English-Chinese Bilingual Teaching: A DECTMT-NBO-DMSFNN Approach for Design and Application of Machine Translation Technology

Yuwei Wang
Sanmenxia College of Social Administration, China
phdyuweiwang@gmail.com

Abstract: *This manuscript introduces a bilingual teaching model prediction system called Deep Multi-Scale Fusion Neural Network (DMSFNN). The system utilizes data from the Back-end database, and a pre-processing step is performed to remove noise and imperfect texts using the Adaptive Iterated Guided Filtering method or a global constant score. The English-Chinese Machine Translation (MT) method presented in this research uses Domain-Specific English-Chinese Machine Translation Namib Beetle Optimization-Deep Multi-Scale Fusion Neural Network (DECTMT-NBO-DMSFNN) to address the issues with current translation systems' frequent and time-consuming mistranslations. The translation process is improved by NBO-DMSFNN after examining the major principles and particular approaches of computer translation from English to Chinese. Pre-processing is done on the English to Chinese translation text data, and DMSFNN quickly extracts and classifies the text's features. The DECTMT-NBO-DMSFNN approach introduces a novel bilingual teaching model for English-Chinese Machine Translation method. Leveraging DMSFNN and NBO, it effectively addresses noise in data through pre-processing, utilizes a Back-end database, and employs feature extraction with the Bilingual Bag-of-Words approach. This unique integration enhances bilingual teaching model prediction and improves English-Chinese MT. Notably, DECTMT-NBO-DMSFNN achieves accuracy level of 99.5% in both languages.*

Keywords: *English, chinese, translation, text, language, communication, teaching, bilingual, vocabulary, learning, phrase.*

Received April 11, 2024; accepted September 12, 2024
https://doi.org/10.34028/iajit/21/6/8

1. Introduction

Recent years have seen tremendous advancements in Machine Translation (MT), particularly with the emergence of neural network-based methods. One such promising approach is Transfer Learning (TL), which improves performance in another domain or language by applying knowledge from that domain or language [4]. This research paper focuses on providing a comprehensive review of TL-based models for English-Chinese Machine Translation (ECMT). The objective is to evaluate their effectiveness, limitations, and potential in addressing real-world translation challenges [11].

Language translation plays a crucial role in facilitating multilingual communication, fostering cultural exchange, supporting international trade, and encouraging global cooperation. Nevertheless, achieving an accurate and contextual appropriate translation between English and Chinese presents unique difficulties due to substantial linguistic and structural differences between the two languages [12]. Traditional rule-based and statistical MT systems encountered limitations in capturing the intricacies of translation, resulting in the development of models for neural machine translation [13].

Neural Machine Translation (NMT) models have shown remarkable performance increases in a variety of language pairings, including English and Chinese. NMT models employ transformer topologies and recurrent neural networks as deep learning techniques [14]. However, these models frequently rely on a large volume of parallel training data, which could be difficult to get for languages like Chinese [18]. To address the challenge of limited parallel data and enhance MT performance, TL emerges as a compelling solution drawn from the field of Machine Learning (ML). By utilizing and modifying information from a language pair with abundant resources, such as English and Spanish, to the English-Chinese context, TL-based ECMT models can grasp common linguistic patterns and general translation principles, resulting in more precise and contextually appropriate translations [6, 10].

The need to address the time-consuming nature and numerous mistranslations associated with standard translation procedures motivates this study's work. As global interactions and cross-cultural communications continue to grow, there is an increasing demand for accurate and efficient bilingual and multilingual translation. Advancements in computer technology, especially in the domains of neural networks and natural language processing, present encouraging prospects to advance MT techniques and raise translation quality [21]. Additionally, MT poses various linguistic challenges, necessitating collaboration between linguists, computer scientists, engineers, and other experts from diverse disciplines. The research aims to not only optimize existing MT approaches but also explore specialized solutions for the specific challenges faced in English-Chinese translation, given the linguistic complexities of both languages [3].

By refining and advancing MT methods, this research seeks to contribute to language accessibility, inclusivity, and improved communication across linguistic barriers in both academic and industrial domains [8, 25]. Ultimately, the goal is to create more effective and accurate MT systems that can facilitate seamless language understanding and foster cross-cultural understanding in an increasingly interconnected world [16]. However, in actual use, it is discovered that the aforementioned conventional approaches have varying degrees of the time-consuming translation methods as well as numerous errors. To solve this problem, the manuscript creates a TL-based MT technique for English to Chinese [5, 18].

1.1. Contribution Statement

The paper's primary contribution is mentioned as follows:

- Creating a MT method for English to Chinese based on TL to overcome time-consuming and frequent errors in standard translation techniques.
- Examining the fundamental ideas and specific approaches of traditional neural MT techniques as well as English-Chinese MT.
- Optimizing the translation process through TL to rise the effectiveness and accurateness of English-Chinese translation.
- Pre-processing English-Chinese translation text-data and extracting relevant features from the text.
- Utilizing feature TL to rapidly classifies of English-Chinese translation text as well as constructs machine models accordingly.
- Demonstrating the proposed method performance through outcomes, showing its ability to achieve design expectations.
- Advantages of the proposed technique include reduced translation time and lesser mistranslations compared to traditional approaches.

