Indonesian Journal of Electrical Engineering and Computer Science
Vol. 40, No. 1, October 2025, pp. 480~489
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v40.i1.pp480-489

War strategy assisted Bi-LSTM for sentiment analysis of customer review

Anilsagar T., Syed Abdul Syed S.
Department of Computer Science and Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, India

Article Info

Article history:

Received May 6, 2024
Revised Jun 27, 2025
Accepted Jul 4, 2025

Keywords:

Bidirectional long short-term memory
Customer service
Positive or negative
Sentiment analysis
Useful information

ABSTRACT

Sentiment analysis (SA) stands as a valuable tool for categorizing reviews to discern positive or negative sentiments. Satisfaction of customers holds a pivotal role in the realm of customer service. Presently, customer expression entails a significant volume of reviews on online platforms. For extracting useful information from massive reviews, the categorization of reviews into positive or negative SA is essential. For enhancing the efficiency of customer review detection, this work presents a war strategy algorithm (WSA)-bidirectional long short-term memory (Bi-LSTM) for customer review classification using the TripAdvisor dataset. Initially, the pre-processing stage is carried out, and the skip-gram-based word embedding is performed. For categorizing the extracted features, the deep learning model Bi-LSTM-WSA is presented. Accuracy and precision values achieved are 97.1% and 97.5% respectively.

Corresponding Author:

Anilsagar T.
Department of Computer Science and Engineering
B.S. Abdur Rahman Crescent Institute of Science and Technology
Chennai, Tamil Nadu, India
Email: aniltsagar@gmail.com

1. INTRODUCTION

Customer satisfaction represents the subjective assessment that consumers make, situated between their initial expectations and the actual experiences they encounter [1]. In contemporary times, a significant number of customers articulate their opinions through reviews posted on online platforms such as Yelp and TripAdvisor, detailing their level of satisfaction with the products or services they have acquired. These customer reviews wield considerable influence, as they can contribute to enhancing the visibility and appeal of the seller's offerings. A restaurant operates as an establishment that both prepares and provides food to customers in exchange for payment [2].

Leveraging customer reviews on restaurants sourced from various websites and social networks presents an easy approach to assist restaurant owners in gaining a deeper understanding of their customers' preferences and sustaining profit. These feedbacks provide customers with a platform for expressing their opinions openly and candidly [3]. Obtaining review data through this method is faster compared to conventional interviews and surveys, with the added benefit of acquiring data in real-time. From the perspective of data collection and analysis, utilizing social media data also streamlines the process, saving time and reducing data collection expenses [4].

Sentiment analysis (SA) serves as a device for extracting the opinions expressed by a customer regarding a specific entity. When applied to reviews, SA delves into investigating the opinions surrounding a product. This analytical process relies on natural language processing (NLP), and text analysis for extracting relevant information while disregarding unnecessary elements. Its objective is to discern the underlying sentiment conveyed in a sentence, whether it leans towards a negative or positive evaluation [5].

Distinguishing negative and positive reviews can be accomplished either in a manual or automatically. Nevertheless, manual detection tends to be costly, time-consuming, and comparatively less accurate when contrasted with automated methods [6], [7]. During the last two decades, significant strides have been made in enhancing automated reviews detection techniques. Machine learning (ML) and deep learning (DL) have emerged as highly effective means for identifying reviews. These methods leverage various features, including user behavior and review content, to precisely categorize reviews as positive or negative. Moreover, maintaining a high accuracy is important. Failure to do so could impede users' access to truthful reviews and undermine the credibility of trustworthy reviewers, potentially diminishing their incentive to contribute to the platform.

Motivation: DL models for identifying fake reviews have three main advantages. Firstly, these models leverage real value based hidden layers to automatically create complex global semantical features, which is challenging to achieve using manually crafted features. This approach effectively addresses the limitations of conventional ML models. Secondly, DL models use cluster-based word embeddings as input, which can be derived from raw input, thereby overcoming the scarcity of labelled data. Lastly, DL models can rapidly learn and understand the consistent structure of text.

The paper follows this structure: section 2 examines related works pertinent to the suggested model. Section 3 provides a concise description of the suggested model. Section 4 presents the findings from the conducted experiments. Lastly, Section 5 concludes the paper.

2. RELATED WORKS

Zhao *et al.* [8] presented a local search improved bat optimizer with Elman neural network (LSIBO-ENN) for SA of online products. Initially, during pre-processing the processes like tokenization, Genism lemmatization, and snowball stemming were carried out. Then, the features were extracted by the term weighting (TW) and classified by the LSIBO-ENN, and achieved a better accuracy of 92% on the movie and TV dataset.

