Leveraging artificial intelligence through long short-term memory approach for correcting faults in Chinese language sentences

Muhammad Afiq Che Lah, Hadhrami Ab Ghani, Nurul Izrin Md Saleh
Department of Data Science, Faculty of Data Science and Computing, Universiti Malaysia Kelantan, Kota Bharu, Malaysia

Article Info

Article history:

Received Oct 31, 2024
Revised Feb 28, 2025
Accepted Mar 15, 2025

Keywords:

Artificial intelligence
Chinese sentence correction
Long short-term memory
Mandarin language education
Non-native speakers

ABSTRACT

This research focus on leveraging artificial intelligence (AI) to manage the challenges faced by non-native speakers in correcting faults and misconstructions in Chinese language sentences. Learners commonly struggle with mispronunciation, incorrect character usage, improper sentence structures, and grammatical mistakes. To tackle these issues, this study generally aims to improve and optimize AI for correcting faults in Chinese language for non-native speakers. This project employs long short-term memory (LSTM) approach based on Hanyu Shuiping Kaoshi (HSK) word ordering errors (WOE) dataset. The effectiveness of leveraging LSTM in detecting and correcting errors in Chinese language sentence have been demonstrated. LSTM shows the capability to be learn Chinese sentence structure, identify mistakes, and correct them. In summary, this research seeks to benefits the power of AI to provide innovative solutions for detecting, correcting faults and misconstructions in Chinese language sentences. This paper essentially useful for those who wish to learn how to correct their Chinese writing and enhance language proficiency among non-native speakers.

Corresponding Author:

Muhammad Afiq Che Lah
Department of Data Science, Faculty of Data Science and Computing, Universiti Malaysia Kelantan
Pengkalan Chepa, 16100 Kota Bharu, Kelantan, Malaysia
Email: afiqclh@gmail.com

1. INTRODUCTION

The advancement of artificial intelligence (AI) has profoundly influenced various domains [1], [2] notably in education, where it is harnessed to augment learning methodologies. In the realm of Chinese language acquisition, there is an escalating demand for AI-based applications that offer tailored feedback on grammatical structures, sentence formation, and address the distinct challenges inherent to the language [3]. The Chinese language, particularly Mandarin, serves as the official language in China, Taiwan, and Singapore, and is recognized as one of the most challenging languages to learn due to its complex grammar, unique writing system, and tonal nature [4], [5]. These characteristics pose significant challenges for learners, often leading to difficulties in sentence formulation and grammatical errors, which can hinder language learning progress [3], [4]. The advent of AI has introduced transformative tools in language correction, utilizing natural language processing (NLP) and long short-term memory (LSTM) to detect and rectify errors in Chinese sentences [6], [7]. Traditional language learning methods may not provide sufficient feedback for personalized learning [8], but AI technology offers enhanced precision and efficacy in correcting textual problems [9]. AI-based language correction tools are especially beneficial for non-native speakers and individuals with learning difficulties, providing real-time feedback to improve writing skills. Despite the potential of AI in language learning, existing tools may not be fully optimized for Chinese language challenges, highlighting the need for specialized tools that address grammar and sentence construction intricacies.

AI integration into education has shown promise in improving students' writing skills and overall learning effectiveness [10]. Various AI-based approaches have been developed for correcting Chinese sentences, categorized into rule-based and machine learning-based methods. Recent studies underscore the critical role of language correction in ensuring effective communication, highlighting the transformative impact of AI technology in refining this process. AI-based language correction tools have significantly improved the accuracy and efficiency of written communication, thereby enhancing the credibility and professionalism of individuals and businesses alike. These AI tools have the potential to significantly elevate learners' proficiency in Chinese, thereby making the learning process more accessible and efficacious on a global scale. Nonetheless, despite these advancements, there are persisting gaps in the application of AI for rectifying Chinese language errors, particularly as previous investigations [11] have not extensively utilized specific datasets like Hanyu Shuiping Kaoshi (HSK) word ordering errors (WOE) dataset [6]. AI-driven mobile applications have demonstrated considerable promise in providing educational resources, especially during the COVID-19 pandemic [12]. Along with the crisis, the number of concern and research related to AI field development for the issue of unsupervised learning is likely to increase steadily. Useful example research conducted by [13] discovered that after applying the autoencoder (AE) method, neither correcting Chinese sentences nor combination of words feature are the important branch core for the Chinese language writing skills learning.

However, issues related to unsupervised learning remain a challenge, underscoring the necessity for further research into deep learning models for language correction [14] proposed the AI approaches for Chinese language correction are primarily categorized into rule-based and machine learning-based methodologies. Rule-based approaches employ predefined grammatical and semantic-syntactic rules to correct errors [15], whereas machine learning-based methods, favored for their ability to learn from extensive datasets, encompass techniques such as support vector machines (SVM) [16], recurrent neural networks (RNN) [17], and convolutional neural networks (CNN)-LSTM models [18]. AI has also shown its capability in enhancing various facets of language proficiency, including grammar, vocabulary, and sentence structure. For instance, AI tools utilizing NLP techniques have been developed to provide real-time feedback on sentence-level errors, thereby aiding in the enhancement of Chinese writing skills [19]. Additionally, AI-powered speech recognition systems have been employed to correct pronunciation errors, thus assisting learners in improving their speaking abilities [20]. The integration of AI-driven robots for assessment purposes has rendered learning more engaging [21], while AI has also been applied to expedite foreign language acquisition [22] and improve human-computer interaction (HCI) accuracy through deep learning models [23].

