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Exploration on the Practice of Translation Teaching for English Majors Based on the Internet of Things and Multimedia Assistance

Abstract: - In this paper, an automatic judgment algorithm of English text is proposed, which is split and filtered first, then extracted and optimized, and finally interactively fused, and a BP neural machine judgment system is designed. After machine judgment and teachers' self-judgment of the same English sentence sample, the test results show that the ETSS system has excellent performance, improves the reliability and accuracy of judgment, and reduces the degree of human intervention and misjudgment rate in English translation judgment work. The results of the model translation of the Generalized Maximum Probability Ratio Detection (GLR) algorithm and its recognition include nested data points so that accuracy cannot be effectively guaranteed. In the GLR based comprehensive evaluation of content recognition acquisition improvement, the ID accuracy rate exceeded 95%, and the total result was 92.3%.

Keywords: English translation, GLR algorithm; BP neural machine; evaluation system

I. INTRODUCTION

The current English noun phrase recognition methods include machine translation-based recognition methods [1-7]. Rule-based identification methods are often obtained automatically through the corpus or written by experts, so they are easy to understand, but they are weak in generality [8-11], time-consuming, and prone to ambiguity. It is simple, flexible, and is not based on a specific language model, but is currently a widespread translation algorithm. However, this method is based on a lot of sample data and is prone to over synthesis [12]. With the advent of artificial intelligence and machine learning methods, neural network-based nominal syntax recognition methods have been applied to English nominal syntax recognition. However, due to the complex rules of English grammar, the accuracy of the recognition of English notional phrases needs to be improved [13]. The education and teaching model based on artificial intelligence is a good way to solve this problem [14]. Artificial intelligence systems can achieve a

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certain level of intelligence by learning from a large number of sample data collected. For example, in the fields of image recognition, unmanned driving, and speech recognition, artificial intelligence has achieved excellent results. In some aspects, especially English translation, it can completely replace human work.

The intelligent evaluation system generally requires algorithm or model fusion to complete the representation of text features. The software extracts the lexical language and semantic features of the text, and then constructs the evaluation weight set according to the rules. Finally, the matching model is used to realize the evaluation and analysis of the English text [22] . The traditional English translation evaluation adopts the fixed weight method, that is, the percentage of each index is summed, and then the overall score is calculated. This fixed weight method is relatively simple, but the rationality of the weight of the data index cannot be guaranteed. [23] proposed to cut through the semantic discreteness and introduce a convolutional neural network training model to improve the text prediction ability. [24] proposed that the rhetorical devices of the article should be considered, and at the same time combined with the English corpus to automatically recognize the text and improve the accuracy of the system. [25] used an autoencoder to reconstruct linguistic features into feature vectors, and obtained good robustness and predictive ability through SVM model training.

Based on the above summary, the use of computer algorithms to optimize English translation work is an urgent problem.

II. LANGUAGE INTELLIGENT RECOGNITION ALGORITHM

2.1 Phrase corpus construction

Corus plays an important role in intelligent English translation mode. By storing the grammar data in the set, the short parts of Chinese and English words can be accurately recognized and the functions of each word can be standardized. In addition, it greatly improves the accuracy and timeliness of automatic identification of English and Chinese codes. Chinese English automatic translation is more accurate in Chinese English translation. The conventional translation of Chinese and English includes converting long sentences into several pairs of short words, and then using a recording algorithm to evaluate the quality of Context Translation and translation for word groups, and expanding the marking range. This method is feasible. Figure 1 shows the flow of ferry group information.
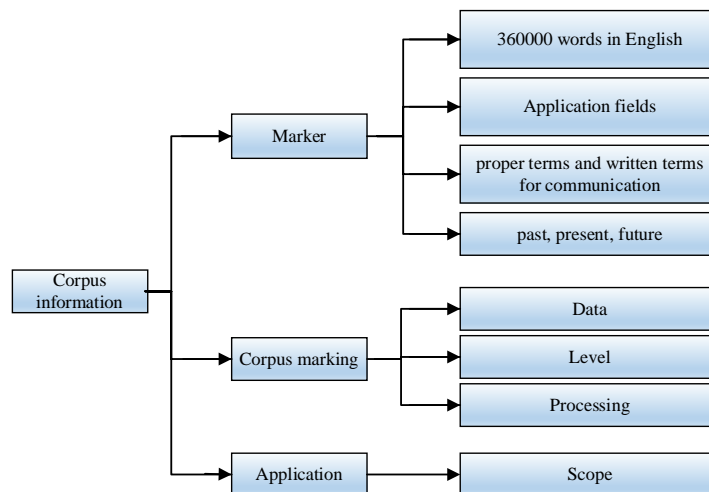