The remaining of the paper is as follows: part 2 clarifies literature survey. part 3 describes proposed methodology. part 4 shows result discussions. part 5 ends this study.

2. Literature Review

The literature recommended several studies related to the studies on the creation and use of an English-Chinese bilingual education model using MT technology.

Zhao *et al*. [26] have successfully deployed the challenges associated with applying a GPU-enabled deep learning MT system that uses a domain-specific corpus to translate text from word-based languages (like English) to Chinese. The inherent difficulties arise from the distinct grammar and the absence of distinct word boundaries in the Chinese language. Their strategy employs an encoder-decoder paradigm with an attention mechanism and was based on Google's Transformer architecture. In the training phase, Simple self-designed entropy loss function and an Adam optimizer were applied to bilingual English-Chinese text sentences extracted from the News section of the University of Michigan Corpus (UM-Corpus). The parallel training process of their model may be executed on desktop computers, normal laptops, and servers with a single GPU.

Bi [1] have examined the prolonged evolution and MT's advancement against the backdrop of globalization. Although MT has made great progress, the quality was still subpar, which makes it difficult to meet user expectations. Artificial intelligence, as a discipline exploring the principles of human intelligent activity, emerges as a potential solution. Integrating artificial intelligence technology into English translation systems, particularly concerning depression and depression in English, when paired with an intelligent knowledge base and the Internet, offers a promising avenue for addressing translation challenges. Against this backdrop, this research focuses on an artificial intelligence system utilizing neural networks and an intelligent knowledge store to translate English. Improving the translation of long English sentences within the primary objective was to maintain the structure of the current English-Chinese MT.

Yang and Luk [23] highlight the historical focus of digital library research on structural and semantic interoperability. Their proposal focuses on the creation of an automatic cross-lingual thesaurus that addresses the preliminary findings of cross-lingual semantic interoperability research, using a parallel corpus of English and Chinese. The proposed thesaurus helps create semantically relevant terms for improved information retrieval. It was produced using the Hopfield network and co-occurrence analysis.

Xu [22] have presented an English-Chinese MT research technique based on TL. First, they clarified the theories about TL, neural MT, and associated technologies. The discussion focused on the nuances of neural MT, highlighting the advantages and drawbacks of several models before deciding on the transformer neural MT model framework. Thirty million parallel Chinese-English corpora, one hundred thousand low-resource parallel Chinese-English corpora, and one hundred thousand parallel the transformer MT architecture was pre-trained with the aid of Tibetan-Chinese corpora.

Yu and Ma [24] have addressed the challenges of low accuracy in recognizing the parts of speech for English phrases, suboptimal English translation outcomes, and extended translation durations inherent in traditional English translation models. They have created an intelligent recognition and deep learning based English translation model. This effort involved creating an English phrase corpus and using the updated Generalized Left-Right (GLR) algorithm to calculate the postscript and antecedent likelihood of phrases using quaternion cluster computations. These computations were used to identify the components of speech for the English phrase corpus. Subsequently, a model for neural MT was created using the best contextual features that could be extracted using the contextual feature extraction strategies that were presented.

Liu *et al*. [9] investigated the contemporary globalization age, where translation technologies have gained popularity in everyday communication, education, and the translation industry. The prevalence of MT usage among translation learners has been observed, raising concerns about the appropriate application versus misuse of MT and its impact on translation teaching. The study aimed to investigate the knowledge of MT, the experiences of both learners and instructors in MT usage, perceived quality of MT, the morality of using MT and the belief that MT and translation training are related. It was intended to determine whether MT training was necessary and how useful MT was in helping people become competent translators.

Sun [17] have addressed the difficulties of translating between languages by utilizing the development of a bidirectional MT model using existing neural network technologies between English and Chinese that focuses on marine science and technology. They generated a specific corpus in English and Chinese that included abstracts and partial whole texts of publications on marine science and technology by employing deep learning techniques. The output from the separate sublayers of the Chinese and English encoders was combined using the bidirectional translation model, which integrated local weight sharing.

Table 1. Summary of limitations in English-Chinese bilingual education models using machine translation.

Study	Approach	Limitations
Zhao *et al*. [26]	GPU-enabled deep learning machine translation using domain-specific corpus, encoder-decoder paradigm with attention	Distinct grammar differences and absence of word boundaries in Chinese create challenges; limited to single GPU.
Bi [1]	AI system using neural networks and intelligent knowledge base for English-Chinese translation	Quality of machine translation still subpar; difficulty in meeting user expectations; limited scope of application.
Yang and Luk. [23]	Automatic cross-lingual thesaurus using Hopfield network and co-occurrence analysis	Focused on legal applications in Hong Kong; relies on specific corpus; may not generalize to other domains.
Xu [22]	Transfer learning with transformer neural machine translation model	Requires extensive pre-training; effectiveness dependent on quality of low-resource corpora; computationally intensive.
Yu and Ma [24]	Intelligent recognition and deep learning based English translation model with updated GLR algorithm	Challenges in recognizing parts of speech; suboptimal translation outcomes; extended translation durations.
Liu *et al*. [9]	Investigation on MT usage among translation learners and instructors	Impact of MT on bicultural understanding is limited; effectiveness depends on learners' proficiency and motivation.
Sun [17]	Bidirectional machine translation model using neural networks for marine science and technology	Specific to marine science and technology; performance improvements are domain-specific; limited generalizability.