Recent progress in deep learning, particularly the employment of LSTM networks, has achieved notable advancements in error correction within Chinese language learning. These models exhibit superior capabilities in capturing contextual errors that may elude other models, thereby providing more precise detection of grammatical issues [24]. However, despite the success of large language models (LLM) such as GPT-4 in text correction tasks, challenges persist in grammatical error correction and spelling checks, especially when compared to smaller, specialized models [25], [26]. Future research should concentrate on optimizing AI models for Chinese language learning to enhance contextual error detection and improve the overall learning experience.

In summary, although AI has demonstrated significant potential in advancing Chinese language learning through various rule-based and machine learning-based strategies, challenges remain in addressing contextual errors. Continued research into specialized models and further developments in AI will be crucial for optimizing language correction tools and enhancing educational outcomes. This paper specific objective is to determine the best deep architecture for Chinese language sentence correction for non-native speakers. Besides, this study seeks to evaluate the utilized dataset in the field of Chinese language sentence correction for non-native speakers and to improve sentence correction accuracy by adding more dimension of data. Thus, this research will focus on detecting and correcting faults or misconstructions in Chinese language sentences, such as incorrect word order, improper use of punctuation and incorrect usage of words.

2. METHOD

Our research proposes a methodology for enhancing Chinese sentence correction utilizing LSTM. LSTM, a variant of RNN, excels in capturing long-term dependencies [27], overcoming limitations such as vanishing gradients that typically challenge traditional RNN models, including gated recurrent units (GRU) and CNN. Its proficiency in managing sequential and contextual information renders it particularly effective for Chinese language correction tasks. By leveraging the strengths of LSTM networks, this methodology not only addresses the syntactic and semantic nuances inherent in Chinese but also enhances the overall accuracy and reliability of sentence correction systems. Consequently, it presents a significant advancement in computational linguistics, offering a robust framework for future developments in language processing technologies. LSTM is a type of RNN models demonstrate significant advantages in the domain of Chinese language correction, particularly due to their ability to retain contextual information across long sequences [27]. This characteristic is crucial for identifying errors such as incorrect or missing characters by considering the sentence's holistic meaning and contextual information renders it particularly effective for Chinese language correction tasks. The model's architecture, featuring memory cells and gates, facilitates the regulation of information flow, thereby enhancing its ability to store and retrieve relevant data over extended texts. Consequently, LSTM models are highly effective in correcting Chinese sentences by maintaining essential context and discarding extraneous information. The methodology involves leveraging extensive datasets comprising correctly structured Chinese sentences and those with errors from non-native speakers. This training data enables LSTM models to internalize typical sentence structures and predict appropriate words for novel sentences, thereby identifying discrepancies by comparing them to the model's learned patterns. Recent advancements underscore the efficacy of LSTM models in improving grammatical error detection, particularly when integrated with techniques like the transformer attention mechanism, which augments accuracy and recall rates in grammar correction tasks.

Another reason LSTM was chosen is by using a memory cell and a set of gates to control the information flow. LSTM can handle Chinese language sentence correction context by using the memory cell that can store and retrieve information over long sequences of Chinese character and words. It can deal with the sequential and contextual information of Chinese characters and words, which are essential for detecting and correcting errors. As LSTM reads through a sentence, it builds an understanding of the sentence’s meaning. For example, if it encounters a common error in Chinese, like a missing or wrong character, the LSTM can remember the context and suggest a correction. Besides, LSTM models excel because they remember the context, even with characters spaced far apart. For example, if a wrong character is used earlier in the sentence, the LSTM can detect it based on the overall meaning of the sentence and suggest the correct character.

This memory cells allow LSTM to maintain important information while discarding irrelevant information, making them suitable for tasks that involve remembering past context and detecting and correcting errors. LSTM can also use special units called gates to regulate the information flow inside the network and preserve the memory of previous state. By training an LSTM on a large dataset of correctly written Chinese sentences, it learns what typical sentence structures look like. So, when given a new sentence, it can predict what each word should be and spot errors by comparing the actual sentence structure to what it expects. In simple term, LSTM network can correct sentences by learning the patterns of correct Chinese and spotting deviations, all while keeping track of context and structure across the sentence is the reason why LSTM is chosen as the method for this study.

Overall, the adoption of LSTM models for Chinese sentence correction offers significant advantages in improving accuracy, recall rates, computational efficiency, and processing time. As research in this area continues to evolve, further advancements in LSTM-based techniques are likely to contribute to the development of more effective tools for language learning and NLP tasks. Focusing on LSTM models for Chinese sentence correction for non-native learners is advantageous due to their ability to handle character-level representations effectively, improve grammatical error detection and correction, and enhance computational efficiency. These models provide a robust framework for developing tools that can aid non-native learners in mastering Chinese with greater accuracy and efficiency. The previous research about Chinese language sentence correction using AI demonstrates in Table 1. However, there are still challenges to be addressed, such as the need for more accurate and robust NLP techniques and the need to ensure that AI-based tools are culturally sensitive and appropriate for Chinese language learners. From the table, we also can figure out that most of the recent studies utilized LSTM for their research.

