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Retraction

Retracted: RNN Neural Network Model for Chinese-Korean Translation Learning

Security and Communication Networks

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Security and Communication Networks has retracted the article titled "RNN Neural Network Model for Chinese-Korean Translation Learning" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

References

[1] Y. Dong, "RNN Neural Network Model for Chinese-Korean Translation Learning," *Security and Communication Networks*, vol. 2022, Article ID 6848847, 13 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2020, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

RNN Neural Network Model for Chinese-Korean Translation Learning

Yang Dong

Nanyang Institute of Technology, Nanyang, Henan 473000, China

Correspondence should be addressed to Yang Dong; 3102081@nyist.edu.cn

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Translation is the expression of words into other forms so that they are mutually understandable. However, the current Chinese-Korean translation information conversion model is not mature enough, and there are many defects and errors. This paper proposes an improved RNN neural network translation model. The translation model proposed in this study is an upgraded RNN neural network (a form of recurrent neural network). A decoder matching mode is included in the model, allowing it to learn both alignment and transformation at the same time. This allows for quicker neural network training, resulting in increased translation speed and efficiency. In addition, this article compares the BLEU scores of the BilingualCorpus Chinese-Korean corpus I, II, and III with those of the standard translation model. The test results suggest that the enhanced RNN model described in this research has an average BLEU score of roughly 45 points. The conventional model's average BLEU score is just approximately 30 points. The BLEU score of the model in this paper has increased by about 15 points, indicating that the translation quality of the translation model in this paper has been significantly improved.

1. Introduction

With the rapid development of globalization and informatization, language translation has become more and more diverse and common. However, there are cultural differences in various countries in the world, and there will inevitably be some differences caused by language translation. At present, although the machine translation system has been developed to the point of perfection, the problems existing in these traditional machine translation systems cannot be completely solved. Therefore, it is necessary to develop a more efficient translation information conversion model to improve the quality of Chinese-Korean translation. This is of great significance to the establishment of diplomatic relations, trade exchanges, cultural dissemination, and tourism between China and South Korea.

Chinese-Korean translation has experienced a unique development process in each historical period. Since the establishment of diplomatic relations between China and South Korea in 1992, especially since the establishment of comprehensive partnership between the two countries, exchanges and cooperation in political, economic, diplomatic, cultural, and other fields have been comprehensively promoted, and diplomacy has achieved great success. At the same time, the demand for high-quality translators is increasing. As a new research topic that has been incorporated into the education system, translation has attracted more and more attention. The innovations of this paper are as follows: (1) This paper first analyzes the background of friendly relations between China and South Korea and explains the value of Chinese-Korean translation. (2) This paper introduces several common methods and models of translation in detail. (3) This paper constructs an improved RNN neural network model, which is faster in calculation and more human-friendly in translation. (4) This paper can better reflect the advantages of the RNN model by comparing it with the traditional translation model.

2. Related Work

Machine translation and interpretation have advanced dramatically in recent years as a result of the use of artificial

intelligence technologies. According to Chang's study, Naver, Hancom Interconnect, and Systran International Co., Ltd. were the first in Korea to provide desktop and mobile-based translation and interpretation services. All three firms employ Neural Machine Translation (NMT), a cutting-edge machine translation technique with varying capabilities. Naver is Korea's most popular portal site, and it uses a variety of material kinds as translation engine data to reply rapidly to spoken and newly formed words. Genietalk was created by Hancom Interconnect. To increase translation accuracy, this hybrid translation engine combines the advantages of NMT with rule-based machine translation (RBMT). Systran works with translation software firms to offer industry- and region-specific translation knowledge. The everyday translating demands of shopping and travel are projected to be met by these emerging machine translators and interpreters [1]. Cultural factors and the untranslatability of language are often cited as reasons why translators "rewrite" while translating literary works from other cultures, according to Shin's study. This is, without a doubt, one of the most important aspects leading to translation rewriting. However, if a translator just rewrites what cannot be translated, the study of rewriting in literary translation becomes predictable and clear. Even if the original text does not include the untranslatable parts, one will have to rewrite everything using different tactics such as footnotes, replacements, and omissions if untranslatable components are detected. Because they cannot translate, translators are more subjective and imaginative. As a result, a descriptive study of rewriting in incomprehensible circumstances might be a useful tool for determining translator subjectivity and the theoretical significance of recommender rewriting [2]. The debate on Chinese characters has not diminished, as knowledge of Chinese characters is considered essential for understanding Chinese and Korean (SK). Lee's research judges whether the strategy of using knowledge of Chinese characters is suitable for the teaching of SK words by analyzing the correlation between SK words and "hun" (Korean-Chinese character translation). Lee's goal is to analyze 11,000 SK words in elementary school textbooks, and highly related words account for 32%, such as bu-mo (parent). Words with low relevance accounted for 16%, such as dan-che (each other); no relevance accounted for 6%, for example, binan (review). Hun languages other than character voices account for 46%, such as Hunbab (citizen). The related words can understand the meaning of the compound Chinese character "Xun," but other words cannot. The strategy of understanding SK words using knowledge of Chinese characters only works for 32%. Therefore, vocabulary education generally cannot adopt this strategy. Furthermore, the understanding of Chinese characters needed by SK Chinese character education is character meaning rather than shape and form. As a result, there is little foundation for Chinese character elucidation or for pupils to learn Chinese characters [3]. The 4th China Symposium on Religious Translation was held in Qingdao, Shandong Province, China, from 1st to 3rd June, 2017. 40 academics from five faiths and six languages will give talks on religious translation. Lectures on religious translation will be given by 40 experts from five faiths (Baha'i, Taoism, Buddhism, Islam, and Christianity) and six languages (Hebrew, Greek, Tibetan, Korean, English, and Chinese). The variety of speeches allows for the development of a scientific religious translation system. According to Yue and Zhu's study, the system comprises both history and methodology. Translation history, significant translators, classics, and religious classics are among the study topics in the history of religious translation. The concepts, techniques, modifications, readers, and tactics of religious translation have all been studied in depth. The two distinctive features that distinguish religious translation studies from translation in other fields are religious and social [4]. Languages have unique properties in recursively inserting tree-based phrases and following a syntactic grammar, according to Arora and Agrawal's study. In the area of statistical machine translation, phrase-based translation is regarded the state of the art, although it ignores the peculiarities of the languages stated above. The goal of hierarchical and grammar-based machine translation is to represent these linguistic features. The linguistic families of English and Hindi are not the same. The English subject-verb-object (SVO) structure must be transformed to the Hindi subject-object-verb (SOV) structure. For language pairings that involve transporting words and phrases across large distances, Arora and Agrawal gave a comparative examination of various models [5]. Text-to-speech conversion is the core technology of intelligent translation and education systems and is very important to English education and development. However, there are certain problems with current text-to-speech conversion factors. To improve the efficiency of text-to-speech conversion, Li's research improved traditional machine learning algorithms. He proposed models using an improved statistical language and support vector machines. Furthermore, the model is built as a training module and a test module. The model combines statistical and rule methods into an integrated framework, making full use of English features for automatic conversion of string and phonetic features. Furthermore, to meet the needs of English text-to-speech conversion, Li's research builds a framework model. In Li's research, he analyzes the performance of the model and designs a control experiment to compare the performance of the model. The research results show that the method proposed by Li has certain effects [6]. Machine translation of rules and statistics is currently the mainstream translation method. However, they are relatively complex and the rules are actually difficult to outline. The neural network model is used to study the machine translation process of language from the perspective of AI to improve translation speed and efficiency. This project will be able to adapt to cultural differences in different places, greatly improving the efficiency and speed of translation.

