Research Article

Analysis of AI MT Based on Fuzzy Algorithm

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The advancement of artificial intelligence technology is highly dependent on advancements in computer technology. The former created the technology for the latter. In the near future, we believe computer artificial intelligence technology will be further developed and better serve people. In other words, the data or note producer will edit the bridge segments with prominent contradictions in each program and broadcast them through the network with the titles that people are interested in, which has gotten a lot of attention and comments. This paper investigates a new fuzzy evaluation model by starting with the current situation. This paper investigates fuzzy algorithm-based artificial intelligence machine translation. The order of machine translation follows the trend in the figure, whereas the distribution of HEMTM machine translation is more concentrated under the HEMTM model. The average reliability ratio of the data mining algorithm is 0.97, the average reliability ratio of the decision tree algorithm is 0.84, the average reliability ratio of the machine learning algorithm is 0.71, and the average reliability ratio of the fuzzy algorithm is 1.34 when the vocabulary index is 15. The proportion of fuzzy algorithms in this paper is the highest of the four algorithms. It can be transformed into the contraction of frequency-domain coefficients in artificial intelligence machine translation using a fuzzy algorithm, greatly simplifying the operation. However, it will cause the ringing effect of fuzzy algorithm boundary in machine translation because it cannot well express the singular information of signals such as boundary. The extent of this effect is determined by the artificial intelligence machine translation breadth.

1. Introduction

Artificial intelligence (AI) is a new technology that uses computer technology to simulate and extend human intelligence. The rapid advancement of artificial intelligence has resulted in significant changes in many aspects of human society. The advancement of AI technology is dependent on the advancement of computer technology, which is the latter’s technology. Computer AI technology [1, 2] is expected to be further developed in the near future to better serve people. This means that data or record producers will edit the bridges in each program with prominent contradictions and broadcast them through the network, matching the titles that people are interested in, attracting a lot of comments and attention from the audience [3]. In recent years, companies such as iFlytek, Google, Baidu, and others have made significant progress in machine translation, promoting the field’s further development. Google proposed using a neural network system for MT, and the Chinese-English translation error rate is as high as 85% [4, 5]. As a result, some argue that “MT will replace human translation,” causing translation professionals to be concerned about their future career prospects. MT is a knowledge-intensive, interdisciplinary technology that requires the collaboration of linguists and computer scientists. Although the research on MT has not been perfect, people have high hopes for it, hoping that it will be as precise as arithmetic operations [6]. The intelligent MT system that resulted has sped up the adoption of AI concepts and technologies: from simple text input to voice input to OCR recognition; from a personal electronic dictionary on a PC to a translation APP for face-to-face communication on a mobile terminal, to a real-time translation system in large conferences using the “cloud + end” mode; and from word translation to free natural language translation, to communication translation...
that meets the needs of culture, emotion [7], and professional fields [8].

This paper investigates a new fuzzy evaluation model by starting with the current situation. The fuzzy evaluation index is created with the help of a fuzzy set, a standard fuzzy division of a domain, and a membership function. A fuzzy algorithm [9, 10] is a fuzzy environment extension. Fuzzy algorithms represent knowledge in a more natural way for human thinking. Pattern recognition [11], machine learning [12, 13], and data mining all use traditional methods. The classification model is induced using a fuzzy algorithm, and the path contains classification information in order to achieve a qualitative-quantitative balance and solve the qualitative problem of teaching evaluation. The fuzzy calculation model is a set of fuzzy conditional sentences in a language form. Its self-learning ability and fault location accuracy are not high due to the need to establish a large number of rules. The goal of a fuzzy algorithm is to achieve high intelligibility and a gradual and beautiful behaviour in the fuzzy system. To expand symbols for the construction and reasoning process, fuzzy sets and approximate reasoning are used. Simultaneously, it borrows a variety of existing methods for dealing with incomplete knowledge and expands them to take advantage of the new information available in fuzzy representation.

