Hindawi
Journal of Mathematics
Volume 2023, Article ID 9792569, 1 page
https://doi.org/10.1155/2023/9792569

Retraction

Retracted: Analysis of Intelligent Translation Systems and Evaluation Systems for Business English

Journal of Mathematics

Received 15 August 2023; Accepted 15 August 2023; Published 16 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Chen, "Analysis of Intelligent Translation Systems and Evaluation Systems for Business English," *Journal of Mathematics*, vol. 2022, Article ID 5952987, 7 pages, 2022.

Hindawi
Journal of Mathematics
Volume 2022, Article ID 5952987, 7 pages
https://doi.org/10.1155/2022/5952987

Research Article

Analysis of Intelligent Translation Systems and Evaluation Systems for Business English

Jianhong Chen

Foreign Languages & International Education College, Quzhou University, Quzhou 324000, Zhejiang, China

Correspondence should be addressed to Jianhong Chen; 33021@qzc.edu.cn

Received 1 December 2021; Revised 24 December 2021; Accepted 27 December 2021; Published 25 January 2022

Academic Editor: Naeem Jan

In order to improve the accuracy of automatic translation of business English, an optimized design of business English translation teaching platform is proposed based on the logistic model combined with deep learning. After using the logistic model to analyze the semantic features of business English translation, the deep learning model is used to segment and mine English images, and the automated lexical feature analysis of business English translation is carried out by using contextual feature matching and adaptive semantic variable finding methods to extract the amount of correlation features between words and vocabulary and to correct the differences in translation in a specific business context to improve the accuracy of English translation. The software design of the platform is carried out under the logistic model, and the platform is mainly divided into a vocabulary database module, an English information processing module, a web interface module, and a human-computer interaction interface module. The test results show that the accuracy of business English translation using this method is good, and the automatic translation capability is strong.

1. Introduction

As machine English translation technology continues to mature, the use of machine English translation for English translation can greatly reduce the time of manual translation and improve translation efficiency [1]. The study of English translation methods based on machine translation has an important role in promoting English education as well as improving the reading efficiency of foreign language literature. In the process of translating business English, the uncertainty and randomness of business English's own context lead to poor accuracy of business English machine translation, which requires the optimal design of a business English translation teaching platform, combined with the improved design of algorithms for business English machine translation, to improve the accuracy and efficiency of business English translation, and the research of related teaching platform design methods has received great attention [2].

The machine algorithm for business English translation currently mainly adopts the limit learning machine algorithm, the machine English translation correction algorithm of support vector machine, and the autoregressive analysis method [3], which combines the semantic features of business English translation for the analysis of language environment and automatic translation feature matching in the translation process to improve the accuracy of business English translation, and uses this as the basis for the teaching platform design of business English translation with high teaching quality [4]. However, the aforementioned methods have a greater problem of contextual interference in conducting large-scale business English translation, resulting in poor accuracy of translation. To address this problem, this paper proposes a design method for a teaching platform for business English translation based on the logistic model, which uses contextual feature matching and adaptive semantic variable finding methods for automated lexical feature analysis of business English translation, and carries out differential correction of translation in specific business contexts to improve the accuracy of English translation [5]. The software development design and simulation experimental analysis of the business English translation teaching platform were also carried out to draw conclusions on the effectiveness. In the following section, we presented the algorithm design for the translation of the English literature. In Section 3, the deep learning solutions are explained. Section 4 carries out the experimental analysis for the validation of the proposed algorithm and its working. Finally, the paper is concluded in Section 5.

2. English Literature Translation Algorithm Design

In this section, the algorithm for the English literature translation is presented. First, the logistic model is explained which is used for semantic feature analysis of English translation. Then, the optimization of the algorithm for English literature translation is given. On the basis of the logistic model for business English literature translation, the machine algorithm design is realized, which in turn acts as a base for the software development design of translation teaching platform.