3. Conversion Model Based on Translation Information

At present, there are many difficulties in the practice of Chinese-Korean translation. These problems need to be dealt with by combining theory and practice in order to

improve the level of Chinese-Korean translation. This article investigates and summarizes the Chinese-Korean translation papers of several major domestic literature websites and a summary of Chinese students studying in South Korea to understand the current status of Chinese-Korean translation. The survey results are shown in Figure 1 and Table 1.

The number of South Korean students has essentially remained constant over time. Following that, it fell somewhat but remained essentially consistent, and the number of Chinese-Korean translation articles grew as well. This feature not only facilitates simple comprehension of Korean culture but also promotes Chinese culture. Also, it continues to encourage friendly interactions between the people of the two countries and improve the two nations' diplomatic condition. The translation fields of Chinese and Korean articles are summarized in Table 1. As can be observed, the majority of the material of Chinese-Korean translations is derived from literature. This also demonstrates that the two nations are actively discussing, learning from, and influencing each other's cultures [7].

3.1. Translation Model

3.1.1. The Method of Translation. From the translation object, it is divided into human translation and machine translation. According to the principle of translation, it is divided into literal translation and free translation, as well as domestication and foreignization. According to the time of translation, it is divided into online translation and offline dictionary translation.

(1) Human translation and machine translation. ① Human translation. It mainly refers to translating a word into other forms through the way of human speech so that people can understand each other, while machine translation is to translate through the program of the machine. Human translation can be changed according to people's own thinking. The human translation process generally includes translation, review, and proofreading. ② Machine translation. Machine translation is also called self-translation, which translates according to the program set by the machine. Machine translation is an efficient form of translation that can translate anytime, anywhere, online or offline. Of course, there are also many limitations and translation problems [8, 9]. For example, the translation is too rigid and lacks the style of the local culture, and there is also missed translation or repeated translation or translation errors (machine translation is a branch of computational linguistics, is one of the ultimate goals of artificial intelligence, and has important scientific research value; the process of machine translation can be divided into several steps: original text analysis, original translation conversion, and translation generation).

(2) Literal translation and free translation and domestication and foreignization. ① Literal translation. Simply put, it is a direct translation according to the surface meaning of a word or sentence. That is, if the translation language conditions permit, the content of the original text and the format of the original text are preserved in the translation. In particular, the metaphors, images, and national and regional colors of the original text are preserved. ② Free translation. Because some words will lose their special meaning in the culture if they are directly translated, which is very different from the original meaning, the method of literal translation is obviously not suitable, and the use of free translation can better express its original meaning. Free translation, as the name implies, means that when the translator is limited by the social and cultural differences of the translation, he questions the similarity between the original content and the main language features, which means that the meaning needs to be abandoned. ③ Naturalization. Naturalization is the process of translating translated information into a local culture. Not only the substance but also the tone of voice should be comparable. This is referred to as "doing as the Romans do." The localization of the source language is known as domestication. The substance of the source text is conveyed in a fashion that readers of the target language are used to in order to target the target language or target audience. Domestication translation necessitates translators' proximity to target language readers. Translators must talk in a native-like manner. If the author wants to communicate with the reader directly, the translation must be done in the author's original tongue. Domesticated translation improves readability and reputation by allowing readers to better grasp the translation. ④ Alienation. Alienation is the antithesis of domestication, and it involves foreignizing translated information to adhere to an alien way of life and manner [10]. Alienation is appropriate for the author's use in translation, as it allows the translator to approach the author and convey the original content by adapting to the language characteristics of foreign cultures, absorbing foreign language expressions, and allowing the translator to approach the author. In other words, the goal is the culture of the source language. The goal of using alienation approach is to account for country cultural variations, retain and reflect the features of other nations and linguistic styles, and keep the subject matter's exoticism.

(3) Online translation and offline translation. ① Online translation usually means using an online translation tool to translate. At present, examples of common translation tools are Baidu Translate, Ali Translate

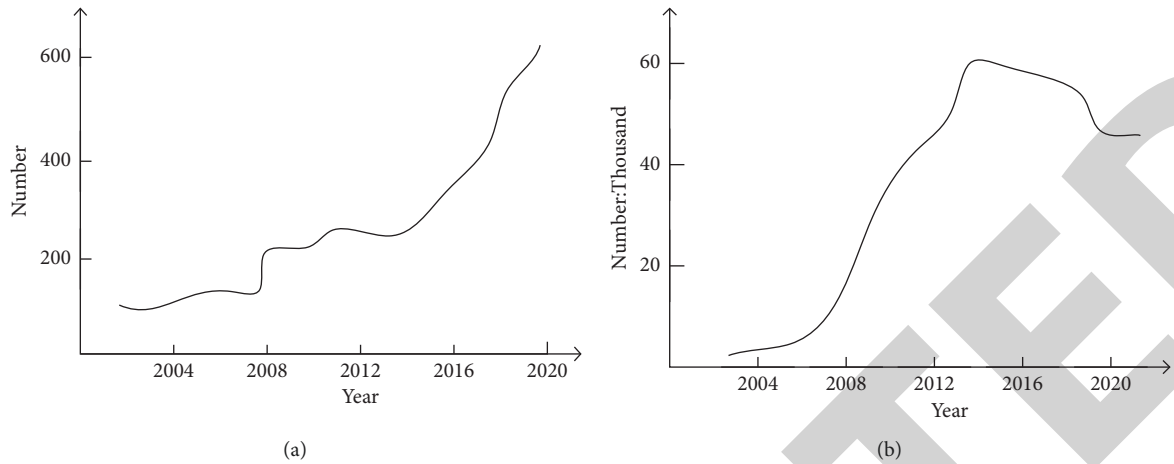

Figure 1: Chinese and Korean translation papers and the situation of international students. (a) Publication status of papers. (b) Changes in students studying in Korea.