The basic idea of the AI MT system based on fuzzy computing is to use computers to automatically realize people’s control experience and operation methods. The fuzzy algorithm is used to describe the process variables and control functions. With these fuzzy concepts and their relationship, the control quantity at the moment can be obtained by fuzzy reasoning according to this fuzzy relationship and the detected value of the process variables at a certain moment. In AI MT based on fuzzy algorithm, it can be converted into contraction of frequency-domain coefficients, which greatly simplifies the operation. However, because it cannot well express the singular information of signals such as boundaries, it will cause the ringing effect of fuzzy algorithm boundaries in MT and the severity of this effect depends on the width of AI MT [14, 15]. Wavelet transform has local time-frequency characteristics, so the application of wavelet transform in the fuzzy algorithm in MT has achieved good results, keeping the details of MT with little loss. The innovations of this paper are as follows:

1. This paper presents an AI MT model based on fuzzy algorithm. The fuzzy MT is processed from coarse to fine. The generator adopts multiscale coding and decoding structure to improve the efficiency of the model, and the context module is introduced in the last layer of coding. The time convolution network is introduced between the network encoders and decoders of different scales of the generator to transmit information across layers, and finally, it is discriminated by the discriminator.

2. An AI MT system based on the fuzzy algorithm is constructed. Under the fuzzy algorithm, AI plays a good role in the MT system, but it also blurs the feature structure of MT. Whether in the time domain or frequency domain, it is difficult to completely separate noise from signal on a single scale. For the case of this study, if the fuzzy structure information is further damaged, it will make MT unable to obtain good quality in the subsequent deconvolution process.

2. Related Work

2.1. Research Status at Home and abroad. Karthikeyan et al. proposed that Chinese scientific research institutions and enterprises have reached an international advanced level in the global AI MT technology competition. Among them, the multidomain MT technology for oral and conference scenes has the ability to integrate the translation knowledge of domain-related external entity words and professional terms, as well as the ability of multidomain fine modelling and optimization, so as to achieve the same general effect and effectively improve the accuracy of translation in various fields [16]. Andriole et al. proposed that the changes in MT come from three aspects: from rule based, to statistical model based, to neural network based; from word based, to phrase based, to whole sentence based; and from the need to use large-scale parallel corpus, to the use of monolingual corpus, to the realization of zero data translation [17]. Chemouil et al. proposed that computers can replace human beings to complete intelligent activities such as numerical calculation, but numerical calculation and intelligent translation are two essentially different abilities of human beings [18]. Wang et al. put forward that the brain’s dynamic thinking process of judging things has not been verified by a complete theory in the fields of medicine and AI. Therefore, if we want to make a qualitative leap in the level of MT, we must first solve this problem [19]. Nabi proposed that traditional artificial translation has been playing an important role before the development of AI technology. Until now, the translation platforms launched by AI industry giants such as Google translation, Alibaba translation, and Baidu translation have gradually occupied the leading position in the translation industry by virtue of the efficiency of their translation process and the accuracy of translation results [20]. Winkler Schwartz et al. proposed that numerical calculation is a completely mechanical and regular operation. Scientific and technological personnel can simulate this process by summarizing the laws and using computers [21]. Nebot et al. translation is influenced by the above three contexts. Linguistic context determines the vocabulary used by the translator in translation, while situational context and cultural context determine the translation style and the translation strategy to be adopted by the translator. Because it is more often based on the analysis of grammar but never goes deep into the semantic level, it is actually a kind of literal translation [22]. Guo Machine translation has no creativity. It can only mechanically and repeatedly recombine the words and sentences contained in the corpus and output the translation results. This translation only gives the literal meaning of the original text and has no spiritual
connotation. It cannot express the deeper meaning contained in the article [23]. Shokouhifar et al. put forward that the brain’s understanding of natural language is accomplished through the influence of the surrounding environment and the examination and analysis of objective things. With the development of history, the fluency of language has its different evaluation methods in different periods. The works are elegant but not vulgar, and they have undergone literary processing, with great human factors [24]. According to Gaobin, et al., the advent of proposer translation is actually a manifestation of the substantial improvement in productivity. First of all, it saves the cost of resources, unlike the traditional manual translation, which requires a lot of manpower to participate, and the complicated process of repeated proofreading and verification in the later stage. The whole process of MT only needs a computer and power supply, and there will be no low-level mistakes such as spelling omissions. The efficiency of its work is unmatched by manual work [25].