Figure 1: Phrase Corpus Information Flow

2.2. Language corpus part-of-speech recognition

In general, because GLR algorithms are more likely to recognize parts of speech, the recognized data points are more likely to be coincidences, which still do not meet the accuracy of recognizing parts of the current speech. This white paper proposes to improve the classic GLR algorithm and analyze the structure of the statement using a gateway center to effectively reduce the possibility of data point synchronization and improve the accuracy of recognizing parts of the voice. The likelihood calculation of the improved GLR algorithm for the context of the phrase is realized by means of quaternary clustering, and the algorithm is shown in formula (1):

$$G_\Sigma = \left(V_N V_T, S, a \right) \quad (1)$$

Formula (2) can be obtained by derivation:

$$p \rightarrow \{\theta, c, x, \delta\} \quad (2)$$

2.3 Correction

At present, English-Chinese machine translation algorithms, the result obtained by matching a hashed phrase to a corpus syntax is often used as the final machine translation result, The context of the ball has not been analyzed and depends largely on the analysis of the language used to generate the final result. The translation is inaccurate. Therefore, this document also considers modifying some of the analysis results of the statement. In the analysis process, the analysis part is to improve the GLR algorithm. GLR uses the linear table analysis algorithm to identify some descriptions caused by errors.The flow of the correction algorithm is shown in Figure 2.
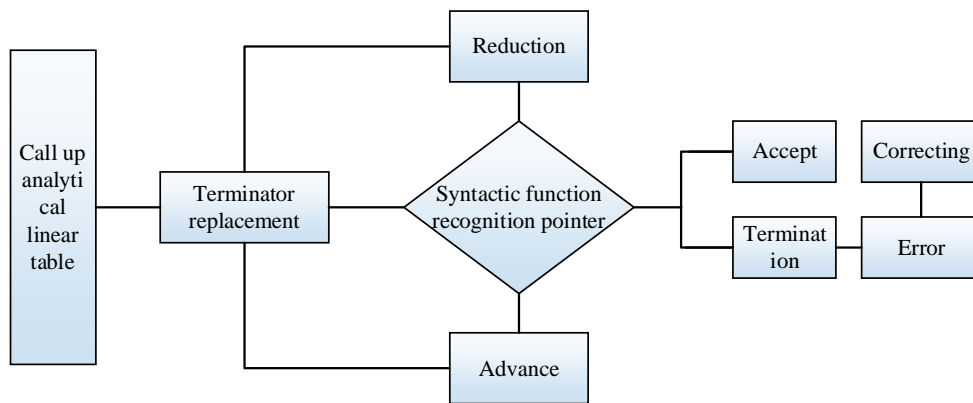

Figure 2: Flow chart of intelligent recognition algorithm correction

From Figure 2, we can see the relationship between the reduction and the promotion index, and the specific relationship is shown in Table 1.

Table 1 Comparison of reduction and propulsion commands

Name	Similarities	Difference
Reduction	The functions of the two are similar	The reduction means that the previous restrictions are ineffective or there are problems with the trading process, and it is necessary to clarify the limits that re-recognize the

		grammatical function.
Advance		Advance points out that in the constant recognition of grammar functions. Then you need to call the analysis linear table again and basically distract a portion of the consensus speech recognition results.