Jain *et al.* [9] developed convolutional neural networks (CNN) with long short-term memory (LSTM) model for SA by user-generated content. This existing model was provided on batch normalization, maxpooling and dropout. Experimentation was performed on Twitter airline and airline quality datasets and achieved a better accuracy of 91.3%.

Kumar *et al.* [10] developed a SA of product review for predicting the satisfaction of customer using EEG response. This existing work aimed for enhancing the performance of rating prediction. Then, the artificial bee colony (ABC) was used for optimizing rating and sentimental scores and random forest was used for classification. Finally, the R2 and root mean squared error (RMSE) values achieved were 0.72 and 0.29.

Kaur and Sharma [11] introduced a DL based hybrid feature extraction model for customer SA. Feature extraction stages like review and aspect based features were used to construct the hybrid feature vector. At last, the LSTM was used for SA and achieved a better precision of 94.4%.

Hajek *et al.* [12] presented an aspect based SA for fake review identification in e-commerce. Through analysis of an Amazon review dataset, an aspect based model identified two critical factors for discerning fake reviews. This underscores the importance of linking these two factors together. At last, the word2vect-LDA was used for performing the aspect based model.

Zhang *et al.* [13] utilized neutral sentimental reviews for improving the satisfaction of customers. The Kano model was used for categorizing the identified requirements of customers into five product attributes. Assessments conducted on laptop and smartphone datasets, demonstrate that the inclusion of neutral reviews significantly alters the categorization of product attributes compared to conventional methods.

Nilashi *et al.* [14] developed deep belief network (DBN) for the analysis of online reviews and reducing dimensionality. Here, the self organizing map (SOM) was utilized to predict the reviews. The LDA (latent dirichlet allocation) was used for feature extraction and the DBN was used for classification. Specificity and sensitivity values achieved were 0.90 and 0.93.

Popular tasks in sentiment analysis using deep learning are CNN [15], [16], 2DCNN [17], [18], 3DCNN [19], LSTM [20], [21], Bi-LSTM [22], GRU [21], BiGRU [23], [24]. Table 1 provides the several potential research gaps and areas for further exploration. By addressing these gaps, future research can significantly advance the field of sentiment analysis, leveraging innovative strategies to enhance model performance and applicability across diverse scenarios.

Table 1. Potential research gaps and areas for further exploration

Area	Research gap	Opportunity
Integration of war strategy concepts	The specific application of war strategy principles in sentiment analysis has not been thoroughly explored. Research could investigate how strategic concepts such as tactical decision-making, resource allocation, and adversarial strategies can be metaphorically applied to sentiment analysis.	Develop novel models or frameworks that incorporate elements of strategic planning and decision-making into the architecture of Bi-LSTM networks for improved sentiment prediction.
Hybrid model development	While Bi-LSTM is effective for sequential data, integrating it with domain-specific strategies (e.g., war strategy) could be underexplored.	Experiment with hybrid models that combine Bi-LSTM with other techniques such as attention mechanisms, reinforcement learning, or game theory to enhance the model's ability to handle complex sentiment prediction tasks.
Dataset and domain-specific challenges	Current datasets may not fully capture the nuances of war strategy terminology and its impact on sentiment in customer reviews.	Create or utilize specialized datasets that include context-specific language and terminology related to war strategy, ensuring that the model is trained on relevant data that enhances its performance in this niche domain.
Interpretability and explainability	The interpretability of models combining complex strategies and deep learning architectures like Bi-LSTM is often limited.	Develop techniques for improving the explainability of the model's predictions, making it easier to understand how war strategy concepts influence sentiment analysis outcomes.
Performance metrics and evaluation	Existing research may lack comprehensive evaluation metrics that specifically assess the impact of war strategy integration on sentiment analysis performance.	Propose and validate new performance metrics that consider both the accuracy of sentiment prediction and the effectiveness of strategic integration.
Scalability and real-time analysis	There is limited research on the scalability and real-time application of such models, particularly in dynamic environments where customer reviews are generated continuously.	Investigate scalable architectures and optimization techniques that allow the model to perform efficiently in real-time scenarios, maintaining high accuracy while processing large volumes of data.
Cross-domain applicability	The current research focus may be limited to specific domains, without exploring the broader applicability of war strategy-assisted sentiment analysis in other fields.	Explore the potential for applying war strategy principles to sentiment analysis in other domains, such as politics, finance, or healthcare, to determine if similar benefits can be achieved.