2.2. Research Status of AI MT Based on Fuzzy Algorithm. This paper investigates AI MT based on fuzzy algorithms and operates the model by searching for a relevant fuzzy algorithm model of English MT. The difference between the fuzzy algorithm and the corresponding English MT support relationship is taken into account during the MT construction process. The model is expected to be used in the creation of English multiple-choice questions. The issue with insert translation is that as the amount of data grows, the comparison times become impossible to predict and continue to grow, negatively impacting runtime efficiency. To improve it now, binary retrieval translation is required. The retrieval algorithm for finding a specific element in an ordered array is known as binary retrieval, also known as half retrieval. Its benefits include shorter comparison times and high retrieval efficiency. The basic idea behind an AI MT system based on a combination of artificial neural networks and fuzzy computing is to learn the artificial neural network that has been constructed first. The content of AI MT is input into the network once the learning effect is satisfactory, and the scope of MT is reduced through a series of calculations. This is the first positioning procedure. Then, using the characteristics of the first positioning results as well as the actual situation of the equipment during operation and maintenance, we locate it again using fuzzy calculation. Artificial intelligence is required for a true automatic high-quality machine translation system, which includes not only a machine dictionary and rule system but also a perfect knowledge base to formalize and store human knowledge for translation. Learning, inference, and other intelligence should be included in any machine translation system. Only in this way will it be able to comprehend and rely on the language environment to solve polysemic, fuzzy language, and rhetoric issues, effectively simulating the brain’s translation process. Statistics-based machine translation is actually a corpus-based machine translation system.

3. Principle and Model of Fuzzy Algorithm

In computer programming, translation is widely used and important. AI MT and external translation are two major components of translation due to the various translation records they handle. The most widely used AI MT, which completely stores the data to be organized in memory before translating it according to their own translation rules, is suitable for element sequences with a small amount of data. The concept behind AI MT based on fuzzy computation is that human control experience can be realized automatically through computation. The procedure entails first establishing a set of fuzzy conditional statements that apply to the equipment and then judging MT’s actual situation using fuzzy conditional statements. It has the ability to deal with inaccurate and incomplete data. The uniqueness of MT is extracted during the processing stage. The goal of a fuzzy comprehensive evaluation is to synthesize each factor in a category and then consider the total impact of all factors. MT and human translation complement each other, and they promote each other and develop together. On the one hand, MT has made great progress, which has brought about changes in the field of translation and saved a lot of time and energy for translators. For example, when doing some simple nonliterary translation texts, MT can quickly complete a lot of translation work, which is unmatched by human translation. To get the overall comprehensive evaluation result for multifactor and multilevel systems, first, we evaluate according to the lowest level of each factor, then comprehensively evaluate according to the upper level of each factor, and then evaluate to the higher level in turn, until the highest level is reached. The weight set of factors for each layer should be established at this time. MT has made significant progress and can now perform some translation tasks, but there are still some translation jobs that it cannot perform, such as literary translation and publications and books. The reason for this is that the current technological level does not yet allow manual translation to be replaced. As a result, not only should we improve our translation skills but we should also keep up with the times in order to remain competitive. Machine translation has come a long way in the age of artificial intelligence, and it can now assist people with some simple translation tasks, but we are afraid there is still a long way to go before it can completely replace human translation. The overall flow of the fuzzy AI MT system is as follows: first, the user inputs AI MT, then artificial neural networks perform the first MT, and then, fuzzy calculations based on the positioning of artificial neural networks perform the second translation. The system flow chart is shown in Figure 1.