Table 1. Recent Chinese language sentence correction using artificial intelligence

Author	Year	Deep architecture	Dataset
[11]	2014	Conditional random fields (CRFs)	HSK WOE dataset, Google Chinese Web 5-gram corpus
[13]	2018	LSTM	NLP
[17]	2020	Hybrid bidirectional encoder representations from transformers (BERT)-GRU	NLPCC 2018 grammatical error correction (GEC) dataset
[28]	2020	DNN	NLPCC-2018 Chinese NER dataset
[29]	2021	ON_LSTM transformer/NLP	Weibo User Generated Content
[30]	2021	BERT-BiLSTM Seq2seq/soft-masked BERT	Wikipedia, Weibo, SIGHAN 2013, SIGHAN 2014, SIGHAN 2015
[31]	2022	NLP/CRF	Speech NLP, MOODLE dataset
[32]	2020	Vision transformer, GRU+CNN, and BERT	NLP
[33]	2018	LSTM	CCL Chinese Corpus, NLPTEA 14-17 CGED

Based on the grammatical error detection and the performance of LSTM, various previous research has shown that the LSTM introduced the concept of learning long-term dependencies that is crucial for understanding context in language sequences. Because Chinese is a complex language with intricate sequential grammar, so to address its unique challenges, the LSTM model was chosen for its proven ability to capture and retain relevant information across extended sequences, making it well-suited for grammatical error correction. In addressing faults and misconstructions bias, the AI model needs to handle variations in writing styles by using large-scale modeling [28]. Besides, by making use of knowledge graphs and adapting contextual understanding, researchers can handle the meaning of something by considering environment, background, challenges in which it exists. Moreover, a quadratic function bias term like Gaussian distribution based on the self-attention score to reduce the attention to the non-error part can be add on [29]. The recall rate of the model will improve due to the enhanced of Gaussian distribution reduces the prediction of error points.

Furthermore, LSTM-based models exhibit computational efficiency through techniques such as prefix tree merging, which reduces the complexity of error correction tasks by streamlining the evaluation of candidate sentences, thus enhancing both accuracy and processing speed. This efficiency positions LSTM models as promising tools for real-time feedback applications. Additionally, LSTM models are adept at handling short- to medium-length texts, prevalent in language learning contexts, offering a computationally efficient alternative to transformer-based models like BERT or GPT. For non-native Chinese learners, LSTM models address common errors in word choice and grammar effectively. By incorporating reinforcement learning (RL), these models continually refine feedback based on user interactions [34], providing personalized suggestions that improve progressively [35]. This system offers a comprehensive solution for Chinese language learning, correcting mistakes while fostering a deeper understanding of language structures. Figure 1 shows the flowchart of constructing the model based on LSTM.

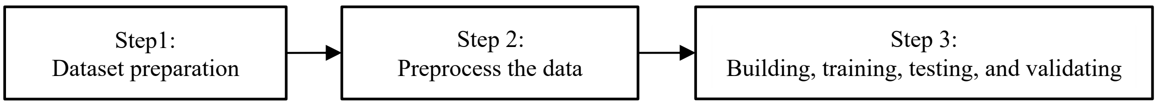

Figure 1. Flowchart of constructing the model based on LSTM

2.1. Dataset preparation

C14 HSK WOE dataset have been used for this research was adapted from [11] research. The HSK syllabus is based on the people's Republic of China's standardized test of proficiency in standard Chinese language for non-native speakers such as foreigners and oversea Chinese. This multi-level proficiency test can be used by many groups of test takers depending on their own objectives [36]. The dataset used in this study was collected from HSK dynamic composition corpus, which is built by Beijing Language and Culture University (BLCU). This corpus contains the Chinese composition articles in HSK examination can be accessed in an open access website (https://github.com/ntunlplab/Chinese-Word-Ordering-Errors-Detection-and-Correction-Corpus). It contains total 8,515 sentences annotated with "word ordering errors" in HSK corpus. To ensure data quality, duplicate sentences and those with special format sentences were eliminated. WOE are manually corrected, and all HSK- provided tags were are also removed from the dataset. This cleaning process resulted in a refined 1,150 unique sentences stored in sent-original.txt for further analysis.