2.1. Logistic Model. The logistic model is used for semantic feature analysis of business English translation. As a typical chaos model, the logistic model has the characteristics of randomness and initial feature sensitivity, and it has the advantage of strong environmental adaption for semantic feature analysis in different contexts of business English [6], and the one-dimensional mapping is used to construct the logistic chaos model as follows:

$$x_{n+1} = \lambda x_n (1 - x_n), x \in [0, 1], \lambda \in [0, 4]. \quad (1)$$

The above equation describes the subcluster Henon attractor for business English translation, and combined with the concept set of English translation output for adaptive context matching, the distribution model of the concept set of textual features for English literature translation is obtained as follows:

$$\begin{cases} \dot{x} = a + by = x^2, \\ \dot{y} = x, \end{cases} a = 1.4, b = 0.3 . \quad (2)$$

Lorenz attractors were introduced for semantic revision of business English translations [7], and the Lorenz function was

$$\begin{cases} \dot{x} = -\sigma x + \sigma y, \\ \dot{y} = -xz + rx - y, \\ \dot{z} = xy - bz, \end{cases} \quad (3)$$

where $[\sigma, r, b] = [10, 28, 8/3]$ or $[\sigma, r, b] = [16, 45.92, 4]$.

In word clustering feature extraction for business English translation, semantic feature clustering is performed under the logistic chaotic attractor by combining the variability of semantic feature distribution of words [8].

According to the English translation clustering model shown in Figure 1, contextual feature matching and adaptive semantic variable finding methods are used for automated lexical feature analysis of business English translation, assuming that the semantic code sequence of the English utterance to be translated is of length N and the set of semantic distribution concepts is x, which can be represented as an $N \times 1$ column feature vector, $x(n) \in R^N$. Using the associative semantic grouping expression method [9], the clustering model for business English literature translation is obtained as described by

$$x = \sum_{i=1}^{N} s_i \Psi_i = \Psi s. \quad (4)$$

2.2. English Machine Translation Algorithm Optimization. Based on the above semantic feature analysis of business English translation using the logistic model, the machine algorithm design for English translation was carried out, using contextual feature matching and adaptive semantic variable finding [10], and the optimal semantic feature matching results for English translation were obtained as

$$J^*(m) = \max{}_\tau \{J^*(\tau) + D_m(\tau) + C\}, J^*(0) = 0. \quad (5)$$

Based on the semantic discretization of the original text information, parametric adaptive estimation of the semantic text feature quantity Y is performed to obtain the feature matching of the English translation output as

$$p\left(x_1^l \mid \alpha\right) = \prod_{i=1}^{L} p(y_i \mid \alpha, r_i, l). \quad (6)$$

Automated lexical feature analysis of business English translation was conducted, and the decomposition results of the associated contextual information of the English translation lexicon were obtained as follows [11]:

$$E_j = \sum_{k=1}^{n} E_{j,k}, \qquad P_{j,k} = \frac{E_{j,k}}{E_j}. \quad (7)$$

The cross-integrated evaluation decision method [12] was used to extract the amount of word-to-word associative features, and the output was obtained as follows:

$$WE_k = -\sum_j P_{j,k} \ln\left(P_{j,k}\right). \quad (8)$$

The semantic ontology information of business English translation is thresholded [13], and the empirical modal decomposition method is used to obtain the output similarity and closeness of the translation results as follows:

$$S_x = E\left[x^3(t)\right] + \sqrt{s}\,\mathrm{bu}\left[s\left(t - \tau_0\right)\right], \qquad K_x = E\left[x^4(t)\right] - 3E^2\left[x^2(t)\right]\mathrm{bn}. \quad (9)$$

Figure 1: Real-life English scenario translation target process.

According to the output similarity and closeness feature extraction results, the differential correction of the translation in a specific business context is carried out, and the corrected set of texts of the English literature translation output is obtained as follows:

$$\begin{aligned}\text{Computation}\left(n_j\right) &= \left(E_{\text{elec}} + E_{\text{DF}}\right) l\delta + E_{T_x}\left(l, d_j\right)\\ &= \left(E_{\text{elec}} + E_{\text{DF}}\right) l\delta + lE_{\text{elec}} + l_{\varepsilon_{fs}} d_j^2\\ &= \left[\left(E_{\text{elec}} + E_{\text{DF}}\right)\delta + E_{\text{elec}} + \varepsilon_{fs} d_j^2\right] l.\end{aligned} \tag{10}$$

To summarize the above algorithm design, machine algorithm design based on the logistic model for business English literature translation is realized, based on which the software development design of translation teaching platform is carried out [14].