At the end of the first stage, the AI MT system is generated and the network of the second stage takes the MT system generated in the previous stage as the input. In order to adapt the output text of the previous stage to the input of the level network, AI MT needs to translate the output text. The MT structure of the finer-level network is basically the same as that of the coarsest-level network. After continuous
iterative optimization, the network outputs the machine-translated text. Therefore, the application of this improved method in the selection translation algorithm is very necessary and effective. The model construction of MT of fuzzy algorithm is shown in Figure 2.

The input is hierarchical English MT, and the output is hierarchical English MT.

4. Results of Model Construction

Firstly, a set of factors that affect the object of MT is established, which is called factor set.

\[ U = \{u^1, u^2, \ldots, u^n\}. \]  

Then, an evaluation set composed of \( n \) MT results is established.

\[ V = \{v_1, v_2, \ldots, v_m\}. \]  

Then, the weight set of each factor is established, which is expressed as a weight vector.

\[ A = [a_1, a_2, \ldots, a_n]. \]  

\( a_i \) is the weighted value of the \( i \) factor, and it is generally stipulated that

\[ \sum_{i=1}^{n} a_i = 1. \]  

The single-factor fuzzy evaluation of the \( i \) factor is the fuzzy subset \( R_i = \{r_1, r_2, \ldots, r_m\} \) on \( v \).

So, the single-factor evaluation matrix \( R \) is \( P \).

\[ R = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m} \\ r_{21} & r_{22} & \ldots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix}. \]  

Then, the fuzzy comprehensive evaluation \( B \) of the evaluation object is a fuzzy subset on \( V \).

\[ B = A \bullet R. \]  

According to the combination of weight set \( A \) and single-factor fuzzy evaluation matrix \( R \), the fuzzy subset \( B \) of evaluation is obtained by comprehensive evaluation. There are three models: Model I: \( M(\wedge, \vee) \); Model II: \( M(\bullet, \vee) \); and Model IV: \( M(\bullet, \oplus) \).

According to \( B = A \bullet R \), the main factor determinant of \( I: M(\wedge, \vee) \) model can be written as

\[ B = [a_1, a_2, \ldots, a_n] \bullet \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m} \\ r_{21} & r_{22} & \ldots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix} = (b_1, b_2, \ldots, b_n). \]  

The \( j \)-th element \( b_j \) in \( B \) can be calculated by the following formula:

\[ b_j = v_{i=1}^{n} (a_i \wedge r_{ij}) j = 1, 2, \ldots, m. \]  

II: \( M(\bullet, \vee) \) principal factor prominent model. We use this model \( b_j \) as \( b_j = v_{i=1}^{n} a_i \bullet r_{ij} j = 1, 2, \ldots, m. \)

When \( \xi \) is a fuzzy set, taking the values \( x_i \), \( i = 1, 2, \ldots, n \) with membership degree, DeLuca and Ter min \( i \), respectively, define its entropy as
MT between words can be evaluated in a better way by using Formula (10), when \( a = 0.2 \) and \( \beta = 0.45 \),

\[
S_\omega(\omega_1, \omega_2) = \begin{cases} 
 e^{-at} \cdot \frac{e^{\beta h} - e^{-\beta h}}{e^{\beta h} + e^{-\beta h}}, & \omega_1 \neq \omega_2 \\
 1, & \omega_1 = \omega_2 
\end{cases}.
\] (10)

Here, if \( \omega_1 = \omega_2 \), its correlation can be regarded as 1 because the information in the designed word network cannot cover all words. Therefore, if \( \omega_1 \) is one, \( \omega_2 \) cannot be covered by the word network, \( S_\omega(\omega_1, \omega_2) = 0 \).

