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Exploring and Practicing the Reconstruction Path of Chinese Language Teaching Content System under the Deep Integration of Intelligent Language Service

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SUMMARY: *Machine translation and speech recognition are major enabling technologies to innovation and application in the language service industry. The current research develops the two methods individually and suggests a DR-Reformer multilingual translation technique based on optimal transportation and a Speech Recognition solution based on TDNN-LSTM to be used in Chinese. Based on this premise, both approaches are included in the reorganization of the Chinese teaching content framework and will define a new way of combining intelligent language services with educational content. To be more precise, the optimized DR-Reformer method is used to facilitate the understanding of language and reduce the level of complexity in learning Chinese, whereas the TDNN-LSTM speech recognition method is introduced in order to create a non-invasive educational setting and improve the quality of education. Each of the two methods is evaluated independently, followed by the implementation of the integrated approach in the teaching practice. The outcomes reveal that the experimental class that adopted this approach had an average of 75.84 12.253 and 86.92 8.074 in midterms and finals respectively, which were 5.55 and 9.36 higher than their counterparts who underwent traditional teaching. The results indicate that the instructional structure, which is backed by multilingual translation and TDNN-LSTM-based speech processing, is workable, efficient, and better than the traditional version, providing valuable directions to Chinese teaching practice.*

KEYWORDS: *Chinese language speech recognition; multilingual translation; TDNN-LSTM; intelligent language service; teaching content system reconstruction*

1 Introduction

As China's comprehensive national power and international status improve, the demand for Chinese language learning is becoming more and more widespread. However, the Chinese language curriculum divides literature and language very clearly, but the teaching contents therein are homogenized, fixed and patterned, ignoring the basic conditions and needs of overseas students and minority students [1-3]. Structurally, students are generally only interested in the grammar and structure of the Chinese language when they are engaged in Chinese language learning, mistakenly believing that as long as they have mastered the rules therein, they have mastered the Chinese language, thus mistaking the rules therein for the language [4, 5]. But in reality, Chinese language teaching is generally static rather than dynamic, and this isolation of static learning from other forms of learning completely isolates Chinese language from life and leaves it out of practice [6, 7]. And intelligent language services bring

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opportunities to the language education and language service industry.

According to the end of 2023, the language service sector of China has grown to be 198.23626 billion yuan in terms of market size, and the number of enterprises that are associated with it reached 1,242,575,000. The introduction of the giant language model based on OpenAI ChatGPT has taken this industry to a new level of intelligence and integration [8]. Intelligent language services can be defined as the combination of Artificial Intelligence (AI) and Natural Language Processing to simulate the human process of language understanding and language creation, thus providing language-focused solutions in a more intelligent fashion. Based on its powerful ability to analyze and generate languages, this area is currently also used in interpretation and translation, writing, editing and proofreading, subtitle creation, multilingual content management, language resources services, language technology R&D, terminology standardization, linguistic data mining, and language education [9-11]. The overall shape of the global intelligent language service industry is already massive and widespread, and its potential of future growth is still significant.

Smart language services based on large models can enhance the effectiveness of classrooms and learning results in Chinese language studies and learning more. In research [12] , an AI-assisted Chinese teaching system was created that takes only 15 seconds and 35 seconds to check vocabulary and grammar respectively, which demonstrates the efficiency and low-consumption nature of digital teaching software. Research [13] proposed a theoretical model and structure of elementary Chinese vocabulary teaching based on AI-generated materials, providing frontline teachers with a fresh and futuristic digital teaching model and driving the movement of Chinese as a second language towards personalization and science. The framework developed in study [14] is based on automatic generation of bilingual subtitles to lecture videos by integrating AI language technologies including automatic speech recognition and machine translation. Not only does this save time spent on subtitles and increase their quality in the source language, but it also assists students in mastering languages across boundaries. Study [15] used multi-scale fusion neural networks and nano-beetle optimization to develop an English-Chinese bilingual machine translation method and incorporated it into bilingual instruction, which increased translation accuracy by 99.5 percent. Study [16] designed an intelligent classroom management system on the basis of cloud computing and speech recognition and deployed it to Chinese courses and improved the outcomes of the instructions by acquiring vocabulary and practicing listening and speaking. Study [17] constructed an intelligent resource-generation system in Chinese teaching with the help of ChatGPT, including demand analysis, content creation, and evaluation, which allowed optimizing construction of international Chinese digital resources and supported the high-quality development of education. Study [18] reviewed the application of ChatGPT in three Chinese courses with teacher feedback indicating that the tool was quite useful in grammar learning, composition revision and academic writing assessment at all levels of beginner, intermediate and advanced and also improved the critical thinking, autonomous learning and general classroom experience among students. A paper published in [19] showed that artificial intelligence-based Grammarly training in Chinese writing classes had a significant positive effect on students’ writing abilities in terms of task-completion, coherence and vocabulary, particularly when working with learners with lower language proficiency. Study [20] explored the application of text-to-speech technology in the process of language learning and discovered that it may be effectively used in promoting knowledge transfer and language proficiency, though it has certain drawbacks in terms of intonation, eye contact and classroom interaction; nevertheless, it is still considered as a valuable instrument in language education support.