Table 1: Chinese-Korean translation content survey.

Translation area	Number of posts
Literature	2463
Science	831
Art	527
Religion	73
Other	1452

1688, and Google Translate. The function of such translation tools is to translate from one natural language (source language) into another (target language) using a computer program. Its principle is to use huge Internet data resources and natural language processing technology to find different patterns in millions of documents and find the best translation. ② Offline translation. Offline translation generally refers to the method of using offline translation library and other applications or tools for machine translation or translation dictionary for manual translation.

3.1.2. Machine Translation System

(1) Rule-based machine translation system. The system is a knowledge source composed of dictionaries and rule bases. The translation cycle of this type is long, the cost is too high, and it is easy to cause rule conflicts [11].

(2) Corpus-based machine translation system. The system consists of a partitioned and labeled corpus that constitutes a knowledge source, without the need for dictionaries or rules. It is also known as a statistics-based machine translation system. This type of translation is a translation of a mathematical statistical model. Its cost is low, but it also suffers from data sparsity and requires the fusion of expert knowledge.

(3) Machine translation system based on neural network.

The system's technological core is a deep neural network with a huge number of nodes (neurons) that can acquire translation expertise from a corpus automatically. After the language's phrases have been vectorized, they are conveyed over the network layer by layer and translated into a computer-readable format. The translations in many languages are then created by numerous levels of sophisticated conduction processes. The "understanding language, creating translation" translation approach is used. The neural network machine translation system offers a high efficiency, low energy consumption, as well as a more fluent translation impact. It is becoming more popular. However, since the existing technology is not flawless, there will be instances of repeated translation or overinterpretation, leading to mistranslation or missing translation [12].

This article collects the usage of the above three machine translation systems from major websites. Table 2 shows the comparison of current machine translation systems. It can be seen from the table that the current rule-based machine translation system still accounts for the majority of the proportion. The proportion of machine translation systems based on neural networks currently exceeds that of corpus-based machine translation systems, and, in recent years, the machine translation of neural network has been continuously improved and developed, and its use has become more and more widely used.

3.1.3. Development of Machine Translation Systems. As demonstrated in Figure 2(a), the early rule-based MT systems account for a significant fraction of the total, because they are the oldest and most developed, and then the discovery of statistical machine translation takes up a major chunk of the time. The discovery of neural networks started to revolutionize around 30 years after the introduction of statistics. In just a few years, it has grown swiftly and absorbed a significant quantity of traffic. [13].

Table 2: Comparison of machine translation systems.

Genre	Pros and cons	Percentage
Rule-based	The translation cycle is long, the cost is too high, and it is easy to cause rule conflicts	57
Corpus-based	The cost is low, but there will also be data sparse problems, and expert knowledge needs to be integrated	16
Neural network-based	The system is not perfect yet, and there will be repeated translations or overinterpretation, resulting in mistranslations or missed translations	27