Direct insertion translation, Hill translation, simple selection translation, heap translation, bubble translation, fast translation, merge translation, and cardinal translation are all different types of translation. These translation algorithms can translate data or records to make searching easier, but each translation algorithm’s data processing methods are different. Manual translation will make the translation more vivid and emotional by combining the translator’s rich social and life experience and then stimulate the readers’ emotional resonance, which is the so-called “elegant” translation environment. From coarse to fine, the fuzzy MT is processed. The context module is introduced in the last layer of coding, and the generator uses a multiscale coding and decoding structure to improve model efficiency. The time convolution network is introduced between the network encoders and decoders of different scales of the generator to transmit information across layers, and it is finally discriminated by the discriminator. Machine translation uses a cyclic neural network to convert the source language text to the target language end. To achieve automatic translation between two natural languages, neural machine translation must first encode the source language text using an encoder and then decode the source language sentence to obtain the target language sentence. In other words, the encoder uses a cyclic neural network to convert the source language text into a dense vector. The decoder’s job is to convert the dense vector into a translation. The octave convolution residual block greatly reduces the model’s parameters and speeds up the network’s MT processing. In the context module, a multilayer empty volume is used, which greatly increases the receptive field and allows for better capture of multiscale context information. The goal of statistically based machine translation is to match segmented words and phrases in a parallel corpus of two language texts and then find the most relevant translation result. The application of artificial intelligence in natural language processing has been continuously developed in the 1990s, with the popularization of the Internet, making it possible to establish and operate large-scale corpora. Machine translation, with statistical translation as its primary function, has entered an unprecedented period of development. The growing demand for internationalization has created a huge market for translation software. Overall, machine translation is inextricably linked to human translation, and human translation requires the assistance of machine translation. The general trend will be the deep integration of the two. We can combine the advantages of both and learn from each other’s strong points in the translation process, which will not only improve efficiency and reduce the translator’s labour intensity but also improve the translation quality. However, it is undeniable that some low-level translators will be eliminated as a result of this process.

5. Implementation of AI MT

5.1. Design of the AI MT System Based on Fuzzy Algorithm.
Many languages, high speed, low cost, and a broad range of applications are all advantages of MT. As a result, it has a lot of advantages when it comes to translating simple and less demanding texts. Many people, for example, will choose software for translation when travelling abroad on business; this paper builds an AI MT system based on a fuzzy algorithm. Some companies with low requirements for translation quality or a large number of texts will choose MT because the system can process a large number of source language texts in a short period of time. Statistical machine translation ignores grammatical rules, despite the fact that it is constantly evolving and improving. A large-scale corpus is essential. For ambiguity resolution and translation selection, it makes use of statistics. The coverage ability of the probability model and corpus ultimately determines the translation effect. As a result, the word and phrase probability matching results fall short of the accuracy of the final sentence translation and the translation results are poor. Previously, only one maximum value was taken out as the keyword value when selecting each scan in translation; however, after improvement, the two maximum values, namely, the maximum value and the minimum value, were selected to exchange with the data, halving the workload and greatly increasing the operational efficiency.

The technicalization of the human translation will become an unavoidable trend in the future, thanks to artificial intelligence, big data, and other advanced information technologies. To begin with, machine translation (MT) powered by AI has resulted in significant changes in the way and content of translation. In this context, translators should not only improve their professional translation skills but also learn and apply new technologies in order to remain competitive in an AI-driven world. It is difficult for MT to figure out the precise meaning of words in a given context, let alone take into account the original text’s textual coherence and cultural background knowledge. He can apply his cultural knowledge to analyse and judge the context of the source text in order to choose appropriate words, sentences, and translation strategies in order to produce a translation that follows the original text’s style and the author’s intent. For today’s MT, these are difficult. The effect of AI on the MT system is positive, but it also makes the feature structure of the MT fuzzy. It is difficult to completely separate noise from signal in a single scale, whether in the time domain or the frequency domain. In this study, further damage to the fuzzy structural information will prevent MT from achieving good quality in the subsequent deconvolution process. The current translation market necessitates the use of translation tools, which could be a future trend. It will be difficult for translators to survive in the technical translation environment if they are unfamiliar with new translation techniques. This necessitates translators staying current with technology, learning and mastering technical translation skills, and putting them into practice.