3. Deep Learning Solutions

Through deep learning-based image recognition and machine translation technology, it is possible to make the computer describe the scene presented in the picture in a few short sentences, and then the image recognized by using the computer is accurately described in English and fed to the mobile phone WeChat app in real time. This allows users to translate the pictures taken by their mobile phones into English vocabulary and sentences through the WeChat applet, which not only allows them to learn English anytime and anywhere but also reduces the inconvenience caused by the language barrier when they are in an English-speaking country [15]. Deep learning-based real-world English scene translation mainly lies in the English translation processing of images; the process first requires scene acquisition and image capture by calling the mobile phone camera through the WeChat applet and then image region segmentation, image feature extraction, image target detection, and English description generation for the captured image, i.e., the scene; Figure 1 shows the target flow of the process. The processing of the live image through the target process can produce a more accurate English description of the live scene.

3.1. Image Feature Extraction. After regional segmentation of the image, the image features are extracted. In this paper, we construct a convolutional neural network model to perform image feature extraction [16]. In this paper, we use the VGG-16 architecture, which consists of 13 3×3 convolution layers and 6 2×2 max pooling layers, as shown in Figure 2, so that the extracted input image features ($3\times W\times H$) generate the corresponding tensor features (where 3 denotes RGB, i.e., the number of channels is 3, W denotes width, and H denotes height) and turn them into $C\times W\times H$. The tensor feature is converted into $C\times W\times H$, where C is a constant number of channels, W is the width, and H is the height. As the pixel image will be converted to a certain level of distortion, the maximum limit of C is set to 512, and the width and height of the image will become 1/16 of the original when C takes the maximum value [17]. The output of the convolutional neural network is positioned at a set of uniformly sampled image locations, and the features of the image are encoded and stored. Extract these features in preparation for target detection.

3.2. Image Target Detection. For target detection, Faster R-CNN [18], a "trendy" technique in the field of target detection, was chosen. The RoI pooling mechanism in Faster R-CNN [20] is replaced by a bilinear interpolation [19] based on Faster R-CNN in order to allow the improved target detection model to propagate the gradient backwards through the coordinates of the prediction region and avoid local optima in target detection. Throughout this paper, the improved neural network is referred to as the "recognition layer."

After receiving the image features extracted in the previous step, when the recognition layer receives an activation tensor of $C\times W\times H$, it internally selects the T regions of interest (T for TOP, merit selection) and returns three output tensors, which give information about these regions [21].

(i) Region coordinates: after merit selection, the T matrix gives the best bounding box coordinates for each output region.

(ii) Region scores: vector of length T gives the confidence score of each output region. Regions with high confidence scores are more likely to be regions of interest.

(iii) Region features: the selected regions are represented by a C-dimensional $X\times Y$ grid, and the image features are bilinearly sampled with the grid to obtain a region feature of size $T\times 512\times 7\times 7$.

The target detection model based on Faster R-CNN is constructed as shown in Figure 3.

3.3. Generate English Descriptions. After the target detection of the image, the English expression of the target features is obtained, and the intermediate output < objects, attributes, activities, scene > is obtained, as shown in Figure 4, and furthermore, the feature words need to form into English sentences according to the scene [22].

In this paper, we use long short-term memory (LSTM) networks to form sentences from real-world features and

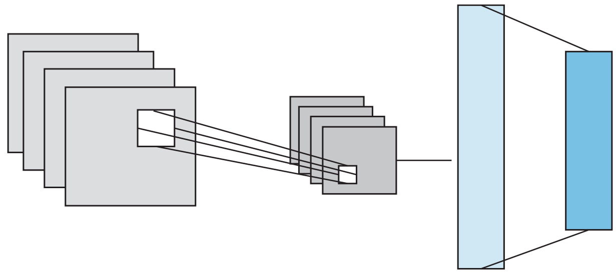

Figure 2: CNN feature extraction model.