Table 1 shows a concise overview of various approaches to English-Chinese bilingual education models utilizing MT technology. Each entry includes the study reference, the main approach, and the key limitations identified in the literature.

3. Proposed Methodology

In this section, Development and application of English-Chinese DECTMT-NBO-DMSFNN is discussed. The block diagram of the DECTMT-NBO-DMSFNN English-Chinese bilingual teaching is represented in Figure 1. It contains 4 stages, like pre-processing, feature extraction, Data acquisition and English-Chinese text classification. Consequently, a thorough explanation of each step is provided below:

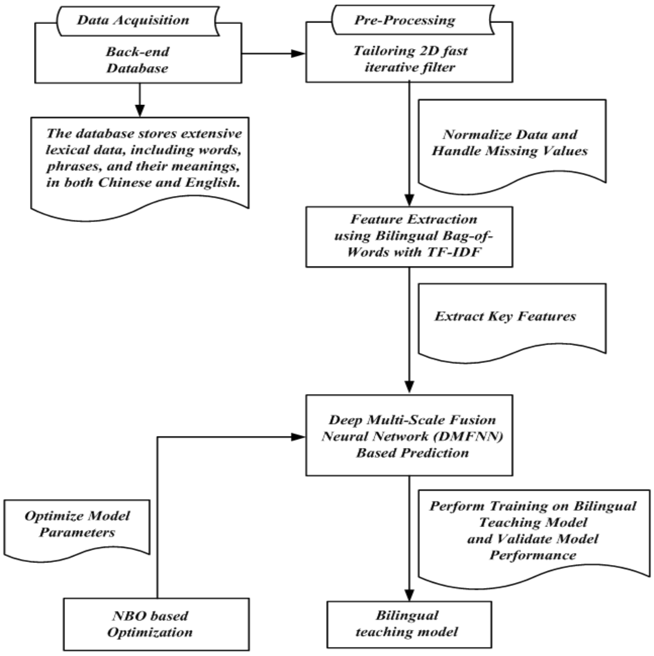

Figure 1. Block diagram of the DECTMT-NBO-DMSFNN technique.

3.1. Data Acquisition

This study describes an application that aims to simplify web access to lexical information for both Chinese and English. Front-end HTML forms are connected by a Visual Basic application to an object-oriented database that is implemented using Logic Programming Associates Prolog++ (LPA Prolog++) on the back end. The program consists of three primary parts:

1) A back-end database that stores lexical data.
2) A Web Client application that receives queries from users on the front end.
3) An Agent application that manages communication between the database and client inquiries. This application's access techniques are based on naturally occurring lexis classes that are defined under thematic, taxonomic, and semantic linkages [20].

3.2. Pre-Processing Using Tailoring 2D Fast Iterative Filtering Algorithm

Pre-processing techniques like the tailoring 2D fast iterative filtering algorithm [15] are used to improve the quality of the data. It iteratively filters raw data, removing noise and irrelevant information. Parameters are carefully chosen, with their impact explained, and tuning processes detailed. Input is raw data, and the output is a refined dataset. Integration with machine learning is highlighted, optimizing data for subsequent models. Illustrative examples demonstrate a practical application, and a comparative analysis justifies its suitability. This concise overview aims to provide transparency and clarity on the pre-processing methodology.

To emphasize the generated text features, before extracting the features, the acquired English-Chinese text data must undergo numerical and standardized pre-processing. In this stage, data pre-processing is carried out using an adaptive iterated guided filter, which effectively eliminates noise and imperfect texts, making it possible to distinguish or attribute them using a Global Constant. By adjusting parameters this technique can protect the given texts. To receive the filtered data with various specifications, data have to be cleaned in difference to results get from each language. To get comprehensive layer information of the overall database, the conventional Multi-Scale method is used. To work with filtered data and various channels hybrid multi-scale method is applied. Even though there are many filters available Guide filter acts as a learning filter. It includes input text data H and pre-processing data P and is represented in Equation (1).

$$O(u,v) = b(i,j)Q(u,v) + c(i,j), \forall(i,j) \tag{1}$$

where, $c(i,j)$ is a square window. The coefficients b and c are constants and is represented in Equations (2) and (3).

$$\arg\min_{b(i,j)Q(u,v)} \sum_{(u,v)\in u_{p,q}} b(i,j)Q(u,v) + c(i,j) - q(i,j)_2 + \in b^2(u,v) \tag{2}$$

$$b(u,v) = \frac{\frac{1}{u_{u,v}} \sum_{(u,v)\in u_{u,v}} Q(u,v) + q(i,j) - \eta(u,v)Q(u,v)}{\alpha^2(u,v) + \beta} \tag{3}$$

Here $\alpha^2(u,v)$ is a number of pixel points in α_l. β and η, are mean values of I in the window α_l. β is the variance. Adaptive iterated guided filter has 2 stages removing and restoring. If the scale is less than the filter size β, Gaussian filter eliminates the structure. Therefore, the filter is used initially and is represented in Equation (4).

