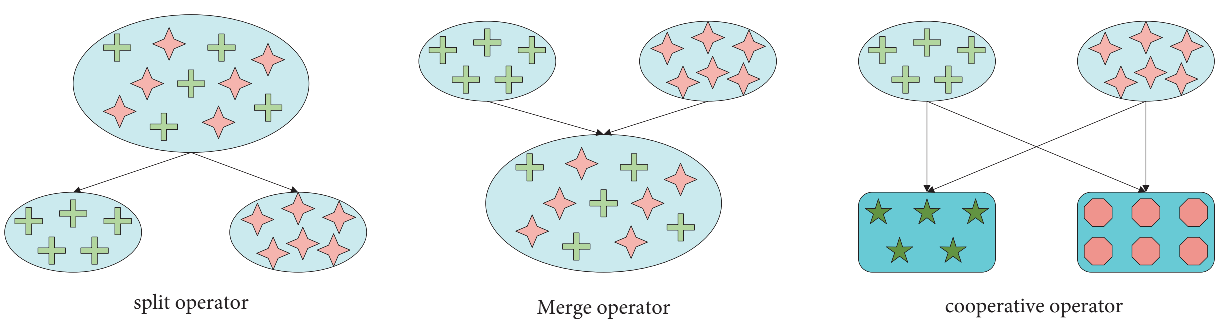


FIGURE 5: Organization evolution operator.

network model falls into the local optimal solution. Through the effect of the split operator on the entire organization, conditions are provided for the subsequent organizational evolution operator:

$$(|\mathrm{org}| > \mathrm{max\_os}) \mathrm{or} \left( (|\mathrm{org}| \leq \mathrm{max\_os}) \mathrm{and} \left( \frac{U(0,1) < |\mathrm{org}|}{N_0} \right) \right). \tag{3}$$

*3.2.2. Merge Operator.* The merger operator is a method designed to merge two organizations into a larger organization by modelling the relationship between competition and annexation between societies in Figure 5. Through the merger operator, two weaker organizations can be merged to form a larger organization with strength and scale. By continuously increasing its own strength, a better organization can be obtained. Merge the organizations $orG_1$ and $orG_2$ into a new organization $orG$. The essence of the merged organization is that a strong organization swallows a weak organization. The merge operator plays the role of distributing the distribution of individuals in the organization. It can also use the organization with high ability to search for new solutions and merge them into the new organization to further improve the organization's ability:

$$\begin{aligned}
ogG_1 &= \begin{Bmatrix} x_1 \\ x_2 \\ \cdots \\ x_p \end{Bmatrix}, x_i = (x_{i1}, x_{i2}, \ldots, x_{in}), i = (1, 2, \ldots, p), \\
ogG_2 &= \begin{Bmatrix} y_1 \\ y_2 \\ \cdots \\ y_p \end{Bmatrix}, y_j = (y_{j1}, y_{j2}, \ldots, y_{jn}), j = (1, 2, \ldots, q), \\
e_{jk} &= \begin{cases} x_k^a, x_k \times U(1 - sR, 1 + sR) < x_k^a \\ x_k^b, x_k \times U(1 - sR, 1 + sR) > x_k^b, k = (1, 2, \ldots, n). \\ x_k \times U(1 - sR, 1 + sR), \text{else} \end{cases}
\end{aligned} \tag{4}$$

*3.2.3. Cooperation Operator.* The cooperation operator is to improve their respective strengths through cooperation between two organizations in Figure 5. The essence is that two organizations $orG_1$ and $orG_2$ generate two new organizations $orG_{n1}$ and $orG_{n2}$. The new organization generated by the cooperation operator is added to the next generation group, and the original two organizations $orG_1$ and $orG_2$ are deleted at the same time.