The present paper suggests a novel approach to teaching Chinese as it introduces the application of the optimal-transport-based DR-Reformer multilingual translation algorithm to enhance Chinese language understanding and optimizes the speech recognition with a TDNN-LSTM-based Chinese speech recognition model, thus, forming a deep immersion mode of enjoying Chinese literary materials. The research also examines the way that the translation sentence types such as declarative sentences and the number of utterances influence the performance of the DR-Reformer multilingual translation model on the basis of optimal transport. The paper also provides various language tasks and measures the recognition performance of the TDNN-LSTM based Chinese speech recognition model in every task situation. The new path, based on the incorporation of intelligent language services into the Chinese instructional material, is introduced into real pedagogical practice, and its efficiency is analyzed by way of comparative analysis.

2 Technological Reconstruction and Path Transformation of Chinese Language Teaching Content System

2.1 Translation techniques

Translation technologies based on artificial intelligence are taking up an increasingly significant role in the language service industry. Traditional forms of translation, which rely on a straightforward and inflexible way of processing information by humans, can no longer address the demands of a dynamically changing market. This will gradually be replaced by machine translation, speech recognition systems, multilingual subtitles generation, and neural machine translation methods.

The current paper will first present an alignment-information approach based on optimal transport to minimize the representational difference between languages and obtain more rich semantic properties. The paper further elaborates on a light-weighted DR-Reformer model that reduces the size of parameters and is more computationally efficient but still maintains the quality of translation.

2.1.1 Information Alignment Algorithm Based on Optimal Transportation

Optimal transport (OT) is used to measure the conversion of a set of distributions into another set of distributions, which is based on the principle of finding an optimal mapping between two distributions to minimize the cost of mapping any point in one distribution to the corresponding point in another distribution.

The information alignment algorithm based on optimal transportation studies how to solve the lexical alignment problem between source and target languages, and then generates a high-quality information-aligned corpus, which facilitates the realization of machine translation tasks. The algorithm establishes correspondences between source and extended vocabularies, which facilitates the learning of more diverse vocabularies in the translation process. Therefore, the alignment problem is transformed into an optimal transmission problem, which transports high-frequency and high-similarity vocabularies to generate high-quality aligned utterances suitable for specific domains. Assuming that enhancement of Chinese-English news data is needed but only monolingual data is available, in this case, the vocabulary extracted from the existing data is called the source vocabulary, while the data generated by back-translation is called the extended vocabulary. In this paper, the vector of source vocabulary and the vector of extended vocabulary are denoted as:

$$s_i = w_{i_1}, w_{i_2}, \cdots, w_{i_t}, e_j = w_{j_1}, w_{j_2}, \cdots, w_{j_t} \tag{1}$$

where the dimension of the vector is denoted as t. Therefore, the matrix containing the alignment information will be defined as:

$$P(s_i) = \frac{Token(s_i)}{\sum_{i \in V_s} Token(s_i)} \quad \sum_{i=1}^{n} P(s_i) = 1 \tag{2}$$

$$P(e_j) = \frac{Token(e_j)}{\sum_{j \in V_e} Token(e_j)} \quad \sum_{j=1}^{m} P(e_j) = 1 \tag{3}$$

$$U(S,E) = \left\{ P \in R_+^{n \times m} \middle| S = s, E = e \right\} \tag{4}$$

where S denotes the source vocabulary with n total number of words and E denotes the extended vocabulary with m total number of words. $P(s_i)$ and $P(e_j)$ denote the marginal probability distribution. The source vocabulary and extended vocabulary have different transportation distances and their preference matrices are calculated as:

$$\underset{i \in V_s, j \in V_e}{M(s_i, e_j)} = \frac{\sum_{a=1}^{t} W_{ia} \cdot W_{ja}}{\sqrt{\sum_{a=1}^{t} (W_{ia})^2} \sqrt{\sum_{a=1}^{t} (W_{ja})^2}} \tag{5}$$

where $M(s_i, e_j)$ is a preference matrix with n rows and m columns. Both source and extended vocabularies are discrete words.

In this paper, information entropy is introduced to align the source and extended vocabularies more equally. Therefore, the information entropy is defined as:

$$\begin{aligned} H(P) &= -\sum_{i,j} P(s_i, e_j) \log P(s_i, e_j) P(s_i, e_j) \\ &= P(s_i) \times P(e_j) \end{aligned} \tag{6}$$

Finally, the problem of aligning the information of the source and extended vocabularies is reconstructed as the following objective function as:

$$d_M^{\lambda} = \min_{P \in U(s_i, e_j)} \sum_{s_i, e_j} P(s_i, e_j) M(s_i, e_j) - \frac{1}{\lambda} H(P) \tag{7}$$

where d_M^{λ} is the distance between two probability distributions and λ is the entropy regularization term that was introduced to trade off similarity against word frequency information.