$$Q(u,v) = q(i,j) - Q(u,v)(i,j) \tag{4}$$

Here $K_j = q(i,j) - Q(u,v)(I,j)$ is used for normalization. β denotes standard deviation. (i, j) denotes filter sub-window. It shows scale sensing properties of iteration guided filter. After Gaussian smoothing edge of the input data record is fuzzy. Size of large scale edge is slowly recollected and it is equal to the text data prediction and is represented in Equation (5).

$$Q(u,v) = \frac{1}{|u_{(i,j)}|} \sum_{u,v\in u_{(i,j)}} b(i,j)Q(u,v) + c(i,j) - Q(u,v)^2 \forall (u,v) \in u_{(i,j)} \tag{5}$$

The preprocessing phase successfully removes the noise and imperfect text can detached or credited using Global Constant or most likely worth utilizing Adaptive iterated guided filtering. Thus the pre-processed text data using adaptive iterated guided filtering are successfully fed into the feature selection technique.

3.3. Feature Extraction utilizing Bilingual Bag-of-Words with TF-IDF

The feature extraction method, Bilingual Bag-of-Words [7] with Term Frequency-Inverse Document Frequency (TF-IDF), captures linguistic features in a bilingual context. It involves constructing a vocabulary set for each language and applying TF-IDF weighting for enhanced representation. Parameters are carefully chosen, and their impact is explained. Input is bilingual documents, and the output is a feature matrix. Integration with the overall methodology is highlighted. Illustrative examples demonstrate its application. This concise overview aims to provide clarity on the feature extraction methodology.

In this section, pre-processed text data is entered into a feature extraction method i.e., Bilingual Bag-of-Words with TF-IDF which can extract the features. Feature extraction for English-Chinese text data involves creating numerical representations from the raw text to enable deep learning algorithms to process and analyze the data. The Bag-of-Words (BoW) representation, which was discussed earlier, can be extended to handle bilingual text data like English-Chinese. Here's the feature extraction process for English-Chinese text data using BoW with equations: Tokenize the English text into individual words or sub words using standard tokenization methods. For Chinese, use word segmentation techniques like Jieba to split the text into meaningful units (words).

Create separate vocabularies for English and Chinese. List all the unique tokens from each language's dataset to form the vocabulary. For English, the vocabulary will be represented as Venglish={word1, word2,…,wordn}. For Chinese, the vocabulary will be represented as Vchinese={word1, word2,…, wordm}.

Next, count the occurrences of each token in the English and Chinese vocabularies for each document, representing each document as numerical vectors (feature vectors) where the elements correspond to the count of the tokens in the vocabularies.

For English, the feature vector for a document *D* is denoted as:

$$F\_english(D) = \left\{ \begin{matrix} count\_english(word\_1), count\_english(word\_2),..... \\ count\_english(word\_n) \end{matrix} \right\} \quad (6)$$

For Chinese, the feature vector for a document *D* is denoted as:

$$F\_chinese(D) = \left\{ \begin{matrix} count\_chinese(word\_1), count\_chinese(word\_2),..... \\ count\_chinese(word\_m) \end{matrix} \right\} \quad (7)$$

To create a joint feature vector for English-Chinese text data, concatenate the English and Chinese feature vectors for each document. This combined feature vector for a document *D* is denoted as Fcombined(D)=Fenglish(D)+Fchinese(D).

Applying a TF-IDF transformation to the combined feature vectors gives more weight to important words and down-weights common words across both languages. The transformed feature vector for a document D is denoted as FTF-IDF(D)=[TF-IDF(word1), TF-IDF(word2), …, TF-IDF(wordn+m)]

The resulting transformed feature vectors can be applied as input for numerous machine learning algorithms for tasks like sentiment analysis, text classification, or document clustering, handling both English and Chinese text data effectively.

Note that this method does not capture the interdependencies between English and Chinese, but it provides a simple and interpretable representation for bilingual text data. For more advanced techniques that consider the bilingual context, you can explore cross-lingual word embedding's or multilingual transformer models.

3.4. Bilingual Teaching Model Prediction using Deep Multi-Scale Fusion Neural Network (DMSFNN)

The Bilingual Teaching Model Prediction using DMSFNN [19] involves Back-end database utilization, Adaptive Iterated Guided Filtering, Bilingual Bag-of-Words with TF-IDF for feature extraction, and DMSFNN for effective bilingual teaching model prediction. It addresses challenges in traditional translation through DMSFNN in English-Chinese translation. Implemented in Matrix Laboratory (MATLAB), the model surpasses existing methods in performance metrics. This concise approach ensures transparency in methodology understanding. DMSFNN learning to get text features for classification and cross-scale information complementation, The fusion feature maps *F* with c channels are constructed by first connecting the many scale-specific attributes f_{b_j}: By connecting the several scale-specific properties, we first generate the fusion feature maps with channels:

$$F = Cat(f_{b_1}, f_{b_2}) \quad (8)$$

Here, the concatenation operation denotes *Cat*. In order to further mining the discriminative features as well as enhance performance, a spatial attention module is then implemented. In this study, each spatial position *u* of *F* is subjected to a global average pooling procedure to produce a global feature map *S*:

$$S_u = \frac{1}{c}\sum_{k=1}^{c} F_{u,k} \quad (9)$$

The spatial attention map f_{att} is then created by applying a sigmoid function to *S* and a 1×1 convolution. As a result, by adding the weighted features, the novel fusion features f_{b_f} may be achieved. The information can be given by:

$$f_{att} = \sigma(W * S + b) \quad (10)$$

$$F = F + f_{att} \otimes F \quad (11)$$

Here, the channel-wise product operation signifies $\otimes$ and the sigmoid function signifies (.). Ultimately, an overall pooling layer is selected to integrate information from several convolutional channels while reducing the dimension of features. The fusion feature maps *F* in this study, both the average-pooling and global max-pooling are utilized. By obtaining the largest value from every zone, max-pooling may efficiently extract the signals' specific and discriminating information. Additionally, average-pooling makes it easier to retrieve the signal's overall information using average operation:

$$z_{b_f} = g_m(F) + g_a(F) \quad (12)$$

Here, the overall average-pooling process signifies g_a. Then, for prediction, features z_{b_f} are used. The objective function in our work is the soft-max classification loss. The information could be given by:

$$L_{b_f} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{C} I\{y_i = k\}\log p(z_{b_f}) \quad (13)$$

3.5. Stepwise Procedure for Namib Beetle Optimization (NBO) Algorithm

The deep multi-scale fusion neural network's parameters are optimized by the namib beetle optimization algorithm [2]. It initializes a parameter population, evaluates fitness iteratively, and introduces movement and adaptation inspired by Namib Beetle strategies. This process converges to yield optimal DMSFNN parameters, enhancing its performance in multi-scale fusion tasks. Namib beetles have an intriguing survival technique in the desert, which is determined by their unique characteristics. This method includes selecting particular insect features and shrinking the insects' size.

Initially, they head for higher altitudes after gathering water, where humidity is greater, in the mountains. As a result, they now have simpler access to water. They ascend the mountain summits and expose themselves to air currents that are heavy with moisture; while doing so, they elevate their bodies to retain the moisture and direct it into their mouths. The control parameter for the DMSFNN is optimized in the current research study using the NBO technique. The step-by-step procedure is determined by,

- *Step* 1. Initialization.

The gain parameters for *F*.

- *Step* 2. Random generation.

After initialization, the input factors are created using random generation.

$$Y = \begin{bmatrix} \varsigma^{11}(t) & \varsigma^{12}(t) \dots & \varsigma^{1m}(t) \\ \varsigma^{21}(t) & \varsigma^{22}(t) \dots & \varsigma^{2m}(t) \\ \vdots & & \vdots \\ \varsigma^{n1}(t) & \varsigma^{n2}(t) \dots & \varsigma^{nm}(t) \end{bmatrix} \tag{14}$$

here, ς indicates gain parameters of *F*.

- *Step* 3. Fitness function.

The technology used for translation reduces text errors.

$$Obj = \min(e_{s,t}) + \max(P_{precision}) \tag{15}$$

here, $(e_{s,t})$ indicates textual error, and $P_{precision}$ denotes precision.

- *Step* 4. Analysis the location of beetle for water collection.

The capacity of every insect to retain water and moisture is essential to its intended purpose. This theory proposes that the problematic beetle is in a prime location, which attracts additional insects and creates pockets of standing water. Every area where beetles are present has the potential to sustain a significant population of beetles, contingent upon variables including as:

$$c_I = c_{MAX}.\sin\left(\frac{F(NB_i) - F_{Min}}{(F_{Max} - F_{Min})}\frac{\pi}{2}\right) \tag{16}$$

here, $F(NB_i)$ indicates capacity of the beetle; c_I indicates ability to count the number of insects in the vicinity; F_{Min}, F_{Max} indicates minimum and maximum levels of population beetle competency; c_{Max} indicates highest quantity of beetles present in a particular location.

- *Step* 5. Moving toward wet areas.

Locating water requires each problem solver to determine which regions contain enough moisture. Two insects' distance from one another is calculated using:

$$D_{IJ} = \sqrt{\sum_{K=1}^{D}\left(nb_{I,K} - nb_{J,K}\right)^2} \tag{17}$$

- *Step* 6. Update the solution by using the movement of wet mass.

It utilized its sense of smell to locate the places and gravity to determine the best course of action.

$$nb_I^{NEW} = nb_I^{OLD} + Rand.(nb^* - \bar{nb}) + L \tag{18}$$

where, $\bar{nb}$ indicates the location of the water-gravity, nb^* indicates place where the maximum moisture is present.

- *Step* 7. Removal of population.

The lizards will occasionally hunt the beetle during its relocation to the hill. This stage involves eliminating these solutions.

- *Step* 8. End criteria.

Check if the end requirement has been met; if so, the procedure is finished; if not, move on to step 3. Figure 2 portrays the flowchart of NBO.