3. PROPOSED METHOD

This study aims to determine the SA of the given review, whether it is positive or negative. To achieve this, the proposed model has applied a range of Bi-LSTM with war strategy algorithm (WSA) to obtain the results. Figure 1 depicts the proposed SA of customer review on Bi-LSTM with WSA which comprises of different stages like collection of data, pre-processing, feature extraction and review classification.

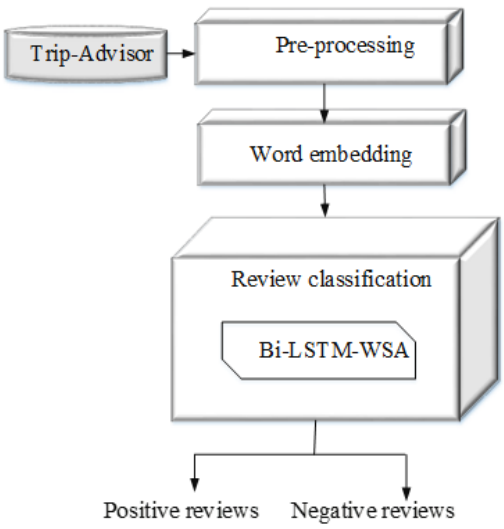

Figure 1. Proposed SA of customer review

3.1. Pre-processing

In the dataset preprocessing stage, the input reviews undergo refinement by removing intricate and irrelevant text. The preprocessing methodology adopted in this study starts with tokenization and culminates in the elimination of insignificant words, and digits. Employing the tokenization, the input reviews are segmented into tokens. Subsequently, stemming is applied to all tokens, reducing it to its singular term. Then, the stop words and special characters are eliminated.

3.2. Word embedding

The skip-gram approach for creating word embedding and trained on the Tripadvisor dataset. To preserve semantic similarity in word representations, the model employs a technique that maps words or phrases from the vocabulary to numerical vectors. In order to train the skip-gram model, a training set is initially constructed using the order of words denoted as $v_1, v_2, v_3 \ldots\ldots, v_T$. This dataset serves as the input for the training process, allowing the model to learn the relationships and contexts between words and effectively capture their semantic meanings. The objective is given as:

$$Word\_embedding = \frac{1}{T}\sum_{t=1}^{T}\sum_{c} log \quad s(v_{t+1}|\, v_t) \tag{1}$$

where $c$is the size of the context and $s(v_{t+1}|v_t)$ is the softmax term.

3.3. Customer review classification by the Bi-LSTM with WSA

Finally, for classifying the reviews as positive and negative, the DL model Bi-LSTM with WSA is presented. The conventional RNN model has the capacity in processing sequential data, such as text, of varying lengths. But, RNN encounters a common issue during the gradient computation phase known as the exploding and vanishing gradient issues. This challenge arises when the backpropagation algorithm attempts to learn long range dependencies, resulting in weight parameters becoming excessively small or large. Consequently, this slows down the network's ability to effectively learn complicated terms. LSTM is presented for mitigating this problem using the memory unit $c_j$to retain the essential information and it has input i_j , output o_j and reset $r_j$gate. Then, the h_j is the output of cell and $g_j$is the global state that makes sharing of various h_j over the LSTM.

$$i_j = \sigma\left(W_{yi}y_j + W_{hi}h_{j-1} + W_{ci}C_{j-1} + b_i\right) \tag{2}$$

$$f_j = \sigma\left(W_{yf}y_j + W_{hf}h_{j-1} + W_{cf}C_{j-1} + b_f\right) \tag{3}$$

$$g_j = \sigma\left(W_{yg}y_j + W_{hg}h_{j-1} + W_{cg}C_{j-1} + b_g\right) \tag{4}$$

$$c_j = i_j g_j + f_j C_{j-1} \tag{5}$$

$$o_j = \sigma\left(W_{yo}y_j + W_{ho}h_{j-1} + W_{co}C_{j-1} + b_g\right) \tag{6}$$

$$h_j = o_j\, tanh\left(c_j\right) \tag{7}$$

But, in certain cases of SA, it is necessary to capture word's past and future dependencies. Bi-LSTM is presented a one more LSTM in which the hidden links flow in the opposite direction. Figure 2 states the structure of Bi-LSTM and it has two LSTM for modeling the sequential information from both directions. During each time step j, the forward and the backward LSTMs operate on the input in opposing directions. They subsequently produce hidden state vectors as output as $\overrightarrow{h_j}$ and $\overleftarrow{h_j}$. These two hidden state vectors are combined to make the final output h_j.

$$h_j = \overrightarrow{h_j} + \overleftarrow{h_j} \tag{8}$$

To optimize the hyper-parameters of the standard Bi-LSTM model, in this work the WSA algorithm is presented for enhancing the accuracy of the model. The WSA mimics the strategic motion of soldiers in the army during the war. This optimizer is based on two mechanisms like attacking mechanism and a defense mechanism. Every soldier updates their position continuously on the basis of emperor and leader. Rank and weight are allocated to every soldier and the weight of each soldier is updated on the basis of their success in increasing the fitness value. Mathematical modeling of the AWSO is explained in the following section.