While the enhanced GLR algorithm is running, you must select a pointer type before replacing the terminator. In the case of a reductive indicator, it is necessary to detect whether the constraint state of the indicator exists in the corpus statement, and if it does not exist, enter it directly into the exit indicator. The termination indicator usually appears at the backup point location along with the structural ambiguity. When querying the exit pointer, a gateway structure tree is formed and a stack of icons is displayed to check whether the center point icon of the backup point exists or not. If there is no incorrect position or position in terms of the exact structure of the sentence, the algorithm calls an error indicator to correct the result of recognizing a portion of the speech.

III. ANALYSIS ALGORITHM BASED ON GLR

The analysis process for each analysis table and each analysis table for the analyzer is similar to the GLR algorithm:

(1) The comparative table analysis includes five measures, including "conversion", "restriction" and "unchanged". "End" and "error" indicate the "error" of the comparison table whose analysis has been completed. The "error" can be divided into two categories: the "end" scheme does not consider the analysis failure, but still retains the current situation. In other words, redefine the currently closed input system in the ratio table analysis and continue the analysis. An "error" in the terminator on the analysis table is considered a failure of the analysis, restores the analysis metrics to the pre-analysis location, and then terminates the analysis in this analysis table.

(2) When you try to reduce it using a rule, check the limits of the rule, and if the value of the conditional logical function is correct, perform a collapse, otherwise perform an exit procedure.

(3) There are multiple cases where a multi-output analysis table, that is, an analytic table, performs a "receive" operation under a terminator, and each "receive" corresponds to a recognizable statement (at the top of the code stack).

(4) A symbol stack and a state stack are used in the analysis, and both of them perform stacking and popping actions at the same time. The symbol stack stores the child sibling tree that represents the symbol. A child sibling tree can effectively represent a tree structure of an indefinite number of child nodes. In the child sibling tree, each node has two pointers: child and sibling; when building a child sibling tree of a non-terminal symbol, first connect all child nodes in sequence with sibling pointers, and then use the child of the non-terminal symbol. The pointer points to the first child node.

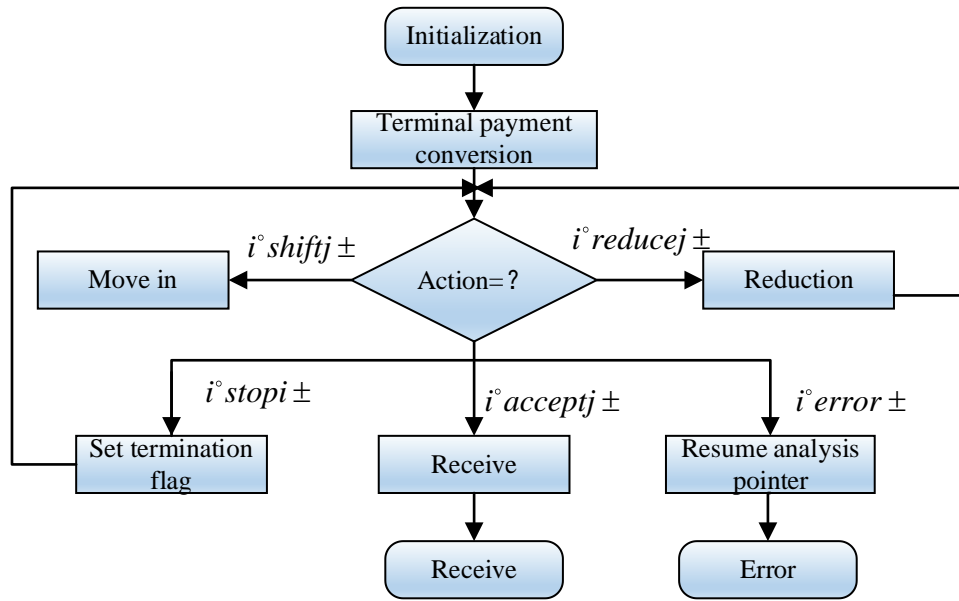The analysis algorithm based on GLR is shown in Figure 3.