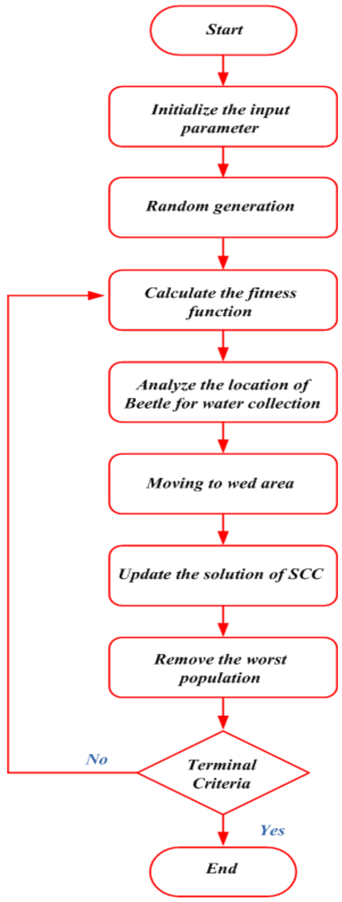

Figure 2. Flowchart of NBO.

4. Result and Discussion

In this section, the experimental result of the proposed DECTMT-NBO-DMSFNN is discussed. The PC is used for the simulations along the keras and tensar flows. Then, MATLAB is used to simulate the proposed method under various performance criteria. DECTMT-NBO-DMSFNN results was examined using the Domain-Specific English-Chinese Machine Translation with Deep Neural Networks (DECTMT-DNN), Domain-Specific English-Chinese Machine Translation with Artificial Neural Networks (DECTMT-ANN), and Domain-Specific English-Chinese Machine Translation with Hybrid Fusion Networks (DECTMT-HFN) techniques currently in use.

4.1. Performance Measures

4.1.1. Accuracy

It is total accurate degree or grouping accuracy, represented in Equation (19):

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{19}$$

4.1.2. Precision

This is shown in Equation (20):

$$\Pr ecision = \frac{TN}{FP + TN} \tag{20}$$

4.1.3. F Score

F score is represented in Equation (21):

$$F\ score = \sqrt{recall * precision} \tag{21}$$

4.1.4. Sensitivity

Sensitivity is represented in Equation (22):

$$sensitivity = \frac{TP}{TP + FN} \tag{22}$$

4.1.5. Specificity

By Equation (23) this is scaled.

$$Specificity = \frac{(TN)}{(FP + TN)} \tag{23}$$

4.2. Performance Analysis

Figures 3 to 8 depicts the simulation outcomes of proposed DECTMT-NBO-DMSFNN method. Then, the proposed DECTMT-NBO-DMSFNN approach is contrasted with current techniques like, DECTMT-DNN, DECTMT-ANN, and DECTMT-HFN respectively.

The accuracy of the model's predictions is a crucial sign of their overall soundness. In the language pair translation scenario, accuracy assesses how well the model is able to generate translations that match the reference or expected translations. A high accuracy score indicates that the majority of the translations are correct. Figure 3 shows the comparative of the accuracy with English and Chinese text data. In English text the DECTMT-DNN method has the accuracy of 81%. The DECTMT-ANN method gives 61% accuracy. The DECTMT-HFN method gives 75% accuracy. The proposed DECTMT-NBO-DMSFNN method gives the maximum accuracy of 99% in English text compared to other existing methods. In Chinese text the DECTMT-DNN method has the accuracy of 77%. The DECTMT-ANN method gives 89% accuracy. The DECTMT-HFN method gives 62% accuracy. The proposed DECTMT-NBO-DMSFNN method gives the maximum accuracy of 99% in Chinese text compared to other existing methods.

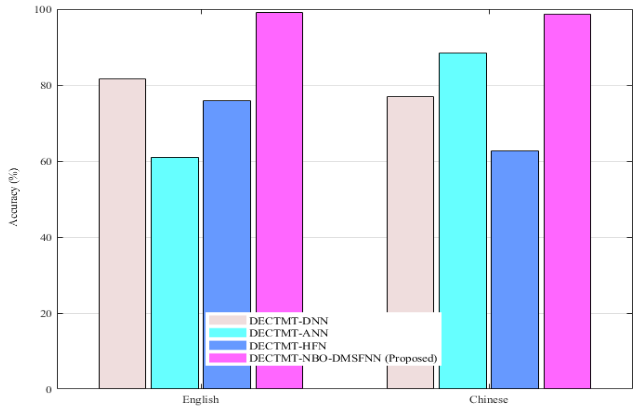

Figure 3. Comparative of accuracy with English and Chinese text data.

Figure 4 portrays comparison of the computation time with English and Chinese text data. The computation time for DECTMT-TL method is 225s. The computation time for DECTMT-ANN method is 170s. The computation time for DECTMT-HFN method is 280s. The proposed DECTMT-NBO-DMSFNN method has the lowest computation time of 80s compared to other existing methods.

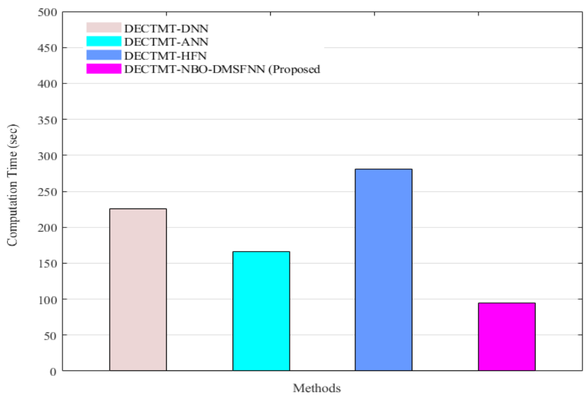

Figure 4. Comparison of computation time with English and Chinese text data.