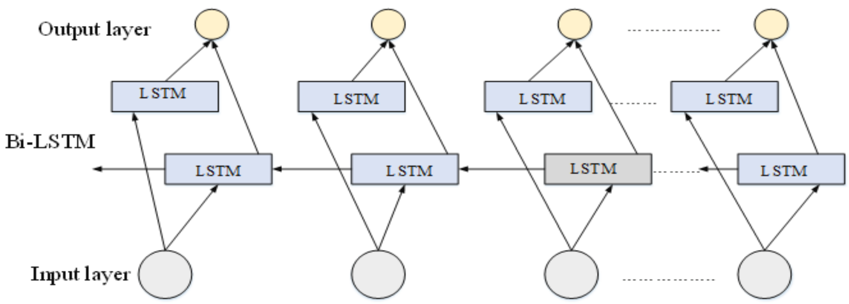

Figure 2. Structure of Bi-LSTM

Attacking mechanism: In this mechanism, the emperor positions himself to attack the opposition with great force. Thus, the soldier who possesses the strongest attack force or level of fitness is considered the king. At the beginning of the war, every soldier will be the same weight and rank. The soldier's rank increases if he successfully employs the plan. But as the war goes on, the effectiveness of the plan will determine how all soldiers are ranked and weighted. The soldiers, leader and emperor are getting closer to the target as the war draws to a close.

$$X_k(t+1) = X_k(t) + 2 \times \beta \times (L - E) + r \times (W_k \times E - X_k(t)) \tag{9}$$

where $X_k(t+1)$ and $X_k(t)$ are the new and previous position,β is the constant parameter, W_k is the weighting term, soldiers, $L$and $E$are the leader and emperor.

The soldier considers prior position, when fitness in the new position $F_m$is less than the prior position F_l, the following expression is utilized.

$$X_k(t+1) = (X_k(t+1)) + (F_m \geq F_l) + X_k(t)) \times (F_m < F_l) \tag{10}$$

When the position of soldier's are successfully updates, the rank $R_k$of the soldier's are updated as:

$$R_k = (R_k + 1) \times (F_m \geq F_l) + (R_k) \times\times (F_m < F_l) \tag{11}$$

Each soldier's rank is determined by his record of success in war, which is determined by following expression and it is influenced by the W_k.

$$W_k = W_k \times \left(1 - \frac{R_k}{Max\_iter}\right)^{\alpha} \tag{12}$$

where $\alpha$is the exponential term.
Defense mechanism: in this mechanism, the position of the army head, random soldier and emperor are utilized to update position. It is given as:

$$X_k(t+1) = X_k(t) + 2 \times \beta \times (E - X_r(t)) + r \times W_k \times (c - X_k(t))) \tag{13}$$

Relocating weak soldier: For each iteration, locate the soldiers with the lowest levels of fitness. In this process, the approach involves substituting the weakest soldier with a randomly chosen one and it is given as:

$$X_v(t+1) = Low + rand \times (Up - Low) \tag{14}$$

where$rand, Up$ and Low are the random number, upper and lower bounds. Algorithm 1 defines the pseudocode of the WSA.

Algorithm 1. Pseudocode of the WSA
```
Initialize the size of soldiers, dimensions, upper and lower bounds
for 1: size of soldiers
For every soldier, attacking force is obtained
While t< 〖max_〗i ter
Arrange the attacking force of all soldiers
First best fitness is considered as the king and the second-best fitness is consider as the emperor
The position of all soldiers is updated by Equation (12)
Else
The position of all soldiers is updated by Equation (8)
Arrange every soldier's fitness
when fitness in the new position is less than the prior position Equation (9) is updated
Rank R_kof the soldier's are updated by Equation (10)
Update the king and emperor's positions
t=t+1
End
```

4. RESULTS ANALYSIS

The following section, assess the effectiveness of the suggested model in accurately categorizing positive and negative review texts by analyzing U_{po} and U_{ne} are the true and false positives, $V_{po}$and V_{ne}true and false negatives. To evaluate the classification performance of the Bi-LSTM with WSA, this work utilized various performance metrics as outlined in Table 2.