2.1.2 DR-Reformer

In this paper, we adopt Reformer as the backbone network. Being a variant of a Transformer-based model, it retains the main strengths of the original framework but adds locality-sensitive hashing and reversible-Transformer mechanisms to solve the problem of long-range encoding and memory usage.

Location-sensitive hashing (LSH) is a technique for approximate nearest neighbor search for high-dimensional data. The computational complexity of traditional dot product attention is $O(L^2)$. In contrast, DR-Reformer replaces dot-product attention with locality-sensitive hashing that projects high-dimensional representations to a lower-dimensional feature space using hash mappings and maintaining relative spatial locations. It is defined as:

$$\begin{aligned} & Attention(Q,K,V)=\sum \exp(Q\cdot K-M-Z)V \\ & where\ M=\begin{cases} +\infty, & if\ first\ word \\ 0, & otherwise \end{cases} \end{aligned} \tag{8}$$

where M is the mask set, Z is a normalization factor. Locality sensitive hashing prevents Q to focus on irrelevant positions and reduces the overall computational cost to $O(L*\log(L))$.

Dropout works by randomly deactivating a portion of the neurons at every training step, which encourages the network to learn features that are stronger and more widely applicable.

The Reduction module presents a trainable dropout matrix that is trained during optimization, reducing the size of high dimensional input vectors to a low dimensional representation without loss of the most informative elements. Also, this linearly transforms the input to the pre-softmax output layer, which results in one-to-one predictions and reduces the number of parameters and computations, as well as their accuracy. It is specified as:

$$\mathrm{Re}\,duction(x)=Concat\left[soft\max\left(W_1x^T\right)x_1,\cdots,soft\max\left(W_nx^T\right)x_n\right] \tag{9}$$

where W is the learnable parameter.Reduction not only reduces the model parameters and computational complexity, but also avoids the overfitting problem and improves the generalization ability of the model.

The goal is to make the scale of the parameters lower and to increase the quality of the translation, therefore, a Dropout1/2D level is added to the Reformer architecture to ensure that redundant features are gradually removed. Simultaneously, a Reduction layer is added to reduce the size of parameters and computational costs. In general, DR-Reformer increases the pace of training and boosts predictive capabilities without affecting the quality of translations.

2.1.3 DR-Reformer multilingual translation algorithm based on optimal transportation

The framework of the optimal transportation-based multilingual alignment information translation algorithm is as follows:

a. Use the optimal transportation-based alignment information algorithm for data enhancement. Specifically, if the target language is a low-resource language, the bilingual parallel corpus is first obtained by back translation. If the target language is a high-resource language, the word lists are directly extracted from the source vocabulary and the extended vocabulary, which are fed into the algorithm of this paper to screen the best replacement words and generate high-quality alignment data, so as to narrow the representation gap between multilinguals.

b. Input the multilingual alignment data into DR-Reformer for pre-training to learn richer semantic information.

c. The data in the target language that needs to be used in the task are next passed through DR-Reformer to fine-tune them, as they seek to eliminate noise introduced in the process of multilingual training and finish optimizing the translation model.

2.2 Speech recognition technology

Speech recognition is one of the central methods that are used in natural language processing and it involves analyzing spoken utterances. It allows machines to automatically recognize and comprehend human speech through the combination of speech-signal processing and pattern analysis.

2.2.1 Acoustic modeling based on time-delay neural networks

A time-delay neural network is a particular type of multilayer feed-forward neural network that typically has three or more layers. It is also known as a one-dimensional convolutional neural network and can be used in processing continuous speech features.

The time-delay neuron (TDN) is the fundamental building block of the time-delay neural architecture formed by the node at a certain time step as well as the nodes connected to the previous and next time intervals.

For example, the time delay neuron time span is set to T, and the node at moment t has N inputs $(x_1(t), x_2(t), \cdots, x_N(t))$, and the first T moments inputs of each input $x_i(t)$ are $x_i(t-n), n = 1, 2, \cdots, T$, weights are $\left(w_{i1}, w_{i2}, w_{i3}, \cdots, w_{iT}\right)$, and neuron outputs are valued as $h(t)$, then the formula is as follows:

$$h(t) = f\left[\sum_{i=1}^{N}\left[\sum_{n=1}^{T} w_{in} \cdot x_i(t-n)\right] + b_i\right] \tag{10}$$

where $f(\cdot)$ is the activation function and b_i is the bias coefficient.

In traditional TDNN all nodes within the time step at each moment in time perform parameter updates, so the activation function of the hidden layer is always computed repeatedly. A large portion of the contextual information contained in neighboring time points overlap, resulting in increasing the training complexity of the neural network, so a subsampling approach can be used to reduce the model complexity during the training process.

In acoustic modeling of speech recognition systems, the network training process can be computed by merging non-adjacent speech frames based on the time span of the TDNN.