2.2. Preprocessing the data-sentence splitting and tokenizing

Two native Chinese speakers were selected and corrected 1,150 sentences with WOE. In this step, the HSK WOE dataset, sourced from [11], was prepared for analysis. The dataset comprises sentences from Chinese language proficiency exams and is based on non-native Chinese learners' composition articles created by BLCU. To enhance the dataset's usability, sentences were divided into input (original) and output (corrected) pairs. After the initial sentence splitting, the input and output sentences were further processed. This involved tokenization, padding, and the conversion of sentences into numerical representations are indispensable procedures for LSTM input. Tokenization is particularly crucial for languages like Chinese, where sentences consist of characters without explicit delimiters, unlike alphabetic languages. This process involves decomposing sentences into individual tokens, such as characters or words, allowing the model to handle sequences methodically. Padding is essential for ensuring uniform input length, which is a prerequisite for efficient sequence processing by LSTM models. By adding placeholder tokens to shorter sentences, padding standardizes sentence lengths across the dataset, thereby preserving structural consistency. Additionally, numerical representation is vital as neural networks are incapable of processing raw text. Transforming tokens into numerical vectors enables the LSTM model to discern and learn patterns within the data. This conversion step is pivotal in translating language structures into a format that is comprehensible to machines, facilitating effective training and error correction. These processes collectively enhance the model's ability to analyze linguistic data, ultimately contributing to improved performance in NLP tasks.

2.3. Building, training, testing and validation

The study utilized the Anaconda platform and Python libraries, notably Keras, for the development and evaluation of LSTM model aimed at addressing grammatical errors in Chinese sentences. The model was constructed to handle the preprocessed HSK WOE dataset. Key stages included optimizing hyperparameters such as learning rate, batch size, and LSTM units to maximize performance. Evaluation metrics were crucial: accuracy measured the model's overall correctness, precision evaluated the relevance of error corrections, recall ensured comprehensive error identification. Post-training, the model underwent rigorous testing on dataset segment to assess its real-world applicability. Validation involved dataset partitioning into training, validation, and testing subsets, supplemented by cross-validation techniques to enhance robustness and mitigate overfitting risks. This comprehensive approach ensured a thorough evaluation of the model's capabilities in detecting and correcting grammatical errors, thereby contributing to improved writing quality in Chinese language processing.

3. RESULTS AND DISCUSSION

3.1. Findings

The study focused on identifying the best deep learning architecture for Chinese language sentences correction, specifically utilizing the HSK WOE dataset [11]. By concentrating on the LSTM model, the research elucidates its proficiency in language correction tasks [37]. LSTM can utilize input-output pairs to enable the model to map incorrect sentences to their corrected forms. The training phase emphasized minimizing a loss function, which measures the disparity between the model's predictions and the actual corrected sentences. To enhance the model's robustness and prevent overfitting, techniques such as dropout were employed. Throughout the training process, we closely monitored loss values to gauge the model's learning trajectory. Notably, by the third epoch, there was a marked convergence of loss values, signifying the model's swift grasp of the correlation between incorrect and corrected sentences. By the fifth epoch, the training loss plateaued, indicating that the model had achieved optimal performance with negligible room for further enhancement. For evaluation purposes, the model was tested on an independent set of sentences from the HSK WOE dataset, ensuring these were not part of the training data. The analysis of the model's performance revealed the following key observations: Throughout the training phase, as shown in Figure 2, the loss values consistently converged. This convergence became evident at the third epoch, signifying the model's swift comprehension of the relationships between the input (original) and output (corrected) sentences. The convergence of loss values indicates the model's proficiency in minimizing errors and disparities between predicted and actual corrected sentences. After epoch 5 onwards, the training loss remains consistent which suggests that the model has reached the point where further improvements are minimum.

The accuracy metrics, as shown in Figure 3, achieved in both training and testing were exceptionally high. The accuracy values converged at roughly 0.99 around the same epoch where the loss values stabilized. This demonstrates the model's exceptional ability to accurately understand and predict corrected Mandarin sentences, reaching a near-flawless level of correctness in its assessments. These findings emphasize the LSTM model's effectiveness within the realm of Mandarin language proficiency evaluation. The model's rapid convergence and superior accuracy levels underline its competence in distinguishing improperly written and corrected Mandarin sentences. This establishes it as a valuable asset for language learners and educators. The model's triumph in this endeavor holds the potential to enhance language proficiency evaluation and correction in educational and broader contexts.

Figure 4 shows the training loss convergence occurs at a value lower than 0.5. This indicates that the model is learning to fit the training data quite well. A training loss lower than 0.5 typically suggests that the model is making relatively accurate predictions on the training data. The accuracy values for both validation and training operations are observed to be very high, which is close to 1.0. However, validation loss fluctuated from epoch 12 onwards. These fluctuations need to pay attention as the model’s performance on validation data is not consistently improved.