Table 2. Performance measures

Metrics	Expressions
Accuracy	$\frac{U_{po}+U_{ne}}{U_{po}+U_{ne}+V_{po}+V_{ne}}$
Precision	$\frac{U_{po}}{U_{po}+V_{po}}$
F-score	$2\times\frac{Precision\times Recall}{Precision+Recall}$

4.1. Dataset detail

The dataset comprises 1,600 hotel reviews, with 800 being truthful and 800 being fake, sourced from a well-known hotel booking platform, Tripadvisor [25]. The dataset creators meticulously selected and refined reviews rated either 5 or 3 stars from twenty hotels located in Chicago. Key attributes of the dataset include the review text, class label, hotel name, reviewer name, and sentiment polarity.

4.2. Comparative analysis

The following section shows the comparative analysis of the different models like RNN, LSTM, Bi-LSTM and the proposed Bi-LSTM with WSA. Figure 3 presents the comparison of the measures like accuracy, precision and f-score on the trip advisor dataset. Here, the methods like RNN, LSTM and Bi-LSTM are compared with the proposed Bi-LSTM with WSA. The performance is carried out by varying the k-Fold values as in Figures 3(a)-(c). In all comparative analysis, the proposed Bi-LSTM with WSA obtained better performance. The existing models suffer from the vanishing gradient problem and are computationally intensive due to their complex architecture, which can result in high training time and high resource needs. So, methods like RNN, LSTM and Bi-LSTM achieved poor performance.

Figure 4 defines the confusion matrix of the Bi-LSTM with WSA model. In this matrix, there are 45.94% of samples are categorized as true negative, 4.06% of samples are categorized as false positive, 11.25% of samples are categorized as false negative and 38.75% of samples are categorized as true positive.

4.3. Discussion

4.3.1. Overall superiority of the proposed model

The proposed war strategy assisted Bi-LSTM model outperforms the traditional Bi-LSTM, LSTM, and RNN models across all metrics (Accuracy, F-score, and Precision). This suggests that integrating war strategy concepts into the Bi-LSTM architecture significantly enhances its ability to analyze sentiment in customer reviews. The high performance of the proposed model, especially in precision, indicates its effectiveness in correctly identifying positive and negative sentiments with minimal errors.

4.3.2. Stability across K-Folds

The performance of the proposed model is consistent across different K-Folds, which demonstrates its robustness and reliability in sentiment analysis tasks. This consistency is crucial for real-world applications where model performance should remain stable across various data splits. The standard deviations in the metrics for the proposed model are relatively low, further reinforcing its stability.