$$
\begin{aligned}
ogG_1 &= \begin{Bmatrix} x_1 \\ x_2 \\ \cdots \\ x_p \end{Bmatrix}, x_i = (x_{i1}, x_{i2}, \ldots, x_{in}), i = (1, 2, \ldots, p),\\
ogG_2 &= \begin{Bmatrix} y_1 \\ y_2 \\ \cdots \\ y_p \end{Bmatrix}, y_j = \left(y_{j1}, y_{j2}, \ldots, y_{jn}\right), j = (1, 2, \ldots, q),\\
ogG_{n1} &= \begin{Bmatrix} r_1 \\ r_2 \\ \cdots \\ r_p \end{Bmatrix}, \in r_i = (r_{i1}, r_{i2}, \ldots, r_{in}), i = (1, 2, \ldots, q),\\
ogG_{n2} &= \begin{Bmatrix} s_1 \\ s_2 \\ \cdots \\ s_p \end{Bmatrix}, s_j = \left(s_{j1}, s_{j2}, \ldots, s_{jn}\right), j = (1, 2, \ldots, q),\\
r_{ik} &= \begin{cases} x_k^a, y_k + U(0,\ 1) \times \left(y_k - x_{ik}\right) < x_k^a \\ x_k^b, y_k + U(0,\ 1) \times \left(y_k - x_{ik}\right) > x_k^b, k = (1, 2, \ldots, n), \\ y_k + U(0,\ 1) \times \left(y_k - x_{ik}\right), \text{else} \end{cases}\\
s_{jk} &= \begin{cases} x_k^a, x_k + U(0,\ 1) \times \left(x_k - y_{jk}\right) < x_k^a \\ x_k^b, x_k + U(0,\ 1) \times \left(x_k - y_{jk}\right) > x_k^b, k = (1, 2, \ldots, n). \\ x_k + U(0,\ 1) \times \left(x_k - y_{jk}\right), \text{else} \end{cases}
\end{aligned} \tag{5}
$$

The three types of organizations mentioned above have different functions. Although the classification operator does not have the ability to search for new solutions, it can balance the role of organizational scale. The main function of the merge operator and the cooperative operator is to search for new solutions.

*3.3. Information Entropy.* Information entropy was proposed by the mathematician Shannon. It is one of the main indicators used to measure the dispersion of sets. At the same time, it can also reflect the amount of information contained in different data sequences. It is widely used in text classification and text extraction. In order to realize the task of English diagnostic intelligence evaluation, information entropy is used to determine the change relationship of different organizational structures, so each organizational structure constitutes a sequence, and information entropy is used to calculate the information amount of the features contained in each factor, that is, the weight $p_{ij}$, where $H(X)$ represents the information entropy value of the sample data $X$:

$$p_{ij} = \frac{p_{ij}}{\sum_{j=1}^{n} p_{ij}}, \quad i = 1, 2, 3, \tag{6}$$

$$H(x) = E(I(x)) = \sum_{i=1, j=1}^{n} p_{ij} \log \frac{1}{p_{ij}}. \tag{7}$$

According to Shannon's theorem, when the information entropy of the image $E = 0$, the information amount of the image is 0; when the probability distribution of each gray value in the image is uniform, that is, when the probability of all different pixels is equal, the information entropy of the image is equal. Maximum value can be obtained. For the English language, its language rules are the key elements of the English diagnostic intelligence assessment. According to the probability distribution of language rules, the information content of the language system can be calculated. Because of the amount of information, the system structure is more complex. On the contrary, the system structure is relatively simple. On contrary, the system structure is relatively simple than information entropy function. We use the standard function, which is expressed and explained in detail in equations (6) and (7)

## 4. Experimental Results and Analysis

*4.1. Dataset and Experimental Setup.* In the experiment, we use the WikiPeda corpus to train to obtain word vectors and use the Twitter phrase text dataset and the established English diagnostic intelligence evaluation dataset for training and testing. In this study, Adam optimizer is used for network model and fitting and optimization.

*4.2. Experimental Results and Analysis.* As shown in Figure 6, we use the multimodule test accuracy to represent the effect of English diagnostic intelligence evaluation. In the figure, A, B, C, and D, respectively, represent the spelling of words, the mapping of pronunciation, the grammar rules, and the correspondence between English and Chinese. From the figure, we can see that the accuracy of the test is not directly related to the number of participations, but its English-Chinese corresponding module scores are generally high, and the word spelling needs further improvement.