2.2.2 Acoustic modeling based on long and short-term memory networks

Recurrent neural networks better highlight the stronger modeling ability for the task of temporal correlated information. The RNN network structure is expanded for the hidden layer, $t-1$, t, $t+1$ denote the temporal sequence. x denotes the input information. s_t denotes the memory at time t. W denotes the weight of the input, U denotes the weight of the input parameters at this moment, and V denotes the weight of the output parameters. At the moment $t=1$, the input $s_0 = 0$ is generally initialized, the values of W, U, and V are randomly initialized, and the value of h_1, the value of s_1, and the value of o_1 are known from the following formula:

$$h_1 = Ux_1 + Ws_0, s_1 = f\left(h_1\right), o_1 = g\left(Vs_1\right) \tag{11}$$

Among them, $f(\cdot)$ and $g(\cdot)$ are both activation functions. $f(\cdot)$ can be activation functions such as Tanh, ReLU, Sigmoid, etc., and $g(\cdot)$ is usually a Softmax function. According to the time sequence, the state s_1 at this time as the memory state at the current moment will participate in the prediction activity at the next moment, at this time, we can introduce Eq:

$$h_2 = Ux_2 + Ws_1, s_2 = f(h_2), o_2 = g(Vs_2) \tag{12}$$

And so on to get the final output value as:

$$h_t = Ux_t + Ws_{t-1}, s_t = f(h_t), o_t = g(Vs_t) \tag{13}$$

Recurrent neural networks tend to be effective in time-series problems. However, in cases where model parameters are not changed in training, gradients are repeatedly multiplied in the backpropagation process and may become too large or too small, resulting in exploding-gradients or vanishing-gradients issues. In order to overcome such problems and to have more appropriate capture of temporal dependencies, Long Short-Term Memory (LSTM) a particular type of RNN is proposed. Unlike a normal RNN, an LSTM network also computes on the basis of the current input x and the previous time step output of the hidden-state, but it changes the inner structure of the hidden state. It has neurons, which consist of an input gate i, a forget gate f, an output gate o, and an internal memory cell C.

The forget gate is controlled by a Sigmoid function that outputs a value f_t between 0 and 1 on the basis of the last hidden-state output h_{t-1} and current input x_t. This value is used to decide whether the data kept in the last memory state C_{t-1} must be completely retained, partially forgotten or forwarded. In this case, w is the weight matrix, σ is the bias vector, and sigma is the nonlinear activation function. It can be expressed in the following way:

$$f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{14}$$

The Input Gate decides which information needs to be updated via Sigmoid, while the Tanh layer is generating new candidate values $\tilde{C}_t$, which may be added to the internal memory cell as a candidate value generated by the current layer. Combining the values generated by the above two parts is done to update the model. Firstly, the product information of the internal memory cell and f_t from the previous layer is used to forget the unwanted information, and then it is added with $i_t \times \tilde{C}_t$ to get the candidate value C_t, which is calculated as:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right), \tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right), C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{15}$$

The final step is to determine the output of the model, which is obtained by multiplying an initial output through the Sigmoid layer with the value of C_t scaled to values between -1 and 1 using Tanh. The representation formula is as:

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right), h_t = o_t \times \tanh\left(C_t\right) \tag{16}$$

2.2.3 Acoustic model based on TDNN-LSTM hybrid network

The architectures of time-delay neural network and long short-term memory network have been described above. The two architectures demonstrate great modeling ability on tasks that have significant temporal correlation but long short-term memory networks are harder to train than time-delay neural networks. Due to this, a TDNN-LSTM hybrid architecture has been used in the acoustic modeling of Chinese speech recognition to ensure adequate contextual information is captured and computational cost reduced. Figure 1 shows the configuration of the hybrid TDNN-LSTM architecture.

The network consists of six hidden layers: layers 2, 4, and 6 use the LSTM structure, and layers 1, 3, and 5 have the TDNN-LSTM structure.