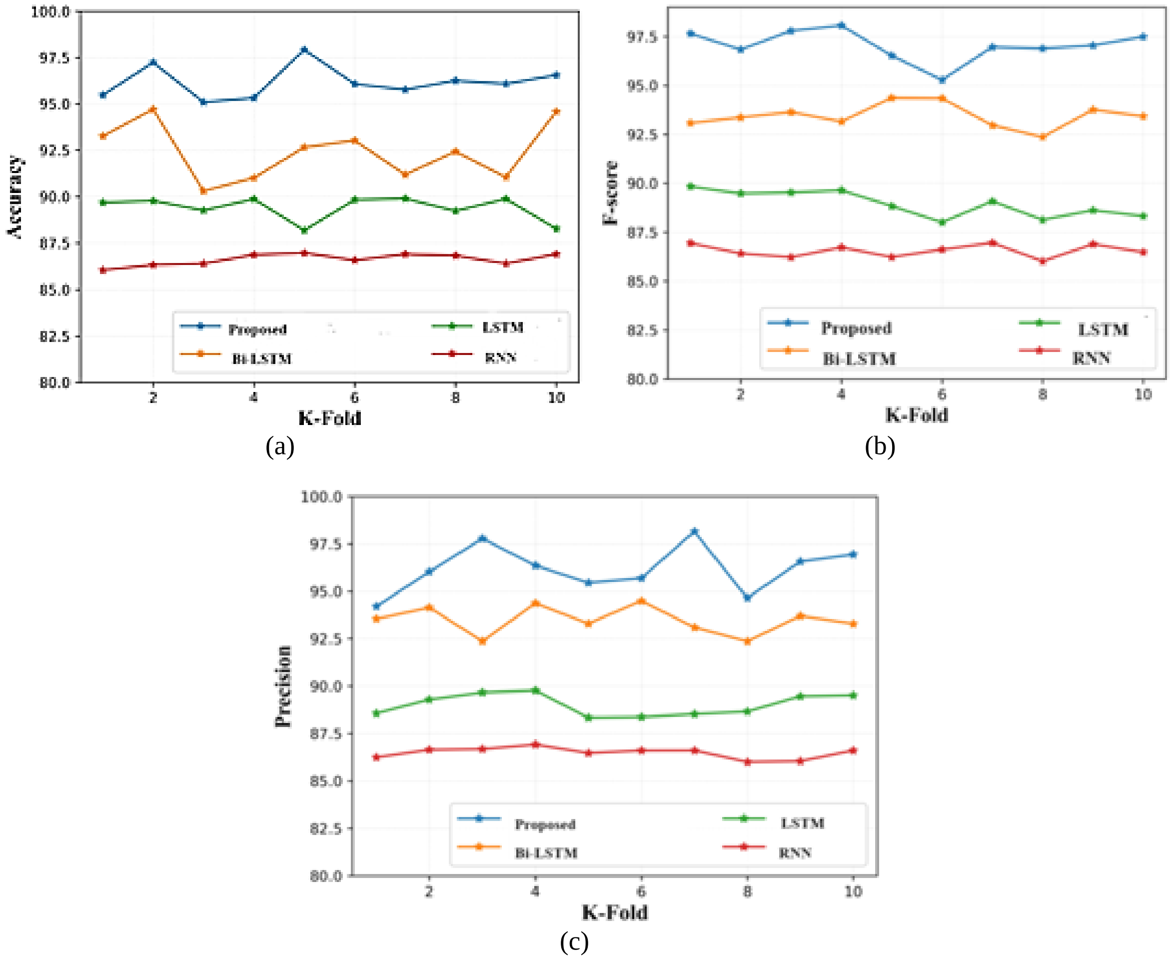

Figure 3. Comparison of (a) accuracy, (b) precision, and (c) F-score

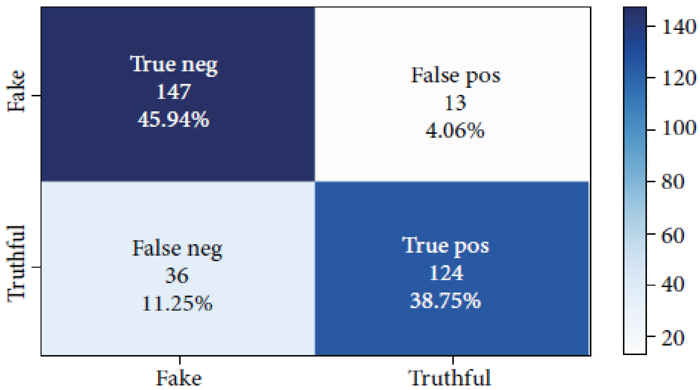

Figure 4. Confusion matrix of the Bi-LSTM with WSA

4.3.3. Comparison with traditional models

The traditional Bi-LSTM, LSTM, and RNN models show a noticeable gap in performance when compared to the proposed model. This gap highlights the limitations of these models in capturing complex patterns in sentiment data that the proposed model can effectively address. The Bi-LSTM outperforms the LSTM and RNN models, which aligns with the general understanding that Bi-LSTM can capture dependencies from both past and future contexts better than unidirectional LSTM and RNN.

4.3.4. Implications for future research

The results suggest that further exploration into hybrid models that integrate domain-specific strategies (like war strategies) can yield significant improvements in performance. Future research could focus on optimizing the integration of war strategy concepts and exploring their applicability in other domains beyond customer review sentiment analysis.

In summary, the figures clearly indicate that the War Strategy Assisted Bi-LSTM model provides a substantial improvement in sentiment analysis of customer reviews, offering higher accuracy, F-score, and precision compared to traditional models. This underscores the potential of incorporating strategic elements into machine learning models to enhance their performance and reliability.

5. CONCLUSION

The proposed work presented Bi-LSTM with WSA model to detect customer reviews using the word embedding model. The proposed work undergoes different pre-processing stages for reducing the training time. The proposed Bi-LSTM with WSA model efficiently identified the positive and negative reviews in an efficient way. The WSA is presented to enhancing the accuracy performance and preventing overfitting issues. The experimentation was demonstrated on the Tripadvisor dataset and achieved better accuracy and precision values of 97.1% and 97.5%. By providing accurate and efficient sentiment analysis, the proposed model can significantly assist customers in making informed decisions about products. For instance, identifying trends in positive and negative reviews can help customers gauge product quality and suitability more effectively. For businesses, such a model can provide deeper insights into customer sentiment, helping in better product development, targeted marketing strategies, and improved customer service. In future, the suggested methodology will be evaluated on the real-time and assist the customers in analyzing the positive and negative reviews of the different products.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

FUNDING INFORMATION

Authors state no funding involved.