Figure 7 shows the mapping relationship between the spelling and pronunciation of a word in English, that is, the pronunciation of a word can correspond to the spelling of a word. Through the method of entropy calculation, we can clearly see the mapping rules between the spelling and pronunciation of American English and British English words, green represents British, and yellow represents American, and obviously British English is higher than American English, showing language rules' complexity.

Figure 8 shows the complexity of English grammar rules. In the figure, blue indicates low complexity, red indicates high complexity, and gradually transitions from blue to red. Usually, the independent variable is represented by the past tense of the verb and the degree of grammaticalization (two axes on the bottom), and the height is used to represent the degree of difficulty. We can see that the past tense of verbs

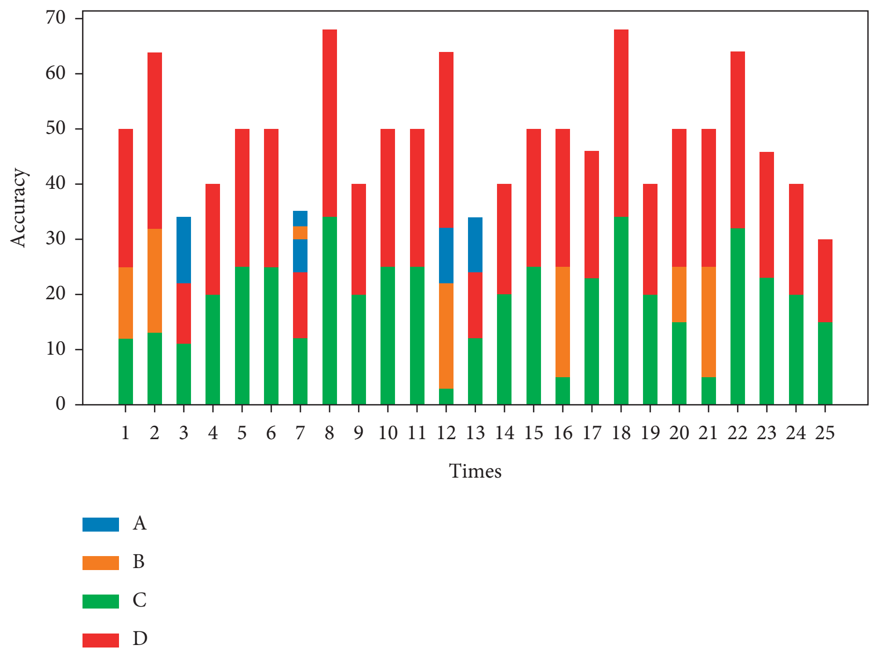


FIGURE 6: Multimodule test accuracy.

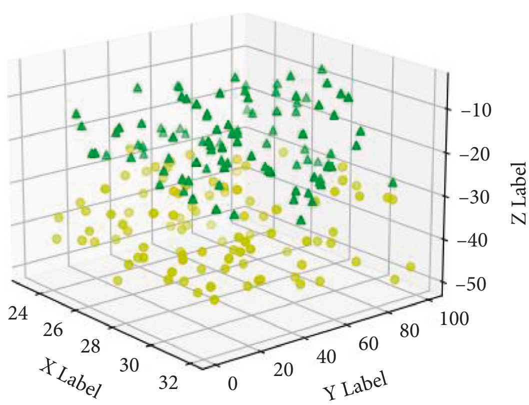


FIGURE 7: The relationship between word spelling and pronunciation.

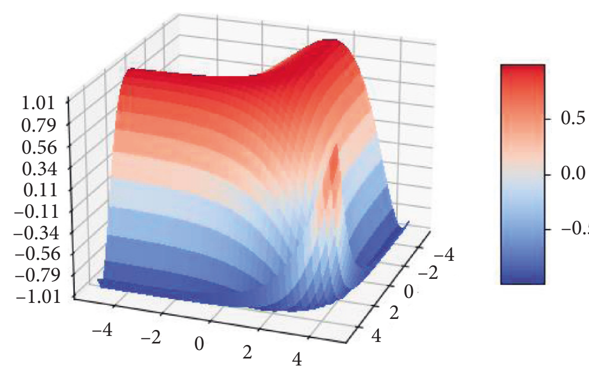


FIGURE 8: The complexity of grammar rules.

has a higher degree of difficulty and a higher entropy value in a certain area. Therefore, when learners learn such words, they need to use more vocabulary and examples to describe the use of these words completely.