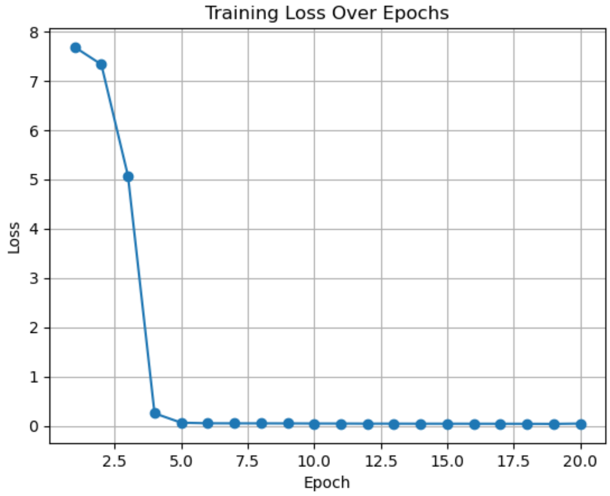

Figure 2. Training loss vs. epoch number

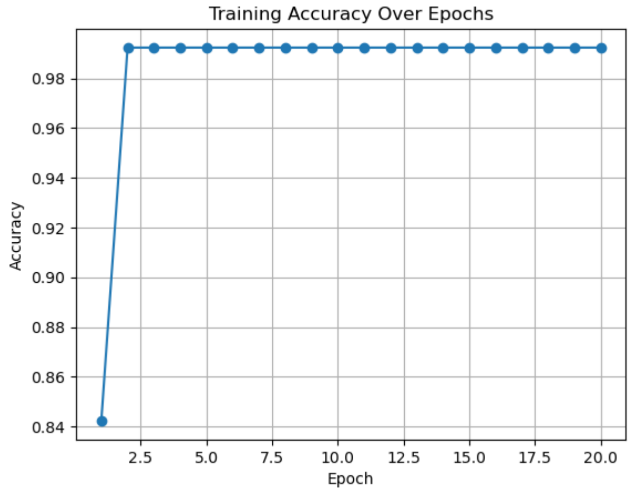

Figure 3. Training accuracy vs. epoch number

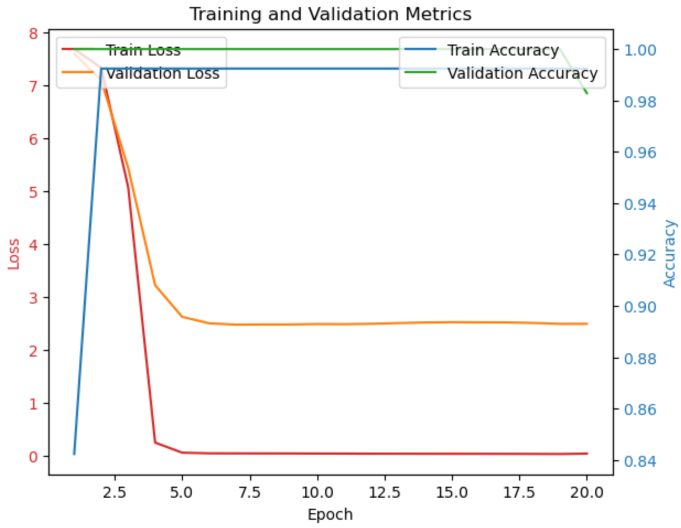

Figure 4. Training and validation vs. epoch number

The evaluation of the model's performance is presented in Figure 5. The data obtained from the evaluation of the model's performance can be improved using these 3 additional alternatives: First solution: using dropout. The overfitting can be reduced by adding dropout layers within the LSTM layers. This prevents the model from over-relying on specific connections during the training. Second solution: using early stopping. Early stopping can be implemented to prevent the model from training too many epochs. It will monitor the validation loss and stop training when it starts increasing. Early stopping callback from the tensor flow can be used to achieve this. Third solution: using early stopping with architecture simplification. The model architecture can be simplified by reducing the dimensions of the latent space. Overfitting can be reduced due to a smaller latent space. We can try reducing the latent_dim to 128.

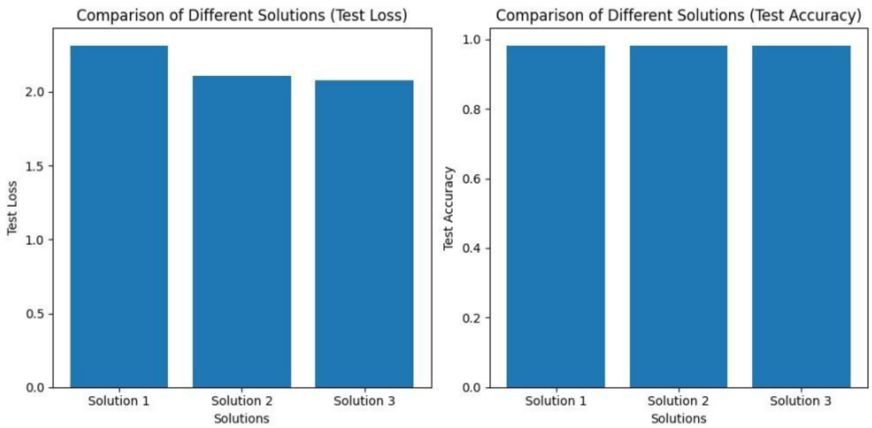

Figure 5. Evaluation of the model's performance

3.2. Discussion

Hence, based on results stated above, the significance of our study lies in the method that will improve language learning outcomes for Chinese language learners and provide a framework for future research and development of AI-based language correction tools for other languages. In addition, this study contributes to the development for the Chinese language teaching and learning that leverages AI technologies and multimedia. Furthermore, these findings in this paper further support the idea of [38] may contribute to improve language learning outcomes for Chinese language learners as well as providing a framework for future research and development of AI-based language correction tools for other languages.