Figure 3: GLR-based syntactic analysis algorithm

IV. ENGLISH TRANSLATION AUTOMATIC EVALUATION SYSTEM

4.1 System basic framework

The basic framework of the ETSS system is shown in Figure 4. The main functions of the system are divided into three core modules: text feature extraction, weight calculation and decision evaluation. The system uses the marked corpus, that is, the translation question text database of a university in the past 8 years, as well as the national college English level 4 and 6 corpus, to build a vocabulary quality evaluation model, a sentence beauty evaluation model and a sentence relevance evaluation model, and then The input text set is evaluated separately, and the BP neural machine model is used for comprehensive evaluation after integration.
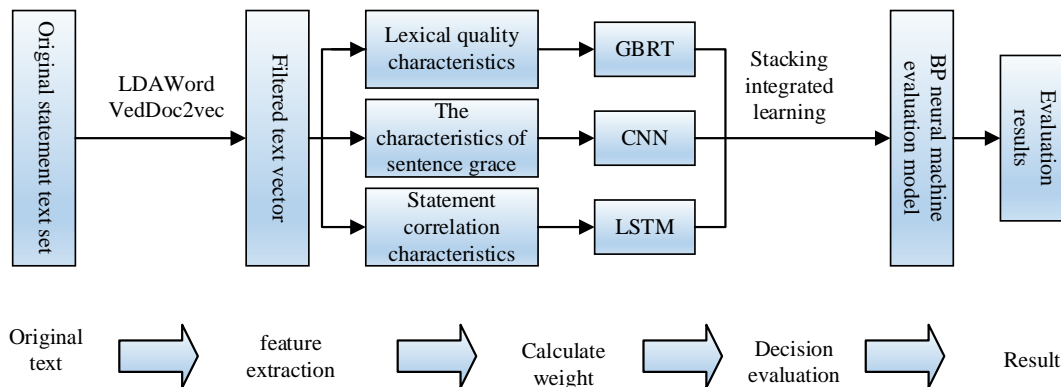

Figure 4: Basic framework of ETSS system

4.2 Extraction of ETSS feature vector

ETSS Feature Text Library. It can be seen from the system structure diagram in Figure 4 that the text database W of the ETSS system needs to establish a vocabulary quality evaluation text database $h[T]$, a sentence beauty evaluation text database $g[T]$ and a sentence relevance evaluation text database $l[T]$. , According to the

comprehensive summary, the basic characteristics of sentence text evaluation include word correct rate, average vocabulary length, number of high-frequency words, number of advanced words, proportion of nouns or adjectives or verbs, number of conjunctions, number of word blocks, advanced sentence patterns, 11 items such as key vocabulary professionalism, word granularity and sentence granularity. The different levels of the system constitute a progressive relationship, so the system database design first needs to analyze and integrate different types of text data and obtain the feature vector of the text. In order to quickly extract feature vectors, the ETSS system has specially formulated extraction standards and numbers, as shown in Table 2. In order to ensure that the system data query, modification and update can be saved in advance, it is necessary to adjust the text library system, which is not only conducive to data management, but also facilitates the system to modify the storage process of the required data according to actual needs and improves the portability of the system source code.

Table 2 ETSs system feature text library

Text library	Number	Features	Feature description	Characteristic degree	Weight
$h[T]$ Vocabulary Quality Evaluation Database	T_1	Word accuracy	Proportion of correctly spelled words	0%-100%	x_1
	T_2	Average vocabulary length	Obtained by median or standard deviation	2-20	x_2
	T_3	Number of high frequency words	Common unmarked words	1-8	x_3
	T_4	Number of advanced words	Commonly used marker words	1-5	x_4
	T_5	Proportion of nouns, adjectives and verbs	The proportion of the number of words with different parts of speech is calculated as the average	0-100%	x_5
$g[T]$ sentence grace evaluation Library	T_6	Number of connectives	It includes words and phrases indicating turning, juxtaposition, choice, cause and effect, etc	1-3	x_6