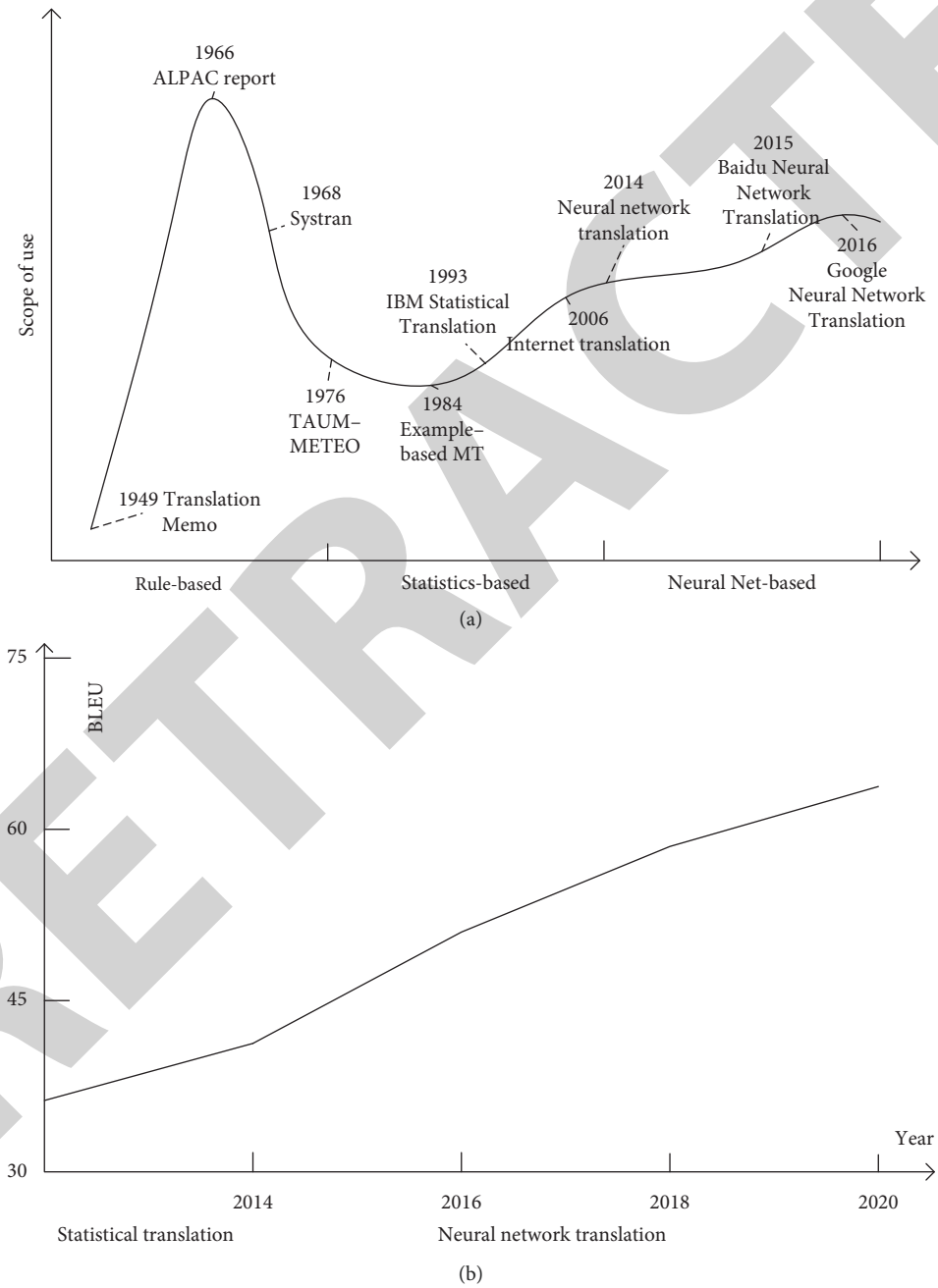

Figure 2: The development of machine translation. (a) Development process of machine translation. (b) Quality score of machine translation.

BLEU is computed on a set (test set) of multiple sentences. Using BLEU to score the statistical machine translation system and the neural network machine translation system is shown in (b). The BLEU score of the neural network is gradually improving, and it is already much higher than that of the statistical machine translation system. This is also the advantage of neural network machine translation [14].

3.2. Translation Information Conversion Model

3.2.1. Semantic Memory Model. The memory necessary to utilize a language, or one's own mental or spiritual vocabulary, and learning related words or other linguistic symbols are all included in hierarchical network models. Their linkages, as well as their meanings and referents, structured vocabulary memory information, are all included. The words and phrases used in the translation may relate to the fundamental units of sentences, such as words and phrases. Furthermore, translation is more than just rephrasing a word or phrase. From source language analysis through semantic expression to target language expression, it is a complex interconnected and interactive process. Text is one of the most crucial among them. In other words, it has evolved into a crucial translation unit. When it comes to the learning, matching, and conversion of word ideas and nouns, misunderstandings of source terms and mistakes in translation creation are nearly unavoidable. As a result, studying the translator's transformation expression and memory expression is important in order to analyze and investigate the psycholinguistic model of translation vocabulary transformation based on the network model [15].

(1) Conceptual type. The connection table symbol type is composed of a word name layer and a concept layer, which is called a two-layer parallel type. This means that the translator's memory system has two independent vocabularies, a concept expression system, and two word noun systems. However, this model only looks at a specific concept or concepts that literally expand the meaning (as shown in Figure 3). In this sense, it is similar to connecting the hierarchical network model and the hierarchical prestorage model.

(2) Shared and dependent type. The concept sharing phenotype consists of a noun layer and a concept layer, which is called a two-layer sharing phenotype. This means that bilingual translators have the same conceptual system and two parallel terminology systems. Specifically, in the data dialects of all dialects, "concept sharing" refers to the translator's mastery of two language systems or a bilingual lexical concept system. However, the model has only one conceptual system. That is, two language (lexical) systems share a system of concepts and are stored in specific locations in the memory system, as shown in Figure 4(a) [16].

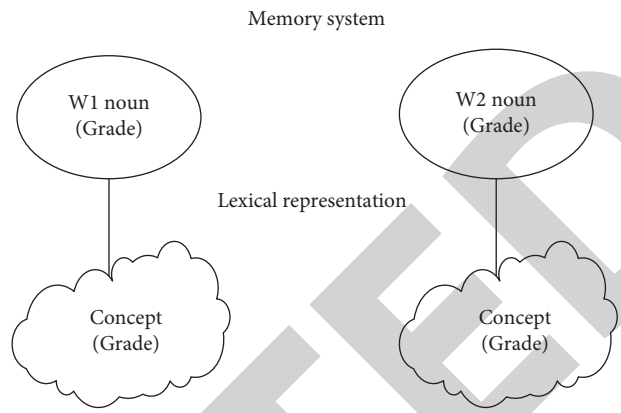

Figure 3: Chinese-Korean vocabulary-memory representation conceptual model.

(3) Dependent type. Concept-dependent representation types mean that translators have the same system and two naming systems. In this sense, second language terms are subordinate to linguistic terms. Therefore, it forms an indirect connection with the conceptual system, as shown in Figure 4(b).

3.2.2. Translation Information Conversion Model

(1) Memory representation-based parallel transformation paradigm. The essential foundation of the Chinese-Korean lexical idea representation model in Figure 3 is followed in this model. The employment of various lines and the insertion of a transformation system in the centre of the model are the noticeable differences. At first sight, the two models seem to be identical, yet the models have distinct meanings. Figure 5 depicts the model. The model-centric transformation system enables you to dock and change two name systems, two concept systems, or two naming concept systems [17].

(2) A two-layer shared distribution model based on memory representation. Figure 6 is a two-layer sharing model borrowed from Figure 4. The two-tier shared distribution model changes the original "concept" to "shared concept" and adds "unique concepts" on both sides. Also, two sets of links have been added, and one set of links has changed. So the format and meaning of the two icons are completely different.