The disadvantage of AI MT based on fuzzy computing is that it requires a large number of diagnostic rules to be established, making its self-learning function weak and unable to update the database in a timely manner, reducing accuracy. Machine translation is, at its core, a simulation of human thinking and language activities. However, translation is a complex brain thinking activity in and of itself. The use of electronic computers to simulate this advanced thinking activity of the human brain adds to the process’ complexity. We all know that there are numerous ways to simulate: the wheel imitates people’s legs and aeroplanes imitate bird flight. This simulation performs similarly to their prototype, but in a completely different way. The MT system has a large corpus and incredible memory terms like bilingual parallel equivalent corpus and bilingual translation equivalent corpus. As a result, manual translation may be inferior to MT for some texts with a large number of professional terms because bilingual knowledge requires long-term accumulation, and it is difficult for people to remember a large number of terms in a short period of time. A good translator not only understands the source and target languages’ cultural backgrounds but also has extensive encyclopaedia knowledge. As a result, the translator can take into account the differences between the two languages and cultures, understand the emotional factors in the works, and guess the author’s thoughts in order to translate more authentic works during the translation process. The standardization of MT systems for fuzzy algorithms is primarily driven by AI and translation technologies. As a result, the MT system’s requirements and testing should incorporate AI technology and the requirements for translation services in other industries, fields, and scenes, extract the basic common technical requirements, and present the corresponding testing methods to form an overall system, with scientific, applicable, and operable technical specification. Furthermore, the MT system can assist translators with a variety of basic tasks while also improving the quality and efficiency of translation, giving them more time and energy to devote to more complex translation projects. So that MT and human translation can collaborate in the face of various translation scenes and tasks. MT will perform some simple, basic, and repetitive tasks to free up time and energy for translators to focus on more complex tasks, allowing them to maximize their strengths in their fields.

5.2 Experimental Results and Analysis. This experiment evaluates these eight elements of AI MT in the fuzzy algorithm and determines the weight distribution of its subsystem elements as shown in Tables 1 and 2. According to the data provided by the manufacturer and the detected data in the preevaluation stage, the membership degree of each element is determined as shown in Tables 1 and 2.

As can be seen from Tables 1 and 2, in the fuzzy algorithm, the weight is not simply valued, but the maximum weight is taken on the premise of considering single-factor evaluation of MT and the maximum membership degree of single-factor evaluation is taken on the premise of considering factor weight. Therefore, the same data will appear in the results of MT. Although a lot of information will be lost, it can better reflect the results of single-factor evaluation of MT and the importance of factors. In this respect, it is better
than the touch type. However, there are still some limitations in multilevel evaluation and multifactor evaluation.

The data set used in this paper is the hierarchical English MT data set collected from TREC2007. There are 40 kinds of reliable graded English MT, which are composed of graded English MT with real semantic only one answer and 20 graded English MT with real semantic multiple answers randomly selected from trec2007. For comparative analysis, this experiment uses three experiments to compare the data mining algorithm, decision tree algorithm, machine learning algorithm, and fuzzy algorithm. FQ model is a model without any feature algorithm. The experimental results are shown in Figures 3–5.