Precision and recall's harmonic mean is the F1 score. It offers an equitable assessment by taking into consideration both false positives and false negatives. In English-Chinese teaching, a high F1 score indicates a well-rounded performance, balancing accuracy and comprehensiveness. It is a useful metric to consider when there is a need for a compromise between recall and precision. Comparative of F-Score with English and Chinese text-data is portrayed in figure 5. In English text data the DECTMT-DNN method has the F-Score of 85%. The DECTMT-ANN method has 65% F-Score. The DECTMT-HFN method has the F-Score of 75%. The proposed DECTMT-NBO-DMSFNN method has the very high F-Score of 99%. In Chinese text data the DECTMT-DNN method has the F-Score of 78%. The DECTMT-ANN method has 88% F-score. The DECTMT-HFN method has the F-Score of 68%. The proposed DECTMT-NBO-DMSFNN method has the very high F-Score of 99%.

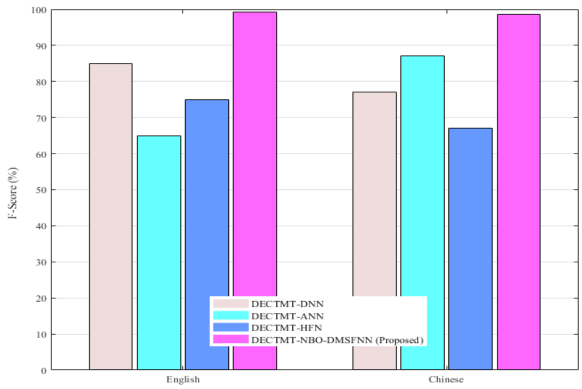

Figure 5. Comparative of F1-Score with English and Chinese text-data.

Figure 6 portrays comparison of precision with English and Chinese text data. In English text a precision of DECTMT-DNN method is 79%. The DECTMT-ANN method has the precision of 90%. The DECTMT-HFN method has the precision of 75%. The proposed DECTMT-NBO-DMSFNN method has the highest precision of 99%. In Chinese text a precision of DECTMT-DNN method is 70%. The DECTMT-ANN method has the precision of 85%. The DECTMT-HFN method has a precision of 72%. The proposed DECTMT-NBO-DMSFNN method has the highest precision of 99%.

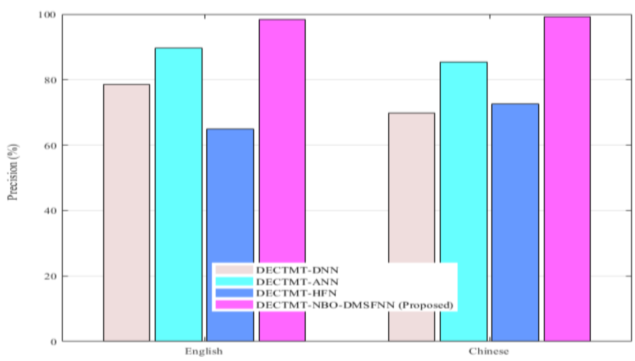

Figure 6. Comparison of precision with English and Chinese text-data.

Figure 7 shows the performance of four different machine learning models on English and Chinese text data, specifically in terms of sensitivity (%). The models compared are DECTMT-DNN, DECTMT-ANN, DECTMT-HFN, and the proposed DECTMT-NBO-DMSFNN.For the English text data, the DECTMT-DNN model achieves a sensitivity of 69%, while the DECTMT-ANN model performs better with 89% sensitivity. The DECTMT-HFN model has a sensitivity of 79%. The proposed DECTMT-NBO-DMSFNN model outperforms all others with the highest sensitivity of 99%.

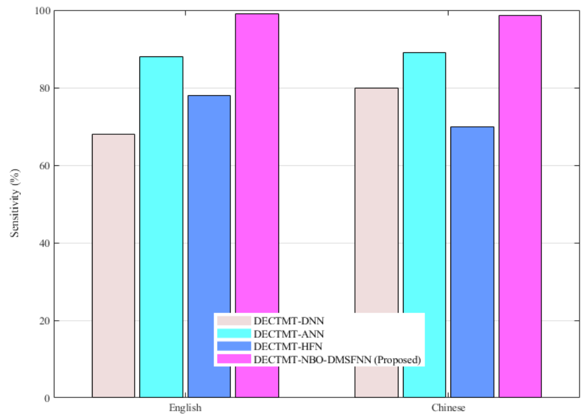

Figure 7. Comparative of sensitivity with English and Chinese text data.

Similarly, for the Chinese text data, the DECTMT-DNN model has a sensitivity of 80%. The DECTMT-ANN model improves upon this with a sensitivity of 90%. The DECTMT-HFN model shows a slightly lower sensitivity at 70%. Once again, the proposed DECTMT-NBO-DMSFNN model demonstrates superior performance with the highest sensitivity of 99%. These results indicate that the proposed DECTMT-NBO-DMSFNN model consistently achieves the highest sensitivity across both English and Chinese datasets, making it the most effective model for identifying positive cases in this context. This high sensitivity is crucial for comprehensive coverage of the content in language education, ensuring that relevant information is not missed during translation.