	T_7	Number of chunks	Including verb phrases, prepositional phrases, adverb phrases, adjective phrases, etc	1-5	x_7
	T_8	Advanced sentence pattern	Including emphasis sentences, clauses, inverted sentences, virtual hypothetical sentences, etc	Y/N	x_8
$l[T]$ Sentence relevance evaluation Library	T_9	Key words: Specialization	The rank of key words in the reference answers	1-5	x_9
	T_{10}	Word granularity	Describe the relevance characteristics of words	0-100%	x_{10}
	T_{11}	Sentence granularity	Describe the semantic dispersion of sentences	0-100%	x_{11}

4.3 Feature extraction algorithm.

The signs used to identify or distinguish text are features, and the vector space model VSM method is used here to filter and extract the feature information in the text. An English sentence text is represented by a feature vector. The vector includes feature items and weights. The feature vector extracted from the text directly represents the original text. Extracting the optimized feature vector is one of the key factors affecting the results of the system evaluation.

In the VSM model, English text is represented by a spatial vector $\left(T_1, X_1, T_2 X_{2,} T_j, X_j\right)$ to represent, where T_j is the feature item, and X_j is the basic weight corresponding to the feature item, which is used to define the importance of the feature item in describing the sentence text. In order to improve the accuracy and speed of feature item acquisition, the Doc2Vec method, NLTK and Stanford Parser toolkit are used here for text filtering, extraction processing (including counting, part-of-speech tagging, averaging, local maxima and minima, word frequency weighting, position weighting, syntax analysis, etc.

Figure 5 shows the filtering and extraction method of the feature vector. The text is parsed through Doc2Vec to obtain text vector features, and the feature details are obtained through NLTK and Stanford Parser toolkit sampling. The second layer decomposition is the same, and the space division is more detailed. The text feature degree cannot be obtained only by one-time filtering and extraction, and the filtering should be repeated several times in succession to avoid mis operation under accidental conditions. Mathematical tools such as wavelet transform, and short-time Fourier analysis are used to process the text features of the sentence again, and a better feature discrimination effect can be obtained.
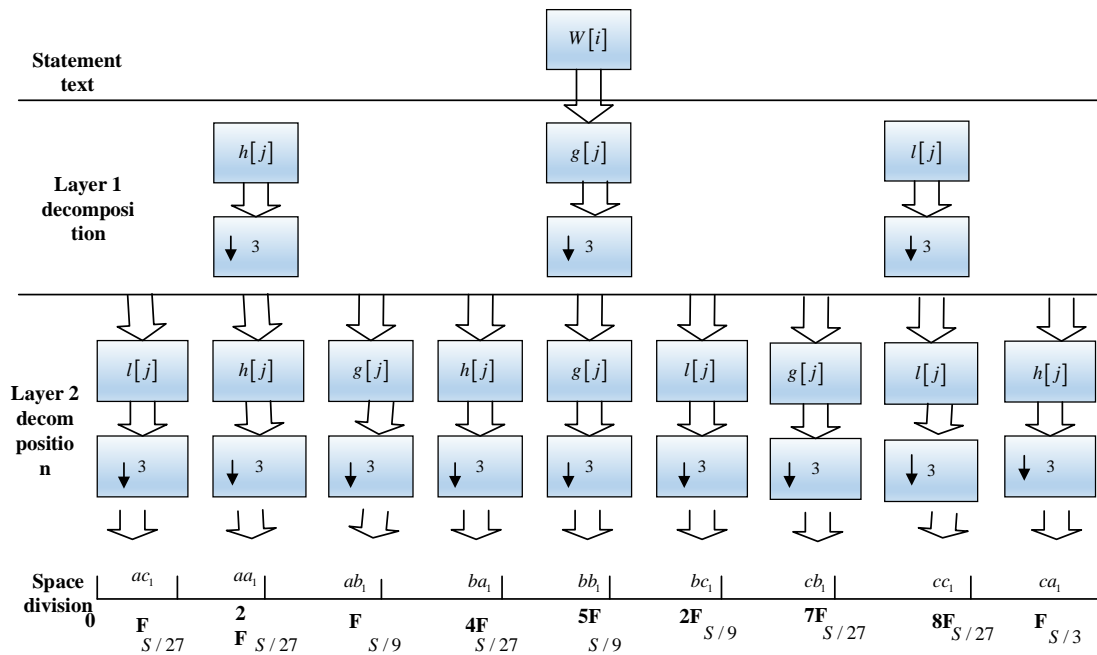