It can be seen from Figures 3–5 that the order of MT has no obvious correlation with the order of the English MT information set. When the vocabulary index is 20, the average reliability ratio of the data mining algorithm is 0.63, 0.61 for the decision tree algorithm, 0.65 for the machine learning algorithm, and 1.08 for the fuzzy algorithm. The proportion of fuzzy algorithms in this paper is the highest of the four algorithms. The reason for this is that, in comparison to the fuzzy algorithm in this paper, data mining, decision tree, and machine learning algorithms have a much larger range. The graded English MT data set collected from TREC2007 was used in this experiment. There are 40 different types of reliable graded English MTs, which are made up of graded English MTs with unique real-word answers and graded English MTs with 20 different real-word answers randomly chosen from TREC2007. This experiment uses data mining algorithm, decision tree algorithm, machine learning algorithm, and fuzzy algorithm to make a comparison in this paper. The HEMTM model is a search and hierarchical English MT model without a feature algorithm. The experimental results are shown in Figures 6 and 7.

As can be seen from Figures 6 and 7, the order of MT conforms to the trend of translation in Figure 7 and the distribution of HEMTM MT is more concentrated under the model of HEMTM. When the vocabulary index is 15, the average reliability ratio of the data mining algorithm is 0.97, that of decision tree algorithm is 0.84, that of machine learning algorithm is 0.71, and that of fuzzy algorithm is

Table 1: Weight distribution of evaluation factors of the MT subsystem.

| Subsystem | C11 | C12 | C13 | C21 | C22 | C31 | C32 | C41 | Weight |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|--------|
| B1        | 0.4 | 0.3 | 0.2 |     |     |     |     |     | 0.2    |
| B2        |     |     |     | 0.4 | 0.5 |     |     |     | 0.2    |
| B3        |     |     |     | 0.5 | 0.3 |     |     |     | 0.1    |
| B4        |     |     |     |     |     |     |     | 0.4 | 0.1    |

Table 2: Judgment results of membership degree of each element.

| Grade     | C11 | C12 | C13 | C21 | C22 | C31 | C32 | C41 |
|-----------|-----|-----|-----|-----|-----|-----|-----|-----|
| Good      | 0.2 | 1   | 0   | 0.4 | 0.3 | 1   | 0.3 | 0.4 |
| Better    | 0.3 | 0.4 | 0.5 | 0.3 | 0.3 | 0.3 | 0.4 | 0.2 |
| Common    | 0.5 | 0.6 | 0.3 | 0.2 | 0.3 | 0.5 | 0.4 | 0.5 |
| Discrepancy | 1   | 0.3 | 0.4 | 0.0 | 0.0 | 0.3 | 0   | 0.5 |
1.34. Among the four algorithms, the fuzzy algorithm in this paper is the highest. MT is handy for dealing with some simple sentence patterns, but when it comes to complicated sentence structures or nested sentence patterns, MT will mechanically decompose them into clauses and then arrange and combine them, which is a kind of out-of-context expression.

6. Conclusions

Artificial intelligence has aided the development of translation services, making it easier for people to grasp the general meaning of languages other than their native tongue. They no longer need to rely on human translation to some extent. Translation by neural machines is no longer “word to word.” Long sentences with complex structures can be better understood as a whole, and the source and target languages can be transformed in conjunction with the context. This paper primarily introduces AI MT using a fuzzy algorithm and establishes a fuzzy algorithm AI MT system. This method combines general and special laws to produce unique results, thereby improving AI MT accuracy. The distribution of HEMTM MT is more concentrated under the HEMTM model, and the order of MT follows the trend of translation in the figure. The average reliability ratio of data mining algorithm is 0.97, decision tree algorithm is 0.84, machine learning algorithm is 0.71, and fuzzy algorithm is 1.34 when the vocabulary index is 15. The fuzzy algorithm in this paper is the best of the four algorithms. The differences between fuzzy-based algorithms and corresponding English MT support relationships are considered during the MT process. It has been confirmed that this model can be used with English multiple-choice questions. It is both a challenge and an opportunity to translate. To turn challenges into opportunities, we must continually improve our competitiveness, keep up with the times, fully utilize new translation technologies, and collaborate to usher in a new era of “man-machine dance.”

Data Availability

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

Conflicts of Interest

The authors declare no conflicts of interest.

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