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
Anilsagar T.,	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Syed Abdul Syed S.		✓				✓		✓	✓	✓	✓	✓		

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

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] R. S. Jagdale, V. S. Shirsat, and S. N. Deshmukh, “Sentiment analysis on product reviews using machine learning techniques,” In *Cognitive Informatics and Soft Computing: Proceeding of CISC 2017*, pp. 639-647, 2019. Springer Singapore, doi: 10.1007/978-981-13-0617-4_61.

[2] S. Yi, and X. Liu, “Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers’ review,” *Complex & Intelligent Systems*, vol. 6, no. 3, 621-634, 2020, doi: 10.1007/s40747-020-00155-2.

[3] R. Bose, R. K. Dey, S. Roy, and D. Sarddar, “Sentiment analysis on online product reviews,” In *Information and Communication Technology for Sustainable Development: Proceedings of ICT4SD 2018*, pp. 559-569, 2020. Springer Singapore, doi: 10.1007/978-981-13-7166-0_56.

[4] A. L. Karn, R. K. Karna, B. R. Kondamudi, G. Bagale, D. A. Pustokhin, I. V. Pustokhina, and S. Sengan, “Customer centric hybrid recommendation system for E-Commerce applications by integrating hybrid sentiment analysis,” *Electronic Commerce Research*, vol. 23, no. 1, pp. 279-314, 2023, doi: 10.1007/s10660-022-09630-z.

[5] P. K. Jain, R. Pamula, and G. Srivastava, “A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews,” *Computer science review*, vol. 41, pp. 100413, 2021, doi: 10.1016/j.cosrev.2021.100413.

[6] N. Punetha, and G. Jain, “Aspect and orientation-based sentiment analysis of customer feedback using mathematical optimization models,” *Knowledge and Information Systems*, vol. 65, no. 6, pp. 2731-2760, 2023, doi: 10.1007/s10115-023-01848-z

[7] A. Dadhich, and B. Thankachan, “Sentiment analysis of amazon product reviews using hybrid rule-based approach,” In *Smart Systems: Innovations in Computing: Proceedings of SSIC 2021*, pp. 173-193, 2022. Springer Singapore, doi: 10.1007/978-981-16-2877-1_17.

[8] H. Zhao, Z. Liu, X. Yao, and Q. Yang, “A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach,” *Information Processing & Management*, vol. 58, no. 5, 102656, 2021, doi: 10.1016/j.ipm.2021.102656.

[9] P. K. Jain, V. Saravanan, and R. Pamula, “A hybrid CNN-LSTM: A deep learning approach for consumer sentiment analysis using qualitative user-generated contents,” *Transactions on Asian and Low-Resource Language Information Processing*, vol. 20, no. 5, pp. 1-15, 2021, doi: 10.1145/3457206.

[10] S. Kumar, M. Yadava, and P. P. Roy, “Fusion of EEG response and sentiment analysis of products review to predict customer satisfaction,” *Information fusion*, vol. 52, pp. 41-52, 2019, doi: 10.1016/j.inffus.2018.11.001.

[11] G. Kaur, and A. Sharma, “A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis,” *Journal of big data*, vol. 10, no. 1, pp. 5, 2023, doi: 10.1186/s40537-022-00680-6.

[12] P. Hajek, L. Hikkerova, and J. M. Sahut, “Fake review detection in e-Commerce platforms using aspect-based sentiment analysis,” *Journal of Business Research*, vol. 167, pp. 114143, 2023, doi: 10.1016/j.jbusres.2023.114143.

[13] M. Zhang, L. Sun, G. A. Wang, Y. Li, and S. He, “Using neutral sentiment reviews to improve customer requirement identification and product design strategies,” *International Journal of Production Economics*, vol. 254, pp. 108641, 2022, doi: 10.1016/j.ijpe.2022.108641.

[14] M. Nilashi, S. Samad, B. Minaei-Bidgoli, F. Ghabban, and E. Supriyanto, “Online reviews analysis for customer segmentation through dimensionality reduction and deep learning techniques,” *Arabian Journal for Science and Engineering*, vol. 46, no. 9, pp. 8697-8709, 2021, doi: 10.1007/s13369-021-05638-z.