Figure 9 shows the complexity of the semantics. As a symbol system, English has many meanings. Although these words have different meanings, they are generally divided into three types: (1) have the same extended meaning in both variants; (2) have the extended meaning in one variant and change in the other and there is no extended meaning in the body; (3) there are different extended meanings in the two variants. Figure 9 shows the connection between the three situations. From the figure, we can analyze the corresponding connection between each two situations.

Figure 10 shows a comparison of the accuracy of various network models and methods. In the image, the $x$-axis represents the interval between different test modules, the $y$-axis represents multiple testing methods, and the $z$-axis represents the corresponding accuracy of the methods. From the figure, we can see that the green area map of the method in this study has a better accuracy value and has a better fitting effect in the correspondence of multiple modules.

Figure 11 shows the confusion matrix, which corresponds to the comparison between the results predicted by the network model and the results of the label. From red to blue, the prediction effect of the model is shown to be very poor, and the value range is [0, 1]. The abscissa and ordinate represent the corresponding instances and labels. From the figure, we can see that some instances perform poorly, and we need to continue to improve and improve in future experiments.

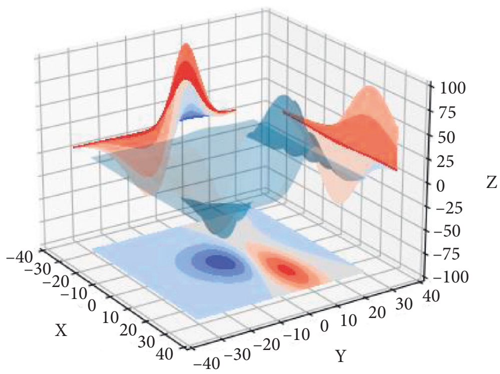


Figure 9: Semantic complexity relationship diagram.

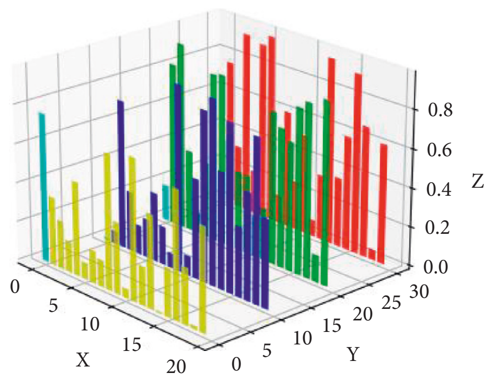


Figure 10: Accuracy comparison of multiple methods.

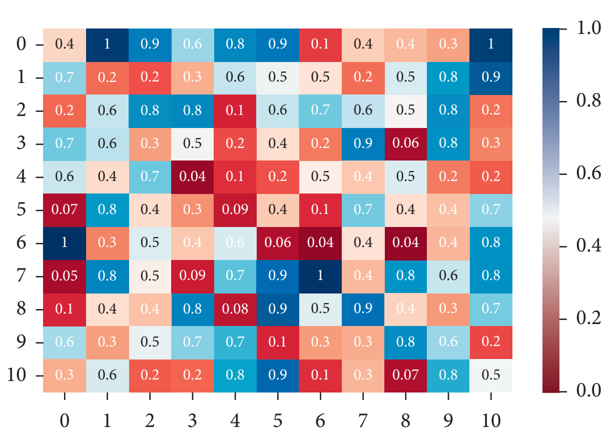


Figure 11: Confusion matrix.

## 5. Summary

This study proposes an English diagnostic intelligence evaluation model based on organizational evolutionary information entropy. This study firstly uses HRNet neural network to extract text features, then uses the organizational evolution method to simulate the population processing process of feature information, and finally optimizes the entire network model through information entropy to obtain the final optimal solution. Compared with other existing methods, the method in this study has better fitting effect and accuracy and has achieved good results in the evaluation of English diagnostic intelligence. In the follow-up work, we should pay more attention to the establishment and improvement of the network model, simplify the structure and complexity of the network model, and improve the prediction effect of the network model.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

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