Although with the LSTM methodology efficiency, the present findings seem to be consistent with other research by [39], which found the complexness of Chinese language including grammar, sentence structure, and the Chinese characters will be going to pose challenges and limitation to identify the mistakes, correcting error and accuracy aspect. However, future research should be done by integrating the LSTM with the other AI techniques to upgrade the accuracy and efficiency of error correction in Chinese sentences. Besides, a further study may explore with more focus on semantic error correction by investigating methods to include semantic analysis into LSTM-based models for detecting and correcting errors related to meaning and context in Chinese sentence is therefore suggested. These results in the above section match those observed in earlier studies by [40], which highlight the self-regulation learning can enhance students' improvement in learning Chinese language as second language by leveraging AI-based language learning.

Meanwhile, the implications of this research can both help teachers and students. For example, one possible implication by leveraging LSTM-based AI model, is that the Chinese language learners can receive instant feedback on their writing, which contributing to faster skill development and improved language proficiency. Based on the findings, this study may help to increase of efficiency as same as effectiveness in communication by using the accurate and corrected Chinese language sentences whether in everyday context, academic, professional or many other situations usage, helping to make more precise and clearer exchanges.

4. CONCLUSION

This paper demonstrates the effectiveness of employing LSTM for detecting and correcting faults or errors in Chinese language sentence correction based on C14 HSK WOE datasets. This is essentially useful for students who wish to learn how to correct their Mandarin writing. Via sentence splitting and tokenization, the proposed model has been demonstrated to be able to learn the Chinese sentence structure and identify the mistakes in the sentence and correct them. It also significant for the non-native learner to use the data for constructing Chinese sentences correctly. This study offers new insights into the optimization of LSTM modules for Chinese sentence correction, highlighting the significant role of deep learning in tackling language proficiency challenges. The research underscores the efficacy of LSTM in this domain, suggesting a promising avenue for further exploration. These architectures could potentially enhance model performance through improved contextual understanding and processing efficiency. Based on the findings and for the future research, more datasets of Chinese sentence correction need to be explored and applied with the LSTM model to backup this paper HSK WOE dataset, for example using different context of non-native speaker dataset. These findings contribute to the development of advanced automatic language correction systems and educational tools designed for Mandarin learners, presenting opportunities for more personalized and accurate language learning experiences. The implications of this research extend to the broader field of machine learning, where continuous advancements in model architecture and data utilization are crucial for addressing complex language-related tasks. This study's importance lies in its method to enhance the learning outcomes for Chinese language learners and establish a framework for AI-based language correction method. It also contributes to Chinese language education using AI and multimedia. Despite of the LSTM's efficiency, the complexity of Chinese language poses challenges in error identification and correction. Hence, Chinese language grammar writing, and sentence correction skills can regulate the student proficiency levels with the support and leveraging AI for correcting faults in Chinese language sentences. This research also benefits not only educators by contributing and improving teaching writing sentences skills, but also may improve the students of Chinese language proficiency. Finally, it also helps to increase the proficiency levels that can indicate decreased mistakes in the sentences.

ACKNOWLEDGEMENTS

The authors wish to express their gratitude for the support and assistance provided by Universiti Malaysia Kelantan, Malaysia, in making this article possible. Additionally, the authors extend their appreciation to fellow researchers who contributed, either formally or informally, to the preparation of this paper.

FUNDING INFORMATION

Authors declare that no funds or grants were received for the preparation of this paper.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhammad Afiq Che Lah	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Hadhrami Ab Ghani	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	
Nurul Izrin Md Saleh	✓			✓		✓	✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

INFORMED CONSENT

Informed consent was obtained from all individual participants involved in the study. Participants were fully briefed on the purpose of the research, their rights, and the voluntary nature of their involvement. All data collected were treated with strict confidentiality and used solely for academic purposes.

ETHICAL APPROVAL

This study did not require formal ethical approval as it did not involve any procedures or interventions requiring such review. However, all research activities were carried out in accordance with ethical research standards, ensuring voluntary participation, informed consent, and confidentiality of participants' information.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [MACL] on request.

REFERENCES

[1] S. Elayyan, "The future of education according to the fourth industrial revolution," *Journal of Educational Technology and Online Learning*, vol. 4, no. 1, pp. 23–30, 2021, doi: 10.31681/jetol.737193.

[2] F. M. Shiri, T. Perumal, N. Mustapha, and R. Mohamed, "A comprehensive overview and comparative analysis on deep learning models," *Journal of Artificial Intelligence*, vol. 6, pp. 301-360, 2024, doi: 10.32604/jai.2024.054314.

[3] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: a review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[4] L. Jin and T. Hongyin, "Chinese language in a global context," in *The Routledge Encyclopedia of the Chinese Language*, London, United Kingdom: Routledge, 2016, pp. 119–136.

[5] S. H. Teoh, B. C. Heng, Y. F. Neo, and J. Y. Y. Tan, "Language proficiency among non-native Chinese language learners: a discriminant analysis," in *International Academic Symposium of Social Science 2022*, vol. 82, no. 1, 2022, doi: 10.3390/proceedings2022082042.