This model provides translators with a more economical memory representation transformation structure. However, the actual text translation conversion situation is not as simple as imagined. For example, in terms of "common concepts" of the two languages, fast and accurate translation conversion processes and conversion results are possible. However, as far as the translation of word names and concepts between languages is concerned, translators can use conversion systems or mechanisms to complete name-to-concept conversion, as well as concept-to-word name translation and

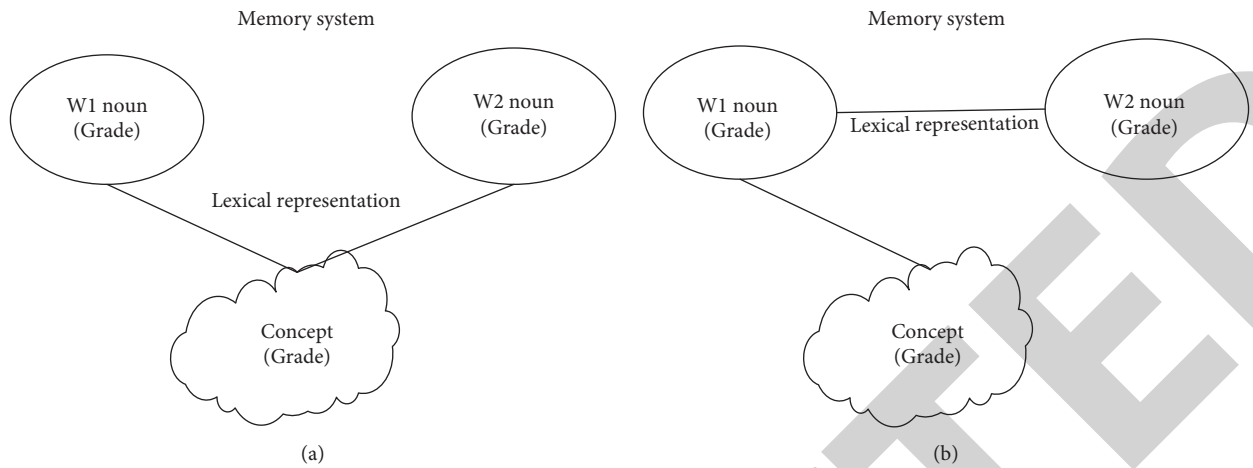

Figure 4: Two-layer sharing and attachment model of memory representation. (a) Two-tier shared type. (b) Dependent type.

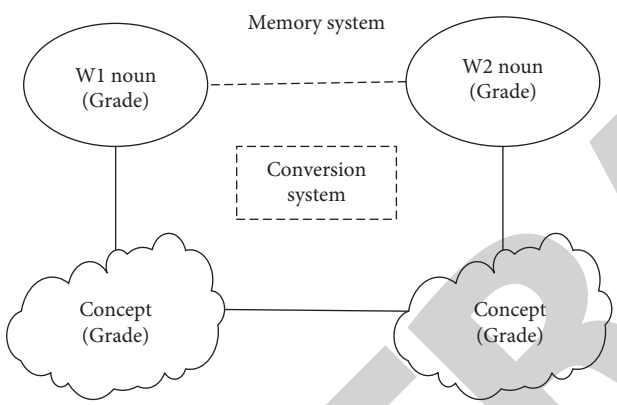

Figure 5: Parallel transformation model based on memory representation.

docking. Efficient translation of the conversion process and conversion results is almost difficult.

(3) Memory representation-based attachment transition model. This model, as seen in Figure 7, also draws from Figure 5's representation-dependent memory model. This model's word translation procedure, on the other hand, becomes tedious and slow [18]. The dependency expression-based word translation transformation representation paradigm leads in inefficient word transformation processes and inadequate word transformation outputs for translators. This is due to the fact that the translator's second language name system does not include a representation of the connecting lines that are directly related to the notion.

These translation transformation models mentioned above are relatively variable and poor real-time performance, and most of them are in the state of theoretical research, lacking practical practice and application.

3.2.3. Neural Network Translation Information Conversion Model. In recent years, with the development of neural network models and deep learning, many recognition and generation tasks have appeared, and everything has new ideas. The task of machine translation application scenarios being highly compatible with statistics and latent variable modeling has also attracted academic attention. A neural network-based machine translation model was born. The performance is clearly improved compared to traditional statistical machine translation methods [19]. The current mainstream neural network machine translation method is an end-to-end encoding-decoding translation system constructed by using RNN and FNN neural network models. Figure 8 shows the commonly used RNN translation model and its calculation method.

Assuming that the external input received by the neuron is y, the update method is u, and the output is a, the representation of a neuron u_s is

$$\begin{aligned} u_s &= g_0\left(Dy_s + Cu_{s-1}\right) \\ a_s &= g_1\left(Cu_s\right) \end{aligned}. \tag{1}$$

In the above formula, g represents the correlation mapping function; D and C represent the set.

y_s is updated as follows:

$$y_s = \left[a_{s-1}; y_s\right]. \tag{2}$$

Information transmission method is as follows:

$$\begin{aligned} g_t &= \mu\left(C_g y_s + d_g\right), \\ u_{s-1} &= g_t \times u_{s-1}. \end{aligned} \tag{3}$$

In the above formula, μ represents the screening coefficient, and d is the offset constant.

Information update method is as follows:

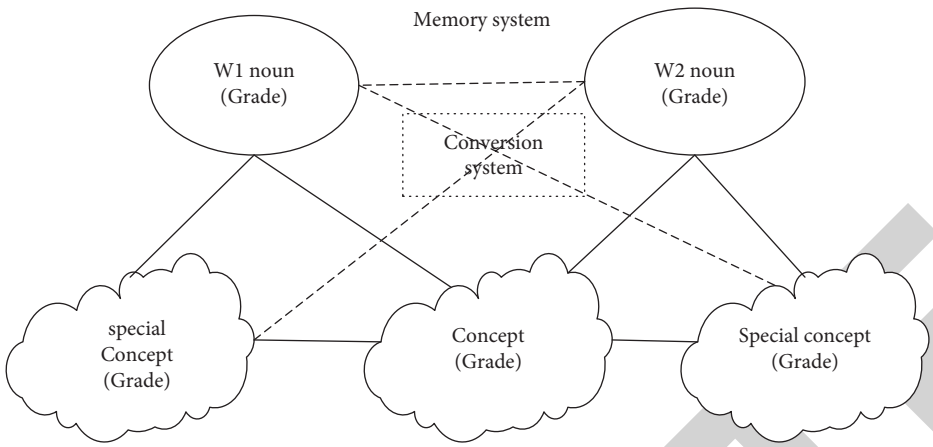

Figure 6: Two-layer shared distribution model based on memory representation.