Figure 5: Two-layer wavelet packet decomposition method for feature text

$$X_{j,i} = \left(\frac{1}{N} \sum_{n=1}^{N} K_{j,n}^2 \right)^{\frac{1}{2}} \qquad (3)$$

In the formula, $X_{j,i}$ is the root mean square value of the characteristic degree of node j under the i th time window; $K_{j,n}^2$ is the nth coefficient at node j; N is the number of all coefficients of node j. In order to judge the weight of the feature degree, first establish the basic assignment table corresponding to the feature degree of the English sentence. Then, through the English sentence rules and translation characteristics, a simulation model of feature weight assignment is established, as shown in formula (4). The reference answer and random answer of the translated sentence are used to simulate the experiment, and the maximum and minimum value of the feature weight are obtained respectively, and the coefficient change after wavelet transform is used as the model basis. Taking the 5-layer wavelet packet decomposition method as an example, the node importance ratio λ is used, the ratio of the importance between 2 to 5 nodes and the importance of 1 node in equation (5) is used as the effective feature weight, and the threshold is set to 0.025, 11 feature degrees are calculated continuously, and within a preset period, the feature weights are obtained through this simulation model.

$$\frac{1}{g}\frac{dg}{dt} = \frac{1}{\tau}\left(\frac{x_j^2}{x_c^2} - 1\right) \quad (4) \qquad \lambda_{j,i}\frac{E}{E_1} = \frac{\sum_{r=2}^{r=j}\sum |u_r(n)|^2}{\sum |u_1(n)|^2} \quad (5)$$

In formulas (4)-(5), g is the derivative value of the characteristic quantity, T is the time constant; X_j is the basic weight assignment; xc is the weight assignment coefficient; $\lambda_{j,i}$ is the characteristic quantity weight; Sum of importance; E1 is the importance of 1 node; $u_1(n)$ is the reconstruction coefficient of 1 node, $u_r(n)$ is the reconstruction coefficient of r node.

V. RESULT

5.1 Algorithm Model Verification

As shown in Figure 8 and Figure 9. In this evaluation experiment, gateway recognition is performed on 50 phrases and 50 random network statements, and presents the experimental comparison results of the human translation translation in Table 3.
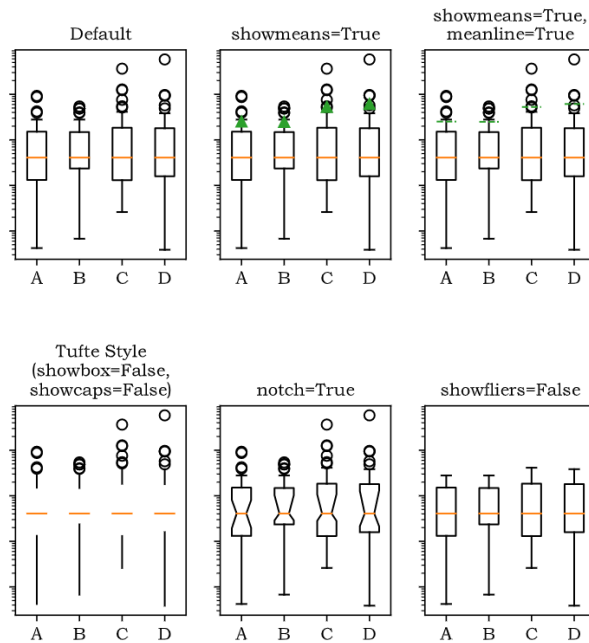