[6] Z. Wang, Q. Yu, J. Wang, Z. Hu, and A. Wang, "Grammar correction for multiple errors in Chinese based on prompt templates," *Applied Sciences*, vol. 13, no. 15, 2023, doi: 10.3390/app13158858.

[7] Y. Liu, H. Zan, M. Zhong, and H. Ma, "Detecting simultaneously Chinese grammar errors based on a BiLSTM-CRF model," in *5th Workshop on Natural Language Processing Techniques for Educational Applications*, 2018, pp. 188–193, doi: 10.18653/v1/w18-3727.

[8] H. P. Wang, B. C. Kuo, Y. H. Tsai, and C. H. Liao, "A CEFR-' computerized adaptive testing system for Chinese proficiency," *Turkish Online Journal of Educational Technology*, vol. 11, no. 4, pp. 1–12, 2012.

[9] M. M. Taye, "Understanding of machine learning with deep learning: architectures, workflow, applications and future directions," *Computers*, vol. 12, no. 5, Apr. 2023, doi: 10.3390/computers12050091.

[10] Y. J. Lan, B. N. Lyu, and C. K. Chin, "Does a 3D immersive experience enhance Mandarin writing by CSL students?," *Language Learning and Technology*, vol. 23, no. 2, pp. 125–144, 2019, doi: 10125/44686.

[11] S. M. Cheng, C. H. Yu, and H. H. Chen, "Chinese word ordering errors detection and correction for non-native Chinese language learners," in *COLING 2014 - 25th International Conference on Computational Linguistics,* 2014, pp. 279–289.

[12] R. Huang, A. Tlili, J. Yang, and T.-W. Chang, *Handbook on facilitating flexible learning during educational disruption: the Chinese experience in maintaining undisrupted learning in COVID-19 outbreak artificial intelligence in e-learning view project m-developer view project*, Beijing, China: Smart Learning Institute of Beijing Normal University, 2020.

[13] M. Y. Chen, T. C. Huang, Y. Shu, C. C. Chen, T. C. Hsieh, and N. Y. Yen, "Learning the Chinese sentence representation with LSTM autoencoder," in *The Web Conference 2018-Companion of the World Wide Web Conference*, 2018, pp. 403–408, doi: 10.1145/3184558.3186355.

[14] H.-P. Zhang, Q. Liu, X.-Q. Cheng, H. Zhang, and H.-K. Yu, "Chinese lexical analysis using hierarchical hidden Markov model," in *Proceedings of the second SIGHAN workshop on Chinese language processing*, 2003, vol. 17, pp. 63–70, doi: 10.3115/1119250.1119259.

[15] Y. Zhang, P. Li, Q. Piao, Y. Liu, Y. Huang, and H. Shu, "Syntax does not necessarily precede semantics in sentence processing: ERP evidence from Chinese," *Brain and Language*, vol. 126, no. 1, pp. 8–19, 2013, doi: 10.1016/j.bandl.2013.04.001.

[16] A. Baharum, R. Ismail, S. H. A. Wahab, F. D. Deris, N. A. M. Noor, and M. S. M. Kasihmuddin, "Chinese character recognition using support vector machine," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 17, pp. 5335–5340, Sep. 2022.

[17] J. W. Chen, X. K. Sigalingging, J. S. Leu, and J. I. Takada, "Applying a hybrid sequential model to chinese sentence correction," *Symmetry*, vol. 12, no. 12, pp. 1–16, 2020, doi: 10.3390/sym12121939.

[18] L. H. Woan and L. S. Tat, "Assessing children's native language in Mandarin using the adapted new Reynell developmental language scales-Mandarin (NRDLS-M)," *GEMA Online® Journal of Language Studies*, vol. 17, no. 2, pp. 123–145, May 2017, doi: 10.17576/gema-2017-1702-08.

[19] S. Shi *et al.*, "Effidit: an assistant for improving writing efficiency," in *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, 2023, vol. 3, pp. 508–515, doi: 10.18653/v1/2023.acl-demo.49.

[20] Y. Atsmon, M. Magni, L. Li, and L. Wenkan, *Meet the 2020 Chinese Consumer*. China: McKinsey&Company, 2012.

[21] E. Chew and X. N. Chua, "Robotic Chinese language tutor: personalising progress assessment and feedback or taking over your job?," *On the Horizon*, vol. 28, no. 3, pp. 113–124, 2020, doi: 10.1108/OTH-04-2020-0015.

[22] W. L. Johnson and A. Valente, "Tactical language and culture training systems: using AI to teach foreign languages and cultures," *AI Magazine*, vol. 30, no. 2, pp. 72–83, 2009, doi: 10.1609/aimag.v30i2.2240.

[23] Z. Lv, F. Poiesi, Q. Dong, and J. Lloret, "Applied sciences deep learning for intelligent human–computer interaction," *Applied Sciences*, vol. 12, no. 22, p. 11457, 2022.

[24] W. Gou and Z. Chen, "Think twice: a post-processing approach for the chinese spelling error correction," *Applied Sciences*, vol. 11, no. 13, 2021, doi: 10.3390/app11135832.

[25] Y. Li *et al.*, "On the (In) effectiveness of large language models for Chinese text correction," *Journal of Latex Class Files*, vol. 14, no. 8, pp. 1-13, 2021.