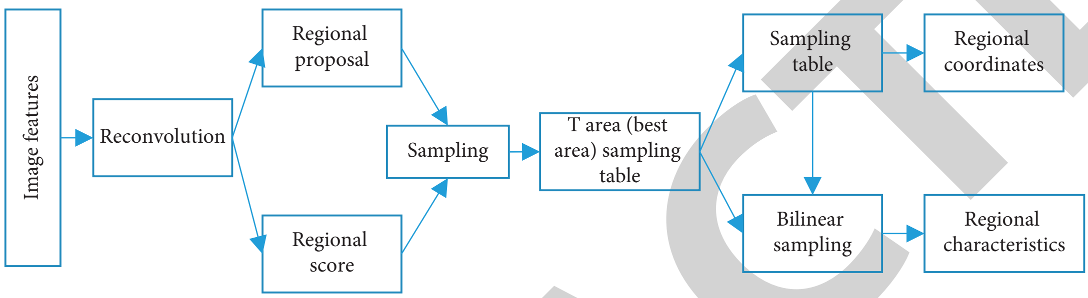

Figure 3: Faster R-CNN-based target detection model.

obtain English descriptions of the scene. The image features extracted by feature extraction, the region features obtained by target detection, and the region coordinates are input into the LSTM neural network to train the sentence formation of real-life words.

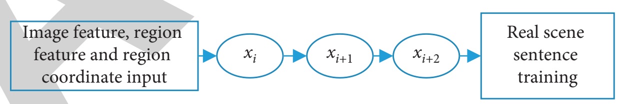

Figure 4: LSTM-based real-world lexical sentence formation model.

4. Experimental Test Analysis

The simulation experiment of the business English translation teaching platform was designed by MATLAB and TinyOS 2.x. The number of data transmission frames for English translation was set to 1200, and the number of English text packets to be translated was 128 Mbit [23]. The number of training samples for business English documents is 12, and the maximum sampling time for semantic features is 24. Based on the above simulation parameter settings, the English translation test was conducted using this method and the traditional method to analyze the correctness of business English translation using this platform. The analysis of Figure 5 shows that the accuracy of business English translation using this method is high, and the output translation error is low.

The time responsiveness of the English translation teaching platform was further tested, and the results were obtained as shown in Figure 5. Analysis of Figure 6 shows that this paper's approach to the design of a business English literature translation teaching platform has a low time overhead in English translation [24].

In order to verify the accuracy of the scene recognition model used in this paper, some images with standard descriptions were selected and put into the training environment for training, as shown in Figure 7, and the one description text with the highest scoring was selected for comparison with the standard description text; it can be seen that the results of this paper can basically and accurately translate the content of the images in the scene.

In a realistic application of the statement, the words "and/or" and "damage or loss" appear in pairs. The word "and/or" is used because the original text indicates "advance freight" and "freight payable at destination." When the two methods are used together or separately, the full amount of the freight must be paid to the carrier. Therefore, it should be translated as "or one of them." With regard to "damage or loss," "damage" refers to an overall loss of value, whereas "loss" refers to a partial loss of overall value. In accordance with the international practice of transport insurance for goods to losses, some policies only cover total loss of goods and some only partial loss, so it is a matter of protection of the interests of the person at the time. Figure 8 shows that, in word cloud analysis, "damage or loss" should be translated as "loss or perish." In order to achieve the effect of euphemism in business English, passive sentences are often used, which are very different from the expression in Chinese. Therefore, there is no ready-made counterpart for translating passive sentences into Chinese, but rather, some appropriate means of expressing the passive meaning of the original text should be selected from a wide range of sentences and auxiliary words according to the customary usage of Chinese [25, 26].