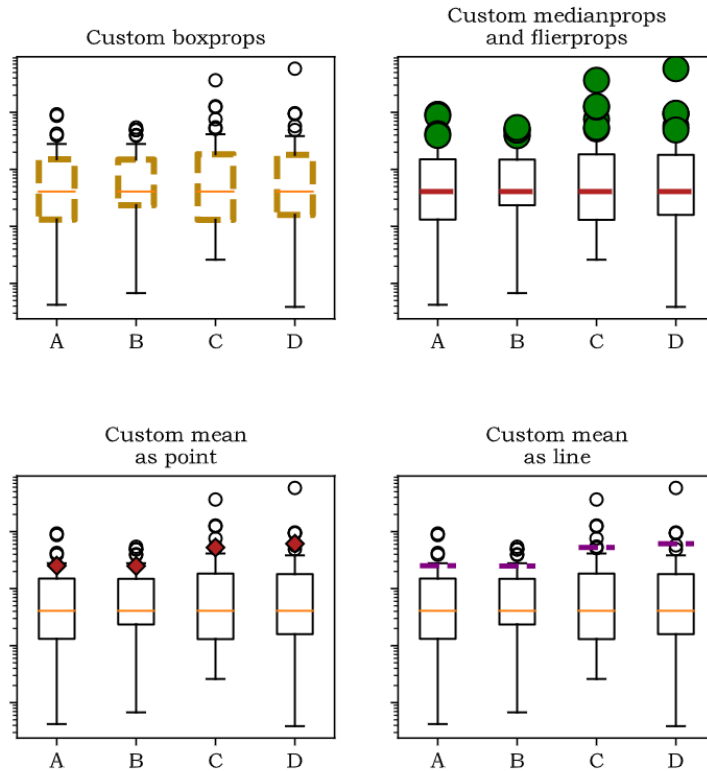**Figure 8 Chinese-English translation algorithm evaluation results**

Figure 9 Comparison of Chinese English Chinese Translation Algorithms Comprehensive Test Scores

Table 3: comparison of translation examples

Translation method	Translation content
Statistical algorithm	Xi'an explained that beef noodles will be reduced: because the price is excessive.
Dynamic Memory Algorithms	Xi'an explained that beef noodles only reduce the reason for the excessive price.
GLR algorithm	The Xi'an Price Bureau explained that beef noodles are falling: because of excessive price increases
Improved GLR algorithm	The Xi'an Price Office provides explanations for reducing beef due to excessive price increases.
Manual translation translation	The Xi'an Price Bureau provides an explanation for the price control for beef noodles: it's just because the increase was too large.

5.2 Validation verification

The calibration test of the English translation of the model from the text is carried out through the experiment, and the data is recorded during the experiment, and the performance of the system is analyzed. The experiment had 400 literal proofing singles, 500 short text proofing quantities, and a vocabulary recognition rate of 25kb/s. Table 4, which compares the accuracy of English translation results after and before calibration.

Table 4: accuracy of English translation before and after proofreading

Experiment No.:	Translation accuracy	
	Before proofreading (%)	After proofreading (%)
1	58.3	99.2
2	72.5	98.7
3	67.6	98.5
4	72.2	99.2
5	75.2	98.6
Accuracy (mean)	69.07	98.75

Table 4 shows that the highest accuracy of the English translation results before calibration is 75.1%, and the accuracy has reached 99.1% after using the intelligent recognition module in the text.

VI. CONCLUSION

The automatic text evaluation algorithm, the identification and extraction of text feature vectors and the fusion and interaction of feature weights play a key role in the correctness of the evaluation results. Designed the basic framework of the English sentence translation evaluation system, conducted a detailed study on the filtering and extraction methods of text feature vectors, and then studied the evaluation models GBRT, CNN and LSTM adapted to different characteristics. After integrated learning by the Stacking method, the input In the BP neural network model, the evaluation results are obtained through interactive fusion training. Through the comparison of machine verification and human evaluation results, the ETSS system has excellent performance, and the reliability and accuracy of the evaluation are high.

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