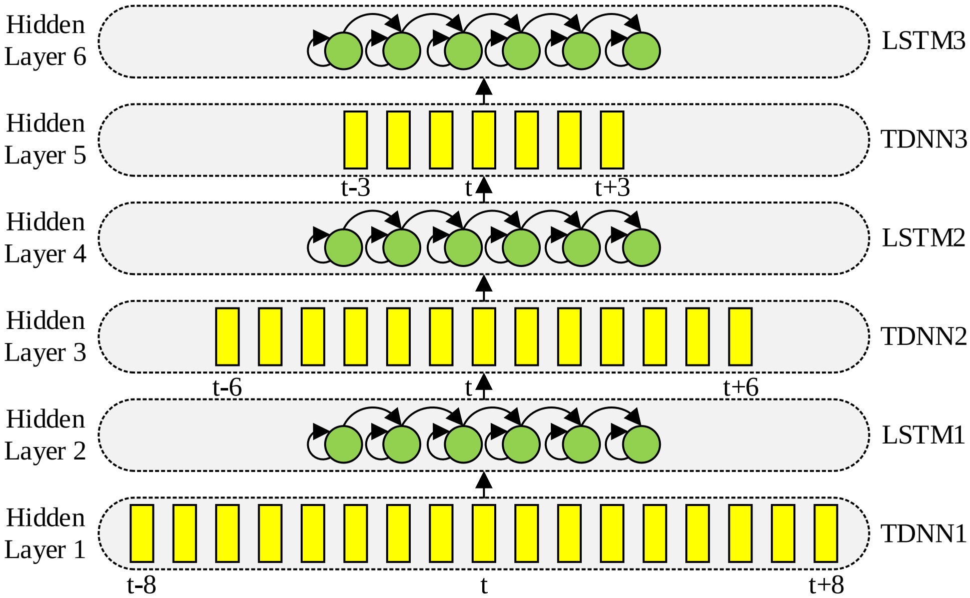

Figure 1: TDNN-LSTM hybrid network structure

2.3 New Path of Chinese Language Teaching Content System

The novelty of this paper is that it suggests a new solution to integrate intelligent language services into the content of teaching Chinese language by using the optimal transport based DR-Reformer multilingual translation algorithm and a Chinese speech recognition model based on the TDNN-LSTM. In particular, the optimized DR-Reformer multilingual translation method is used to improve the understanding of Chinese language, whereas the TDNN-LSTM speech recognition framework is implemented to create an immersive literature experience. Not only does this combination make understanding Chinese easier, but it also helps students develop an appreciation of Chinese literature.

(1) Utilizing translation technology to update Chinese language understanding

Because the teaching of Chinese language and literature is frequently required to include the historical background, key concepts, and information about the writers, and because these aspects are associated with a considerable amount of data, translation technologies need to be implemented to facilitate teaching in the classroom. Teachers can alleviate instructional stress and have students comprehend the meaning of the text more efficiently using multimedia presentation by integrating the author biography, the content of the text, and appropriate historical documents as part of multimedia-based translation materials and creating courseware as such.

(2) Speech recognition technology to create immersive literature appreciation

In the context of teaching Chinese language and literature, it is essential to assist students in comprehending the literary text but it is also vital to enhance their capability to enjoy and analyze literary pieces to enable them cultivate their creative thinking and literary sensitivity even more. Actually, the time spent on teaching a class is often restricted. University teachers need to utilize the intelligent language service strategies in providing literary education more effectively by incorporating literary texts, recitations, commentaries and other relevant materials into short video clips. It will help students get a better idea of the works using video-based learning, have a greater insight into the meanings expressed in Chinese language and literature, and develop their capacity to perceive literary texts over time.

3 Practical application of the new path of Chinese language teaching content system

3.1 Evaluation of the performance of new translation technologies

3.1.1 Effect of Translated Sentence Types on Model Performance

The types of utterances set for automatic machine translation are declarative sentences, special usage sentences, interrogative sentences, and juxtaposed compound sentences, in order to test the translation quality of the DR-Reformer multilingual translation algorithm model based on optimal transportation. The training set and test set for multiple languages in the evaluation process are 5000 translated statements, and the translation quality result statistics of the translation model in this paper are shown in Fig. 2.

The DR-Reformer multilingual translation algorithm based on optimal transportation has the best quality of Chinese language-Chinese language translation, with 26 errors in declarative sentences and 29 in interrogative sentences. When the algorithm converts Chinese to French, 102, 184, 136 and 161 errors occur in declarative sentences, special usage sentences, interrogative sentences, and juxtaposed composite for each sentence type, and the error rate is in the range of 2.04% to 3.68%.

The DR-Reformer multilingual translation algorithm based on optimal transportation has more errors when translating special usage sentences, and the error rate of translating special usage sentences in multilingual is in the range of 1.28%~3.68%.

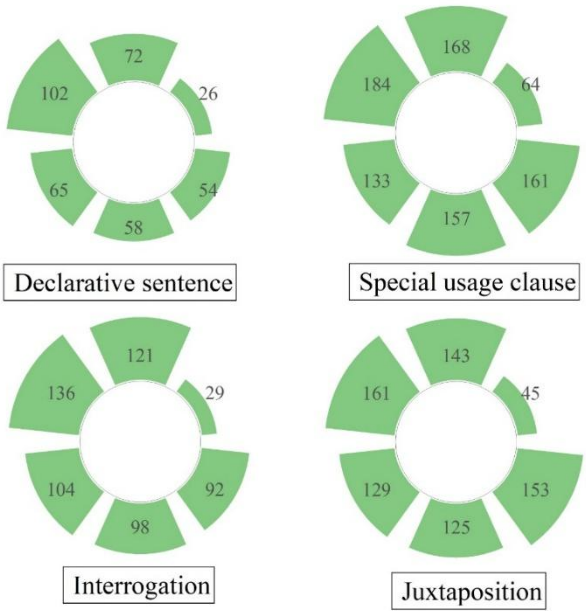

Figure 2: The translation quality results of this article are calculated

3.1.2 Effect of number of statements on model performance

Bilingual Evaluation Alternate (BLEU) Score: For a given sentence, there is actual translation quality information A1, and there is a proposed model evaluation result A2, for A2, it is judged how many correct evaluation results of the proposed model evaluation result A2 have appeared in A1, and this ratio is the BLEU score.