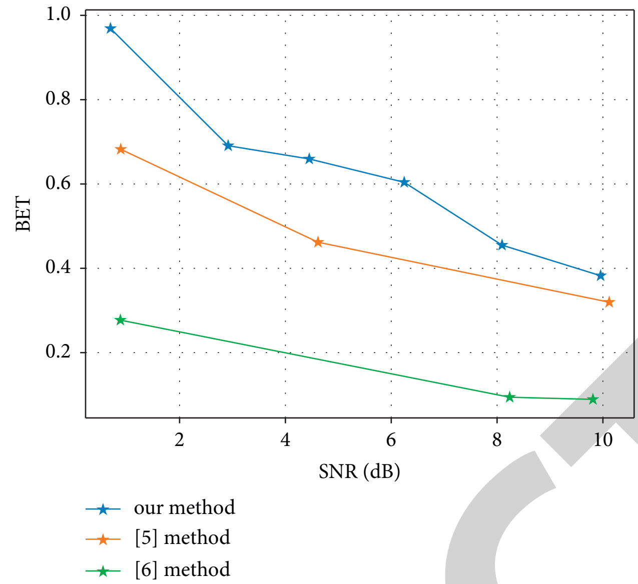

FIGURE 5: Comparative test of accuracy of English translations.

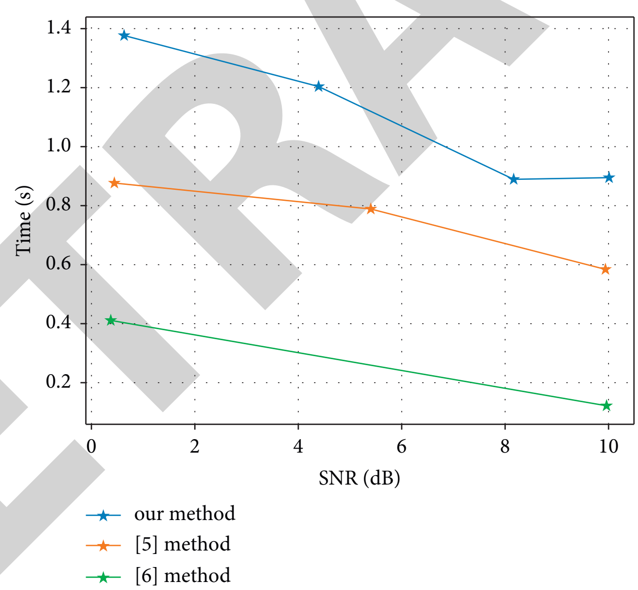

FIGURE 6: Time performance comparison.

Figure 7: Example of image description results.

Figure 8: Business English word cloud analysis.

5. Conclusions

In the process of translating business English, the uncertainty and randomness of the business English context lead to the poor accuracy of business English machine translation. This paper proposes a design method based on the logistic model for translation. The research has shown that the translation designed in this paper is superior in terms of time responsiveness and accuracy of English translation. There is no ready-made counterpart for translating passive sentences into Chinese, but rather, some appropriate means of expressing the passive meaning of the original text should be selected from a wide range of sentences and auxiliary words according to the customary usage of Chinese.

Data Availability

The datasets used during the current study are available upon request to the author.

Conflicts of Interest

The author declares that he has no conflicts of interest.

References

[1] M. King, "Accuracy and suitability: new challenges for evaluation," *Language Resources and Evaluation*, vol. 39, no. 1, pp. 45–64, 2005.

[2] J. Cadeanes and A. G. Arrieta, "Development of sign language communication skill on children through augmented reality and the MuCy model[J]," *Advances in Intelligent Systems & Computing*, vol. 292, pp. 45–52, 2014.

[3] A. Rocha, H. Adeli, and L. P. Reis, "Advances in intelligent systems and computing trends and advances in information systems and technologies," vol. 2, p. 745.

[4] J. Gutiérrez-Artacho, M.-D. Olvera-Lobo, and I. Rivera-Trigueros, "Human post-editing in hybrid machine translation systems: automatic and manual analysis and evaluation," *Advances in Intelligent Systems and Computing*, pp. 254–263, 2018.