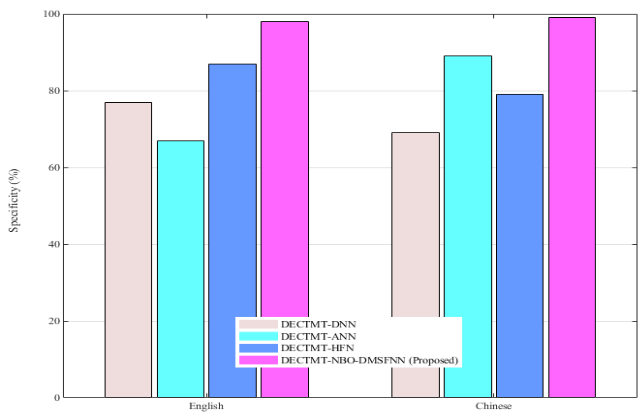

Figure 8. Comparison of specificity with English and Chinese text-data.

Figure 8 shows the specificity (%) of four machine learning models-DECTMT-DNN, DECTMT-ANN, DECTMT-HFN, and the proposed DECTMT-NBO-DMSFNN-when applied to English and Chinese text data. Specificity, in this context, measures the models' ability to correctly identify negatives, indicating how well they distinguish between actual positives and false positives. For the English text data, the DECTMT-DNN model demonstrates a specificity of 78%, while the DECTMT-ANN model shows a lower specificity of 68%. The DECTMT-HFN model performs better with a specificity of 89%. The proposed DECTMT-NBO-DMSFNN model achieves the highest specificity of 99%, outperforming the other models.

In the case of Chinese text data, the DECTMT-DNN model has a specificity of 69%, and the DECTMT-ANN model improves upon this with a specificity of 89%. The DECTMT-HFN model exhibits a specificity of 79%. Again, the proposed DECTMT-NBO-DMSFNN model leads with the highest specificity of 99%. These findings highlight that the proposed DECTMT-NBO-DMSFNN model consistently achieves the highest specificity across both English and Chinese datasets. High specificity ensures that the model's translations are accurate and relevant, which is critical in educational settings to provide precise and reliable information, thereby avoiding potential misunderstandings.

The current methods for performance analysis such as DECTMT-DNN, DECTMT-ANN and DECTMT-HFN are considered observations values of the proposed. The accuracy of the proposed approach is 99%. The accuracy of the competitive algorithms, such as DECTMT-DNN, DECTMT-ANN and DECTMT-HFN is 81%, 61% and 75%. The proposed DECTMT-NBO-DMSFNN technique has a precision level of 99%, whereas for the existing techniques like DECTMT-DNN, DECTMT-ANN and DECTMT-HFN the precise values are 79%, 90% and 75% respectively. This indicates there is a high level of precision in the proposed approach. The proposed method has sensitivity and F-score values of 99% and 99%%, respectively. It is evident from the results that the DECTMT-NBO-DMSFNN technique outperforms other algorithms in terms of F-Score, sensitivity, accuracy, and precision. As a result, the DECTMT-NBO-DMSFNN algorithm's accuracy reached 99%. When compared to other algorithms, the proposed approach achieved the highest accuracy. According to the experimental results, the proposed procedure is effective at classifying English and Chinese texts.

5. Conclusions

In this research, a DECTMT-NBO-DMSFNN-based English-Chinese MT approach is developed to address laborious and prone to errors in translation. In order to construct machine models for translation, NBO optimizes the translation procedure. Features of the text translated from English to Chinese are extracted using the Bag-of-Words methodology and classified by DMSFNN. The proposed technique is executed in the MATLAB platform. The proposed DECTMT-NBO-DMSFNN technique provides a maximum accuracy of 97% in English text and 99% in Chinese text compared to other existing DECTMT-DNN, DECTMT-ANN, and DECTMT-HFN approaches. The investigational outcomes demonstrate the efficiency of the DECTMT-NBO-DMSFNN technique in achieving shorter translation times and reducing mistranslations. The study showcases ongoing human end beavers to explore knowledge, especially in MT, displaying promising improvement forecasts in both application and scientific research, despite being at an early stage.

Limitations in English-Chinese teaching currently include challenges in addressing the diverse language backgrounds and learning styles of students, as well as the need for personalized and adaptive learning approaches. MT tools, while valuable, may not capture the nuances of each language accurately, hindering effective communication. Additionally, the lack of immersive language environments for learners can impede their practical language application. Future work should focus on developing advanced AI-driven language learning platforms that cater to individual needs, integrate cultural elements, and offer real-world language experiences using hybrid optimization algorithms. Collaboration between educators, technologists, and linguists is crucial to refine language models, enhance interactive language learning tools, and create comprehensive curricula that foster proficiency in both English and Chinese.

Data Availability Statement

This article does not fall under the data sharing policy because no new data were created or analyzed for it.

Funding Information

No specific grant was obtained for this study from public, commercial, or charitable funding agencies.

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Yuwei Wang female, Han nationality, 1979.12.31, Master's Degree, Lecturer. She is currently working, Sanmenxia College of Social Administration. Her research interests include English Language Teaching (ELT)