The BLEU score may be calculated at the sentence level, based on translation errors in the test set, to determine the effectiveness of the suggested method and the impact of the number of utterances on model assessment is shown in Figure 3.

The findings demonstrate that the variations in the size of the utterances do not seem to have any apparent impact on the outcomes of the assessment of the proposed approach. When the optimal-transport-based DR-Reformer multilingual translation algorithm is analyzed and the number of utterances is increased, starting with 1,000 then increasing to 6,000, the BLEU scores rise to 93 and 98 respectively and the practical performance is improved.

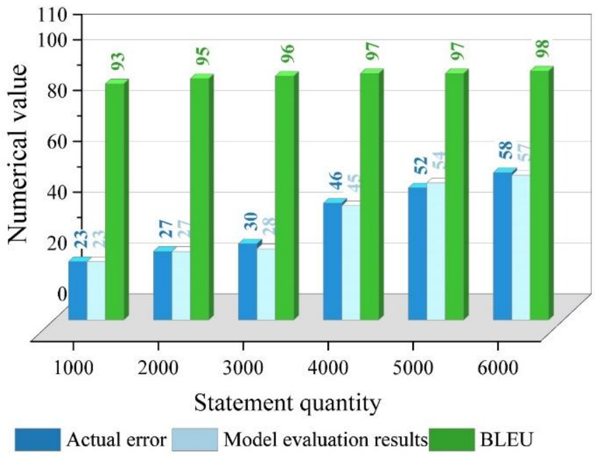

Figure 3: The number of statements affects the performance of the model

3.2 Performance Evaluation of New Speech Recognition Technologies

Figure 4 shows the impact of linguistic diversity on Chinese speech recognition and offers a comprehensive comparison of the effects that various language pairings have on recognition outcomes in tasks that include five language varieties: Hakka, Nanchang, Changsha, Hebei and Sichuan.

In five single-task settings, the TDNN-LSTM based Chinese speech recognition system attains a score of 0.674, 0.653, 0.621, 0.665, and 0.669, in the case of Hakka, Nanchang, Changsha, Hebei, and Sichuan, respectively.

When pairs of languages are learned jointly, the highest recognition score of the TDNN-LSTM-based Chinese speech recognition system reaches 0.672 for the Hakka－Nanchang combination. The model also shows strong performance for the Hakka－Hebei pair.

The results indicate that, under a single learning task, the gain in recognition quality is relatively limited. As the number of learning tasks increases, the overall recognition capability improves progressively. However, once too many learning tasks are introduced, recognition of the current target language, namely Chinese, begins to decline, and overfitting may emerge.

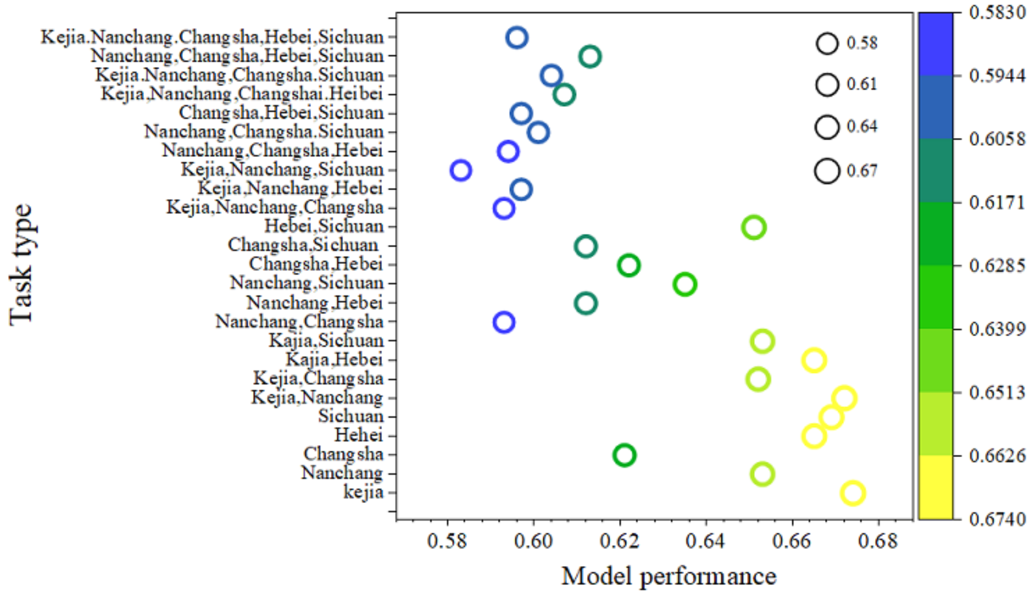

Figure 4: The effect of different languages on speech recognition of Chinese language

The Chinese language speech recognition performance comparison is shown in Figure 5, where a meta-learning speech recognition model (meta-reptile) is added as a benchmark model. meta-reptile mainly uses the reptile algorithm, where each parameter update is done at the first-order gradient on each task, which improves the model's arithmetic speed and reduces memory consumption.