[5] H. Singh and I. Daly, “Translational algorithms: the heart of a brain computer interface,” *Brain-Computer Interfaces*, vol. 74, pp. 97–121, 2015.
[6] C. T. Lopes, D. Dias, and C. Ribeiro, “Using domain-specific term frequencies to identify and classify health queries,” *Advances in Intelligent Systems and Computing*, vol. 206, pp. 221–226, 2013.
[7] V. Gupta, “Automatic stemming of words for punjabi language,” *Advances in Intelligent Systems and Computing*, vol. 264, pp. 73–84, 2014.
[8] C. Castellanos and D. Correal, “A framework for alignment of data and processes architectures applied in a government institution,” *Journal on Data Semantics*, vol. 2, no. 2-3, pp. 61–74, 2013.
[9] A. A. Kostoglotov and A. A. Kuznetsov, “Synthesis of an intelligent measurement procedure based on error minimization,” *Measurement Techniques*, vol. 48, no. 7, pp. 637–645, 2005.
[10] A. A. Krizhanovsky and A. V. Smirnov, “An approach to automated construction of a general-purpose lexical ontology based on Wiktionary,” *Journal of Computer and Systems Sciences International*, vol. 52, no. 2, pp. 215–225, 2013.
[11] R. Navigli, P. Velardi, and A. Gangemi, “Ontology learning and its application to automated terminology translation,” *IEEE Intelligent Systems*, vol. 18, no. 1, pp. 22–31, 2003.
[12] S. Das and S. Banerjee, “Pattern recognition approaches to Japanese character recognition,” *Advances in Intelligent and Soft Computing*, vol. 166, pp. 83–92, 2012.
[13] B. M. Singh and A. Mittal, “A novel method for straightening curved text-lines in stylistic documents,” *Eurasip Journal on Image & Video Processing*, vol. 2014, no. 1, pp. 1–8, 2014.
[14] M. Nodine, “On the impact of ontological commitment,” *Ontologies for Agents Theory & Experiences Whitestein*, pp. 19–42, 2002.
[15] J. Numrich, S. Ruja, and S. Voß, “Global navigation satellite system based tolling: state-of-the-art,” *Netnomics: Economic Research and Electronic Networking*, vol. 13, no. 2, pp. 93–123, 2012.
[16] P. Kevin, W. Laura, and K. M. Basen-Engquist, “Cyber infrastructure for comparative effectiveness research (CYCORE): improving data from cancer clinical trials,” *Translational Behavioral Medicine*, vol. 1, no. 1, pp. 83–88, 2011.
[17] I. Porto-Díaz and D. Martínez-Rego, “Information theoretic learning and local modeling for binary and multiclass classification,” *Progress in Artificial Intelligence*, vol. 1, no. 4, pp. 315–328, 2012.
[18] R. S. McCallum, “Context for nonverbal assessment of intelligence and related abilities,” *Handbook of Nonverbal Assessment*, pp. 3–21, 2003.
[19] É. Székely, I. Steiner, Z. Ahmed, and J. Carson-Berndsen, “Facial expression-based affective speech translation,” *Journal on Multimodal User Interfaces*, vol. 8, no. 1, pp. 87–96, 2014.
[20] P. D. Moral, A. A. Tantar, and E. Tantar, “On the foundations and the applications of evolutionary computing,” *Studies in Computational Intelligence*, vol. 447, pp. 3–89, 2012.
[21] M. Butt and T. H. King, “Urdu in a parallel grammar development environment,” *Language Resources and Evaluation*, vol. 41, no. 2, pp. 191–207, 2007.
[22] A. Alnusair, T. Zhao, and G. Yan, “Rule-based detection of design patterns in program code,” *International Journal on Software Tools for Technology Transfer*, vol. 16, no. 3, pp. 315–334, 2014.
[23] R. Lacuesta, G. Palacios-Navarro, and C. Cetina, “Internet of things: where to be is to trust,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, pp. 1–16, 2012.
[24] M. Fernández-López, A. Gómez-Pérez, and M. C. Suárez-Figueroa, “Methodological guidelines for reusing general ontologies,” *Data and Knowledge Engineering*, vol. 86, no. 4, pp. 242–275, 2013.
[25] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, “Forest fire recognition based on feature extraction from multi-view images,” *Traitement du Signal*, vol. 38, no. 3, pp. 775–783, 2021.
[26] D. Croce, R. Basili, and A. Moschitti, “Semantic tree kernels for statistical natural language learning,” *Harmonization and Development of Resources and Tools for Italian Natural Language Processing within the PARLI Project*, vol. 589, pp. 93–113, 2015.
[27] F. Li, T. Gu, G. Cai, and L. Chang, “Symbolic ZBDD representations for mechanical assembly sequences,” *Intelligent Information Processing VI*, pp. 208–215, 2012.