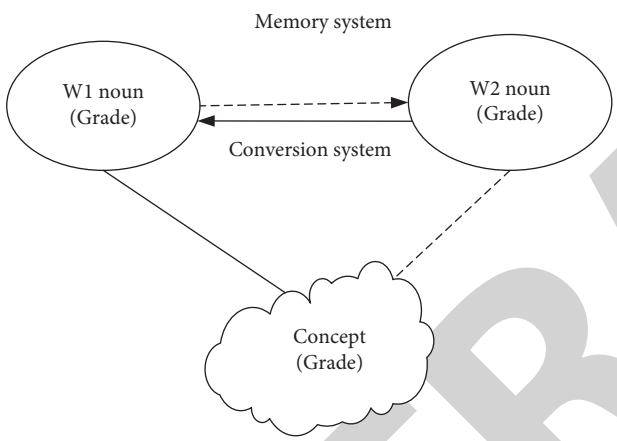

Figure 7: Attachment switching model based on memory representation.

$$\begin{aligned} u_s' &= \mu\left(C_i y_s + d\right)_i \times \tanh\left(C_u y_s + d_u\right), \\ u_s &= u_{s-1} + u_s'. \end{aligned} \tag{4}$$

Information filtering method is as follows:

$$a_s = \mu\left(C_a y_s + d_a\right) \times \tanh\left(u_s\right). \tag{5}$$

The splicing method of the bidirectional recurrent network is as follows:

$$a_s = C_a\left[a_{fw}; a_{bk}\right] + d_a. \tag{6}$$

The decoding method can be expressed as

$$\begin{aligned} u_s &= g_0\left(u_{s-1}, a_{s-1}, e\right), \\ a_s &= g_1\left(u_s, a_{s-1}, e\right), \end{aligned} \tag{7}$$

where e represents the sentence vector value.

The decoding result of the current step is the dimension that takes the maximum value of the final output vector:

$$f_s = \arg\max\left\{\left(C_f a_s + d_f\right)\right\}. \tag{8}$$

It defines the loss function as F and follows the chain method to get backpropagation:

$$\begin{aligned} \frac{\partial F}{\partial C} &= \frac{\partial F}{\partial a_s} \times \frac{\partial a_s}{\partial u_s} \times \frac{\partial u_s}{\partial u_0} \times \frac{\partial u_0}{\partial C}, \\ \frac{\partial u_s}{\partial u_0} &= C^{s-1}. \end{aligned} \tag{9}$$

The decoder DC takes the last value and the nondominated state of the neural network as the input this time and gets

$$a_s = DC\left(u_{s-1}, f_{s-1}\right). \tag{10}$$

The input value is then used to match the correlation with the nondominated state P_j at each step of the encoding stage for normalization. It gets the attention score:

$$\begin{aligned} S_{\text{core}}\left(a_s, p_j\right) &= w^x \tanh\left(C_x\left[a_s; p_j\right]\right), \\ \beta_{s,j} &= \frac{ex\left[S_{\text{core}}\left(a_s, p_j\right)\right]}{\sum_{i=1}^{X} ex\left[S_{\text{core}}\left(a_s, p_i\right)\right]}, \end{aligned} \tag{11}$$

where w^x represents the weight and ex represents the training experience.

Finally, the nondominated vector is obtained by weighting and summing the scores as weights:

$$e_s = \sum_{j=1}^{X} \beta_{s,j} \times p_j. \tag{12}$$

Taking the proportion as the calculation score, the meaning score of m yuan is obtained:

$$EQ_{m,r}\left(e, u\right) = \frac{\min\left[p_{m,r}\left(e\right), p_{m,r}\left(u\right)\right]}{\sum_i p_{m,i}\left(e\right)}. \tag{13}$$

The final evaluation index BLEU value is

$$B_M\left(e, u\right) = BQ\left(e, u\right) \times ex\left[\sum_{m=1}^{M} c_m \log EQ\left(e, u\right)\right]. \tag{14}$$

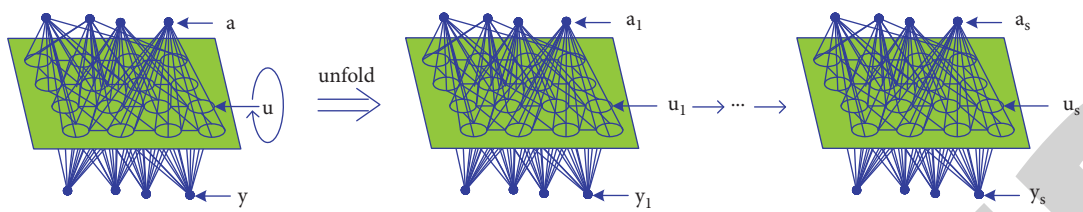

Figure 8: RNN model.

Table 3: Distribution of translation fields in China and South Korea.

Fields	Doctoral dissertation	Master's thesis	Journal article	Proportion
Literary translation	6	51	12	25.45%
Translation teaching	9	61	33	31.25%
Translation skills, strategies	7	11	43	8.04%
Translation instance	0	30	71	13.39%
Theory, history	0	18	58	8.04%
External appropriate translation	1	30	50	13.84%
Total	23	201	267	1

3.3. Chinese-Korean Translation

(1) The current situation of Chinese-Korean translation. Such frequent exchanges also require a large number of Chinese-Korean and Korean-Chinese translators. However, compared to other languages, research on Chinese-Korean and Korean-Chinese translation is relatively weak [20].

The numbers and proportions in Table 3 indicate how this research classifies Chinese-Korean translation studies published in China into six groups. The precise use of language abilities, as well as the application and selection of translation methodologies in the translation process, turns out to be the most popular issue among translation scholars, accounting for about half of all study outputs. Translation studies of individual literary translations are second in the total distribution, followed by translation teaching studies. However, the proportions of journal articles, Master's theses, and doctorate dissertations varied somewhat. A bulk of translation scholars that publish journal papers on CNKI are university professors. The research and advancement of translation education must begin with the duties of university instructors. As a result, translation education research is the second most popular subject for journal publications, followed by literary translation research. There are both theoretical and historical studies on Chinese-Korean translation, as well as translation examples that may be used in real-life situations. In terms of synchrony, the distribution of these themes has been quite consistent throughout time. In translation studies, it has always been the most prevalent, essential, and beneficial topic. Foreign publicity translation research, which has the lowest proportion, is a research topic that has attracted more and more attention from researchers in recent years.

(2) Chinese-Korean translation skills.

This paper summarizes years of translation experience and existing research materials from the aspects of Chinese-Korean and Korean-Chinese translation and attempts to study translation methods and techniques. How it translates for students studying Korean aims to provide technology. It applies the knowledge gained from the research to improve the translation effect.