The TDNN-LSTM model has the best performance of 0.937 for Chinese language speech recognition, the model's performance ranking for Chinese language speech recognition is: meta-reptile<DNN-HMM<LSTM<LSTM+CTC<Bi-LSTM+CTC<TDNN-LSTM.

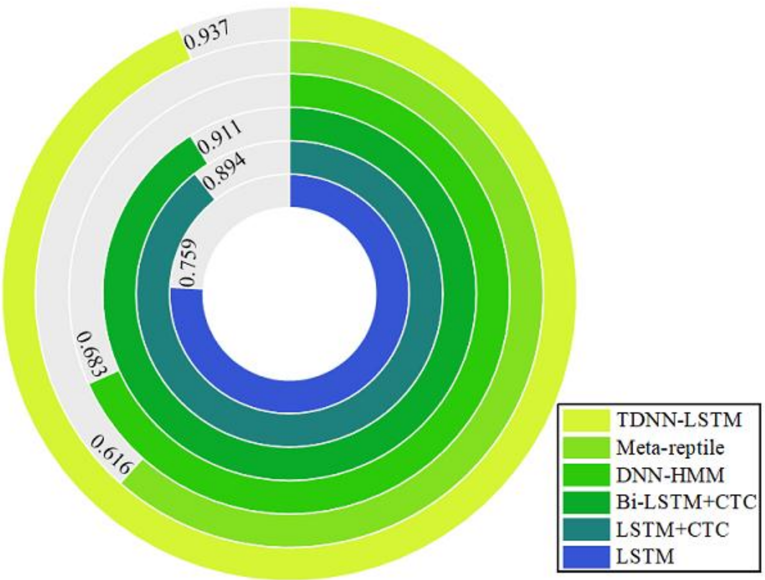

Figure 5: Comparison of speech recognition performance in Chinese language

3.3 Analysis of the effect of the new pathway practice

3.3.1 Contrasting designs

This section will compare the results of the academic performance of the experimental group (Class A) and the control group (Class B). All the reliability and the validity of the test papers, the importance of score differences, as well as the results of the midterm and final exams in both classes are thoroughly investigated using SPSS in order to assess the impact of integration of Intelligent Language Services into Chinese language instruction on teaching effects.

The experimental class and the control class were taught Chinese language for one semester, and the achievement data of their learning performance were analyzed through the three stages of pre-school test, mid-term test and final test. The pre-school test is a feeler test, the main purpose of which is to see the general situation of Chinese language proficiency of the two classes, while the mid-term and final tests are the stage tests and the final outcome tests at the stage of the application of the teaching method.

Examination time: the teaching period is from September 15, 2025 to December 26, 2025, the pre-school test is arranged on September 3-5, the mid-term test is arranged on November 3-5, and the final test is arranged on December 26-30.

3.3.2 Comparative analysis

(1) Reliability and validity of test papers

SPSS statistical software was used to evaluate the reliability of the midterm and final examination results of both the experimental group and the control group. The reliability coefficients of the midterm and final test papers of these two groups are all above 0.7 i.e. alpha is greater than 0.7, which means that the exam scores of the students are reliable and the test paper has a high level of internal consistency.

The correlation analysis was also carried out on the midterm and final scores of the experimental group. Because the Pearson coefficient, Kendall Tau coefficient, and Spearman's Rho are all greater than 0.9, the relationship between the two exams is extremely strong, which indicates that their test validity must be very high. The Pearson coefficient of the control group is 0.875, Spearman s Rho is 0.943 and Kendall Tau is 0.890. These figures also show that there is a significant connection between the two tests and that the test validity is acceptable.

(2) Significance of differences in grades

In order to ascertain whether the use of parametric analysis would be suitable, the midterm and final results of both groups were initially tested to check on their normality. Table 1 indicates the result of the one-sample K-S test of the midterm performance of the experimental class and the control class.

Based on the table, the one-sample K-S statistics of both the midterm and final examinations indicate the asymptotic two-tailed significance values to be more than 0.05. This means that score distributions in the two groups may be considered normal, which is a requirement of an independent-samples t-test.

Table 1: Test results of a single sample of the midterm exam results

Class	Period	Kolmogorov-Smirnov Z	Asymptotically significant (double)	Conclusion
Laboratory class (Class A)	Midterm	1.134	0.426	It's in the normal distribution
Cross-reference class (Class B)		0.926	0.652	
Laboratory class (Class A)	Final term	0.725	0.854	
Cross-reference class (Class B)		0.689	0.787	

(3) The midterm and final examination scores of the two classes were compared

To analyze examination results of the experimental group and the control group, descriptive statistics were utilized. The given approach is an immediate depiction of the features of the samples and allows comparing the assessment findings of the two groups in a simple way.

Figure 6 shows the descriptive findings regarding the two groups of examination scores.

The mean values and standard deviations of the two examinations in the experimental group (Class A) were 75.84+12.253 and 86.92+8.074, respectively. The corresponding ranges were 43.58 and 27.89.