[26] Y. Cui, Z. Yang, and X. Yao, "Efficient and effective text encoding for Chinese LLaMA and Alpaca," *arXiv-Computer Science*, pp. 1-21, 2023.

[27] M. Z. Ansari, T. Ahmad, M. M. S. Beg, and N. Bari, "Language lexicons for Hindi-English multilingual text processing," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 2, pp. 641–648, 2022, doi: 10.11591/ijai.v11.i2.pp641-648.

[28] W. Song and C. Zhu, "Chinese wrong words detection and correction algorithm based on sentence perplexity and iterative correction," *Advances in Intelligent Systems and Computing*, vol. 1147, pp. 474–479, 2020, doi: 10.1007/978-3-030-43309-3_66.

[29] F. Sun and J. Zhang, "Research on grammar checking system using computer big data and convolutional neural network constructing classification model," *Journal of Physics: Conference Series*, vol. 1952, no. 4, 2021, doi: 10.1088/1742-6596/1952/4/042097.

[30] C. Li, C. Zhang, X. Zheng, and X. Huang, "Exploration and exploitation: Two ways to improve Chinese spelling correction models," in *59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing,* 2021, vol. 2, pp. 441–446, doi: 10.18653/v1/2021.acl-short.56.

[31] X. Wang, T. Gulenman, N. Pinkwart, C. De Witt, C. Gloerfeld, and S. Wrede, "Automatic assessment of student homework and personalized recommendation," in *2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT), Tartu, Estonia,* 2020, pp. 150–154, doi: 10.1109/ICALT49669.2020.00051.

[32] G. Zhao, Y. Guo, F. Xia, and C. Ma, "A multimodal method for Chinese spelling correction," in *2022 International Joint Conference on Neural Networks (IJCNN)*, Padua, Italy, 2022, pp. 1-7, doi: 10.1109/IJCNN55064.2022.9892297.

[33] Y. T. Shiue, H. H. Huang, and H. H. Chen, "A Chinese writing correction system for learning Chinese as a foreign language," in *27th International Conference on Computational Linguistics: System Demonstrations*, New Mexico, USA, 2018, pp. 137–141.

[34] J. Zhao, "Construction of college Chinese mobile learning environment based on intelligent reinforcement learning technology in wireless network environment," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–10, Apr. 2022, doi: 10.1155/2022/5164430.

[35] Z. Yang, "FCM clustering on interaction pattern analysis of Chinese language learner behavior," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–8, Jun. 2022, doi: 10.1155/2022/8256646.

[36] Y. Peng, W. Yan, and L. Cheng, "Hanyu Shuiping Kaoshi (HSK): a multi-level, multi-purpose proficiency test," *Language Testing*, vol. 38, no. 2, pp. 326–337, 2021, doi: 10.1177/0265532220957298.

[37] Y.-T. Shiue, H.-H. Huang, and H.-H. Chen, "Detection of Chinese word usage errors for non-native Chinese learners with bidirectional LSTM," in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, 2017, vol. 2, pp. 404–410, doi: 10.18653/v1/P17-2064.

[38] Y. Jing, "Design and application of teaching system for Chinese language and literature major drove by interpreted AI technology," *Applied Artificial Intelligence*, vol. 37, no. 1, 2023, doi: 10.1080/08839514.2023.2203573.

[39] L. H. Lee, B. L. Lin, L. C. Yu, and Y. H. Tseng, "Chinese grammatical error detection using a CNN-LSTM model," in *Proceedings of the 25th International Conference on Computers in Education,* 2017, pp. 919–921.

[40] H. Qiao and A. Zhao, "Artificial intelligence-based language learning: illuminating the impact on speaking skills and self-regulation in Chinese EFL context," *Frontiers in Psychology*, vol. 14, Nov. 2023, doi: 10.3389/fpsyg.2023.1255594.

BIOGRAPHIES OF AUTHORS

Muhammad Afiq Che Lah obtained the bachelor's degree in the Chinese language from Beijing Language and Culture University (BLCU). And master's degree in Department of Resources and Information Technology from Education, Universiti Kebangsaan Malaysia (UKM). Now continuing Ph.D. at Universiti Malaysia Kelantan (UMK) in Faculty of Data Science and Computing and at the same time working as a teacher, at Sekolah Menengah Imtiaz Yayasan Terengganu Besut, Terengganu. He can be contacted at email: afiqclh@gmail.com.

Hadhrami Ab Ghani received his bachelor degree in electronics engineering from Multimedia University Malaysia (MMU) in 2002. In 2004, he completed his master's degree in telecommunication engineering at The University of Melbourne. He then pursued his Ph.D. at Imperial College London in intelligent network systems and completed his Ph.D. in 2011. He can be contacted at email: hadhrami.ag@umk.edu.my.

Nurul Izrin Md Saleh obtained a bachelor's degree in information technology from Multimedia University Malaysia (MMU). She completed his master's degree in computer science at The University of Putra Malaysia. Then complete a Ph.D. at The University of Brunel London in the same field of study. She can be contacted at email: nurulizrin.ms@umk.edu.my.