Korean modifiers generally have long and complex sentence patterns. Korean is a morphological language and long sentences are common in Korean. This is because word format and inflection changes can show different relationships. This is also the difficulty of translating from Chinese to Korean. In Korean, auxiliary verbs and inflection systems are more important, but ordinary sentences come in the form of compound sentences and rebirth sentences. Compound sentences should not contain many phrases, and various phrases and conjunctions are connected. In Korean, the long attribute is often used for change, and the subject of the sentence is in the restricted position of change, which is the biggest difference between Korean and Chinese. This difficulty is also common when translating from Chinese to Korean [21].

(3) Difficulties in Chinese-Korean translation teaching. First is the problem of nonmaterialization of educational goals. Human resource development goals for Korean majors should be directly linked to learners' employment issues after graduation. Therefore, the educational goals of translation courses should fully reflect the goals of human resource development and at the same time reflect the actual characteristics of the courses. A larger proportion of graduates work for a company. This implies that, at the conclusion of four years of

professional study, graduates should have improved their practical language abilities. However, the features of strategic objectives that fulfil real demands have not been adequately represented in contemporary Chinese-Korean translation education goals of domestic colleges and universities. The atypia of instructional materials is the second issue. The present textbooks are insufficiently authoritative, and the subject of instruction is determined by the professors themselves in most colleges. As a result, the challenge that has to be addressed right now is achieving educational objectives while also improving the translated instructional materials after practice. Third, the teaching staff is not professional enough. Currently, some teachers at the forefront of translation education are not experts. In other words, some teachers lack practical experience. However, teachers need to gain more practical experience and teach students translation practice more effectively through practical interpreting and translation practice activities.

4. Improved RNN Translation Model Performance Test

4.1. Improved RNN Model Design

(1) Design ideas. The decoder matching mode is introduced based on the improved method. The model has excellent processing power when dealing with long sentences. Hidden nondominated vector expressions contain information about the entire input sequence. Hidden layer representations of RNN models tend to represent more information near words. Therefore, the hidden nondominated vector information of each word mainly focuses on the context information around that word, and each word can contain contextual information for a specific word. On this basis, the decoder introduces a matching mode to decode the output sequence more reasonably and accurately.

(2) Match the pattern. For each cycle, the bilingual sentence was matched to the input model. The process of training and decoding the model is computationally intensive. Therefore, in order to reduce the computational complexity, this paper uses a perceptron to accomplish such a function.

(3) Training interpretation. The process of generating an explanation model is similar to the training process of a translation model. Based on existing RNN and CNN networks, the models are trained using paraphrase corpora, respectively, and paraphrase models are obtained from machine translated texts and reference translated texts. After the model is implemented, the machine translation results are input into the "paraphrase system" for translation, and the ideal sentence-level paraphrase results are generated for the input sentences.

4.2. Model Testing Experiment. In this paper, the translation process of the translation system designed by MVC is shown in Figure 9. The MVC three-tier architecture promotes system organization of code, reduces coupling, and improves reusability through the separation of business logic, data, and interface display. The system has low life cycle cost and high maintainability. When the system receives a source sentence that needs to be translated, the sentence is input into the model, and the source sentence is sent to the remote server through the controller, that is, the system workflow server in Figure 9, and then uses the recurrent neural network described in the previous section. The sentences are first translated by the translation model, and then the interpretation is optimized based on the machine translation fusion model of interpretation to improve the readability of the translated text. The remote server then sends the processed statement back to the mobile device via the controller and finally displays the result on the mobile device [22].

The main purpose of the system is to translate Chinese into Korean. When using this system to enter a sentence to be translated, click the corresponding button to translate the word or sentence. The English entered after clicking translate will be sent to the server for translation. After translation and interpretation, the translation results are displayed in the interface for users to view. This paper uses the previous BLEU algorithm to evaluate the score of the system. The experimental test is the BilingualCorpus Chinese-Korean corpus I, II, and III. Table 3 lists the BLEU algorithm scores for the three corpora [23].

4.3. Experimental Results. According to the previous translation process, multiple groups of translations are performed, and the BLEU algorithms of the three corpora are obtained as shown in Table 4.

As can be seen from Table 4, the improved RNN model studied in this paper has a minimum BLEU score of more than 41 points and an average score of about 45 points. Figure 10 shows the comparison of the BLEU scores of the traditional machine translation model and the machine translation model of this paper.

It can be seen from the figure that the test BLEU scores of the three corpora of the improved RNN translation model have been significantly improved. The traditional average BLEU is around 30 points, and this paper's is around 45 points, an increase of nearly 15 points. It shows that the improved RNN translation model in this paper has a significantly better translation effect.

5. Discussion

Although the current research has achieved some results, many tasks and potential attempts still need to be completed in the research of combining language knowledge such as morphology and syntax with machine translation.

(1) The grammatical structure guides translation. Encoding and decoding are ideas that follow the way human language is constructed. An ideal modeling approach should be extended to a new