The control group (Class B) had a mean value and standard deviation of 70.29+15.956 and 77.56+7.536 with corresponding ranges of 50.21 and 24.05

The average score of Class A in the Chinese midterm examination was 5.55 points higher than the average score of Class B. Also, the standard deviation of Class A was less than Class B, which means that the midterm performance of the experimental group was more focused, and score variation was relatively low. When taking the range and standard deviation into consideration, the overall variation in the results achieved by the experimental group were slightly bigger, but the difference in fluctuations in the two groups was not significant. The mean score of Class A on the final examination was 9.36 points higher than class B and this difference was also higher than what was observed in the midterm examination. Based on these observations, a more distinct difference can be seen in the final examination results: the final scores of the experimental group were more than those of the control group.

Reliability, validity, and discriminatory power of the two tests were evaluated in the two groups with the use of SPSS separately. As the findings indicate, the two test papers had high reliability and validity. In contrast, the independent-samples t-test revealed that there were no statistically significant differences between the two groups on the two assessments. Nevertheless, in both examinations descriptive statistics indicated that the experimental group scored higher average values compared to the control group in each case. It implies that the introduction of Intelligent Language Services had a more visible and favorable impact on the acquisition of the Chinese language than the traditional educational methodology used in the control class. All these findings combined point to the fact that the students who were taught according to the Intelligent Language Service framework had higher Chinese learning results then the students who studied based on the traditional instruction.

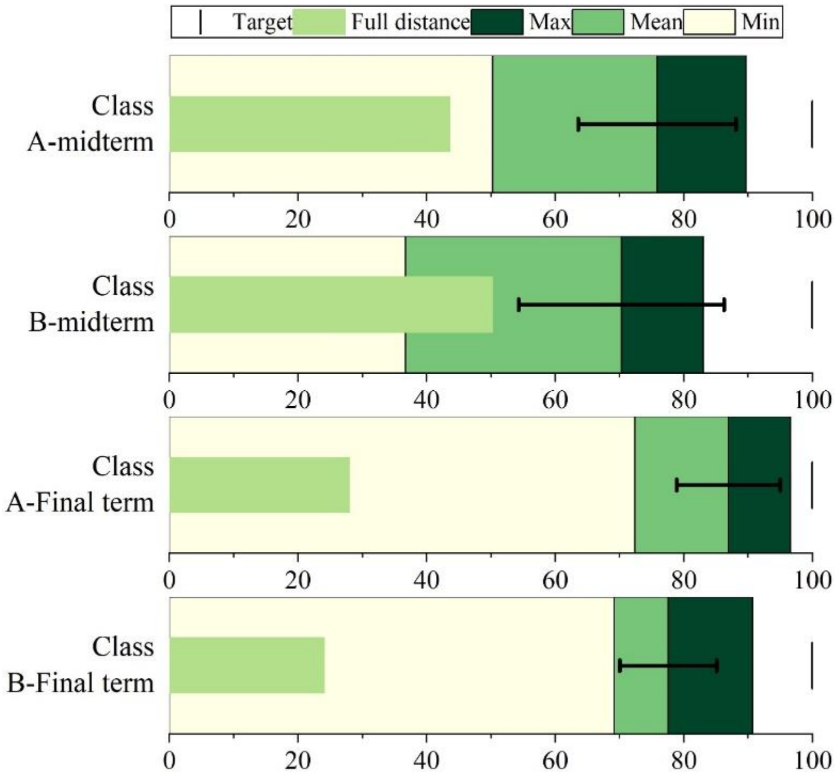

Figure 6: Descriptive statistical results of midterm and final exam scores

4 Conclusion

The paper contributes to the development of translation and speech recognition technology and suggests a new way of the intensive integration of intelligent language services into the Chinese language learning system. This assesses the quality of the DR-Reformer multilingual translation method based on optimal transport and TDNN-LSTM Chinese speech recognition system, and additionally explores the application of this new route in practice.

(1) The multilingual translation of Chinese into Chinese, English, French, and other languages using the optimal-transport-based DR-Reformer method may be successful. Of the tasks, Chinese to Chinese setting has the least error rate. The amounts of translation errors in declarative sentences, special-use expressions, interrogative sentences and coordinate compound sentences are 26, 64, 29, and 45 respectively and the error rates are 0.52% -1.28%. Even though model evaluation is affected by the number of utterances to some degree, it does not significantly change quality of translation, which has an error rate of 0-1.28%. This strategy can thus be used in Chinese-language classes so that students can acquire more profound language comprehension. Besides, the Chinese speech-recognition framework based on TDNN-LSTM can also efficiently recognize Chinese content in various language-related tasks, which will also facilitate the development of enhanced Chinese-language educational resources and instructional design.

(2) The new path of integrating intelligent language services with the Chinese language teaching content system is practically applied, and the comparison of the data results shows that the Chinese language teaching content system under the deep integration of intelligent language services can effectively improve the Chinese language learning performance, and the new path provides new development possibilities for the renewal of the Chinese language teaching content system.

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