[15] T. Diwan, J.V. Tembhurne, “Sentiment analysis: a convolutional neural networks perspective,” *Multimedia Tools Appl*, vol. 81, no. 30, pp. 44405–44429, 2022, doi: 10.1007/s11042-021-11759-2.

[16] D. Dangi, A. Bhagat, D.K. Dixit, “Sentiment analysis on social media using genetic algorithm with cnn,” *CMC-Comput Mater Cont*, vol. 70, no. 3, pp. 5399–5419, 2022, doi: 10.32604/cmc.2022.020431.

[17] M. Kamyab, G. Liu, A. Rasool, M. Adjeisah, “Acr-sa: attention-based deep model through two-channel cnn and bi-rnn for sentiment analysis,” *Peer J Comput Sci*, vol. 8, pp. 1–12, 2022, doi: 10.7717/peerj-cs.877.

[18] F. B. Silva, R. D. O. Werneck, S. Goldenstein, S. Tabbone, R. D. S. Torres, “Graph-based bag-of-words for classification,” *Patt Recogn*, vol. 74, pp. 266–285, 2018, doi: 10.1016/j.patcog.2017.09.018.

[19] Y. Shen, H. Guo, “New breakthroughs and innovation modes in english education in post-pandemic era,” *Front Psychol*, vol. 13, pp. 839440–839440, 2022, doi: 10.3389/fpsyg.2022.839440.

[20] V. Mittal, D. Gangodkar, B. Pant, “Deep graph-long short-term memory: a deep learning-based approach for text classification,” *Wirel Personal Commun*, vol. 119, no. 3, pp. 2287–2301, 2021, doi: 10.1007/s11277-021-08331-4.

[21] L. Han, W. Pan, H. Zhang, “Microblog rumors detection based on bert-gru,” *In: artificial intelligence in China*, pp. 450–457, 2021, doi: 10.1007/978-981-15-8599-9_52.

[22] M. Schuster, & K. K. Paliwal, “Bidirectional recurrent neural networks,” *IEEE Trans Signal Process*, vol. 45, no. 11, pp. 2673–2681, 1997, doi: 10.1109/78.650093.

[23] W. Li, W. Shao, S. Ji, E. Cambria, “Bieru: bidirectional emotional recurrent unit for conversational sentiment analysis,” *Neurocomputing*, vol. 467, pp. 73–82, 2022, doi: 10.1016/j.neucom.2021.09.057.

[24] X. Jia, L. Wang, “Attention enhanced capsule network for text classification by encoding syntactic dependency trees with graph convolutional neural network,” *Peer J Comput Sci*, vol. 7, pp. 2466–2480, 2022, doi: 10.7287/peerj-cs.831v0.1/reviews/2.

[25] “TripAdvisor Hotel Reviews” 2013, [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/trip-advisor-hotel-reviews, doi: 10.34276/1822-009-003-033.

BIOGRAPHIES OF AUTHORS

Anilsagar T. earned his Bachelor of Engineering (B.E.) in Computer Science and Engineering from Visveswaraiah Technological University, Belagavi, Karnataka, in 2013, where he laid a solid foundation in core concepts of computer science. Building upon this, he pursued and successfully completed his Master of Technology (M.Tech.) in Computer Science and Engineering from the same university in 2015, further deepening his knowledge and expertise in the field. Currently, Anilsagar is engaged in the pursuit of a Ph.D. in Computer Science and Engineering at B S Abdur Rahman Crescent Institute of Science and Technology, Vandalur, Chennai, where he continues to explore novel avenues of research and innovation. Anilsagar's research interests span a wide range of topics, including conversational AI, sentiment analysis, web app development, and cloud services. He is particularly fascinated by the intersection of these areas and the potential they hold for revolutionizing various aspects of technology and human interaction. He can be contacted at email: anilsagar123t@outlook.com and aniltsagar@gmail.com.

Syed Abdul Syed S. received his B. Tech in Computer Science and Engineering in 2004 from University of Madras, M. Tech CSE in 2009 from Dr. M G R Educational & Research Institute, Chennai and Ph.D. IT in 2021 from AMET University, Chennai. His primary research work is routing protocol in MANET. Currently working as Associate Professor and DCOE in B S Abdur Rahman Crescent Institute of Science & Technology, Chennai, India. Dr. S Syed Abdul Syed has published his research articles in many reputed international journals out of which 2 papers are in unpaid Scopus indexed journals, and also guided many B.Tech. and M.Tech. students for their academic projects and publications. He can be contacted at email: syedabdulsyed@crescent.education.