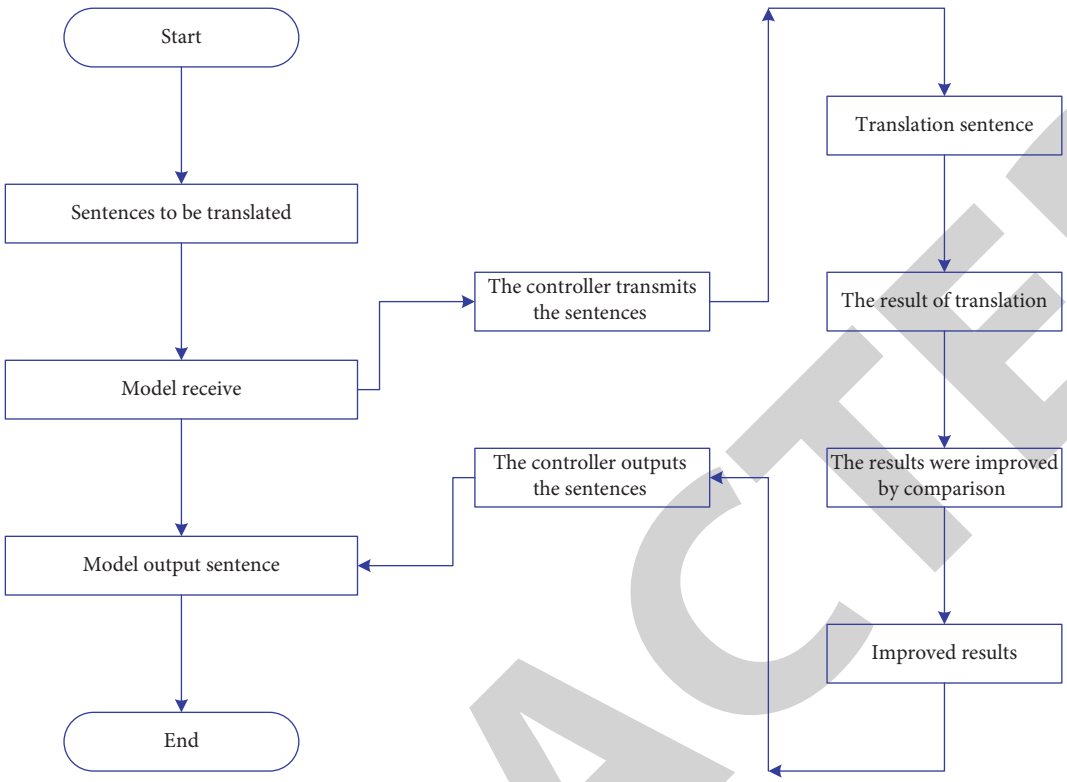

Figure 9: Machine translation process.

Table 4: The BLEU algorithm scores of the three corpora.

Corpus	Chinese-Korean	Korean-Chinese	Average
I	46.53	42.68	44.605
II	47.25	46.21	46.73
III	49.01	41.07	45.04

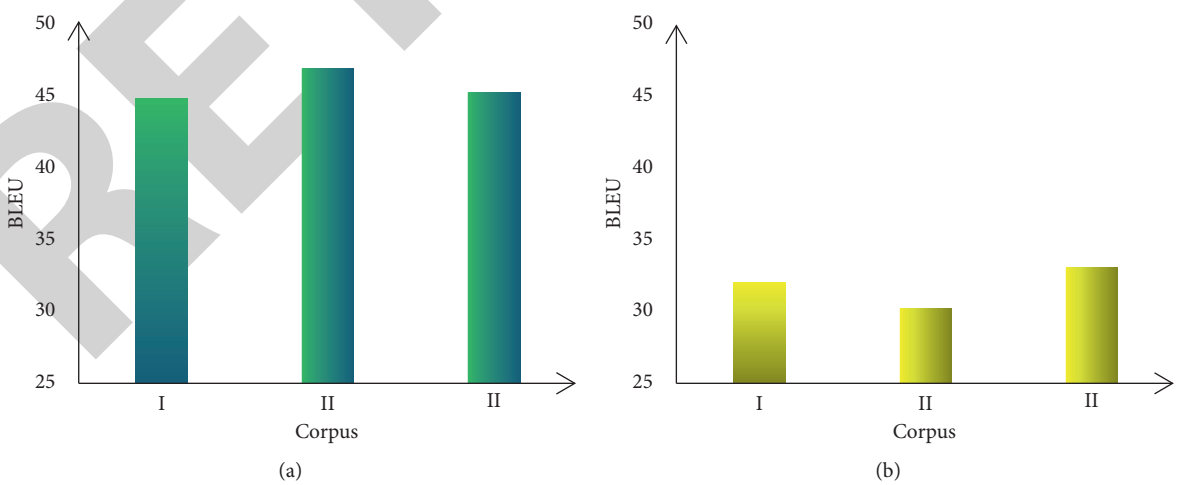

Figure 10: Comparison of average BLEU scores. (a) Improved RNN model. (b) Traditional model.

natural language based on the syntactic hierarchy, the compression semantics on the encoding side, and the hierarchy on the decoding side. At present, the use of syntactic information is still limited to the traditional model structure, and the new neural network model structure suitable for syntactic modeling needs further research.

(2) The various methods used in this paper have specific scalability, such as the idea of multitask learning. In addition to optimizing the recall of named entities, larger model-scale auxiliary tasks such as NER and grammar tagging can be used. Numerous studies have shown that pretrained language models can improve various neural network-related natural language processing tasks, and the low-level parameter requirements of the neural network are the same for multiple tasks, suggesting this possibility. They have a positive effect on each other. Appropriate addition of other natural language processing tasks is expected to have a positive impact on the ability of neural networks to handle machine translation tasks [24].

(3) Lexicon and syntax are classic concepts in the field of linguistics, and the knowledge that can be obtained goes far beyond named entity recognition and relying on syntactic information. There are many backgrounds to try machine translation tasks. For example, for transliterated word creation rules, a translation model of transliterated words can be trained. For other special parts of speech, such as linguistic pronouns, a specific processing method is used to optimize the translation effect, using the syntactic labels in the phrase structure syntactic tree to expand the word vector, the definition method, and so forth.

6. Conclusions

This article first introduces the general background of the friendly exchanges between China and South Korea and analyzes the current situation of students studying in South Korea and the number of Chinese and South Korean papers. It also understands the current situation of Chinese-Korean translation and analyzes the significance of Chinese-Korean translation between the two countries. Then, in the relevant work part, it analyzes the current research results of some scholars on Chinese-Korean translation and understands their shortcomings. Then the theoretical part studies the translation-based information transformation model. Several methods of translation are introduced in detail, and several machine translation systems in the current computer age are mentioned. Then it talks about the translation information conversion model and leads to the neural network translation model that this article focuses on. In this part, we focus on the RNN neural network translation model diagram and calculation method. Finally, the theoretical part introduces the current situation, skills, and existing problems of Chinese-Korean translation.

In the experimental part of this paper, an improved RNN model is designed. The model introduces a new encoder that speeds up translation. This paper uses this model to perform translation tests on the BilingualCorpus Chinese-Korean corpus I, II, and III and finally get the BLEU score comparison of the test. The results show that the BLEU scores of the three corpora tested by this model are around 45 points, while the traditional ones are only around 30 points. It shows that the translation effect of the improved RNN model designed in this paper has been significantly improved. However, there are still shortcomings in the experimental design of this paper. In the future work, more corpora need to be tested in multiple groups, and the model needs to be further improved to improve the translation quality.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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