# Amazon Product Review-Based Product Recommendation Using Optimized Bert Approach

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***Abstract*—As Amazon e-commerce expands rapidly, a significant number of consumers are posting reviews of products online. The business-to-consumer relationship, as reflected in product reviews, is essential for understanding consumers' sentiments about services and products. Education on online shopping has led to an increase in online consumer reviews, resulting in a more intricate process of product selection. In the past, sentiment analysis (SA) frequently failed to recognize the emotions conveyed in the posts on the product review. This paper offers a Particle Swarm Optimization with a Bidirectional Encoder Representation by the Transformers (PSO-BERT) to address the above issues. The information gathered in this proposed method will include customer reviews on different products based on the Amazon data. Prior to calculating, the acquired data were filtered with the SentiBagofWordNet (SBWNet) algorithm to eliminate irrelevant text content (reviews) and keep only the required data. Following that, the Term Frequency Word2vector (TFW2v) technique is used to determine the relationship between words in reviews. In this paper, the Random Gradient Emoji Weight Rate (RGEWR) method is proposed for identifying text-weighted emojis in the Amazon products dataset. The proposed PSO-BERT method is expected to be beneficial for product ranking, leveraging a bio-inspired, optimized BERT approach. The findings indicate that the suggested PSO-BERT demonstrates the best training and testing precision on a dataset gathered on Amazon.**

***Index Terms*—Emoji weigh identification, bio inspired, product recommendation, ranking, sentiment analysis, reviews.**

## I. INTRODUCTION

E-commerce growth on Amazon has enabled various consumers to share their subjective opinions on products over the internet. This is because the information that consumers receive through online review systems on contemporary e-commerce platforms influences their decision on whether to make an online purchase or not. The way online reviews are measured is a factor that should be considered, as it enables consumers to obtain considerable information from various reviews and make informed decisions regarding products and services based on essential aspects [1]. A numerical evaluation of the customer's total experience can be used to provide a product review; a textual explanation frequently accompanies this rating. This data has resulted from a wealth of marketing literature on customer reviews [2].

These days, researchers and industry specialists examine e-commerce customer reviews, which are the focus of numerous sentiment analysis studies. Instead of using emotion-based analysis, customer reviews are examined here to gather more detailed opinions about the product [3]. Since accurately identifying customer needs is still difficult in the global marketplace, businesses are attempting to do so by aiming for customer happiness [4]. There are several criteria that customers will use when assessing products and services. Rating can be achieved through ads, reviews, and specifications. Customer reviews are one of the most significant drivers of sales for a product or service. Manually assessing reviews to analyze business models and make judgments is difficult [5]. Emotions expressed in online comments, particularly emoticons, are typically difficult for previous SA to discern.

Recently, systems have produced petabytes of content (e.g., reviews, ratings) that require more elaborate methods to be leveraged for better recommendations. To address the problem, a novel PSO-BERT scheme was used. With such system architectures in place, the combination of PSO and BERT for improving the intelligent product recommendation systems holds the potential to be highly efficient. As for Amazon product recommendation systems, our proposed PSO-BERT can help analyze customer reviews better. PSO-BERT helps extract relevant features from reviews, such as polarization, discussion topics, and user preferences. PSO-BERT transforms reviews into meaningful vector representations, enabling more effective interpretation of overall user preferences and informed product recommendations.

PSO is a population-based metaheuristic inspired by the movement of a flock of birds or a school of fish. In PSO, the set of solution searches was designed as particles and flew through the solution space with the guidance of swinging the current best swarm. Every particle updates its position according to its own experience and the experience of other nearby particles until an optimal or near-optimal solution is arrived at. BERT is a transformer-based language model that enables deep, bidirectional learning from text and has had a significant impact on NLP. Unlike other models that approach text from left to right, BERT also adopts a right-to-left approach to establish a broader perspective on features within the text. This makes BERT well-suited for tasks such as text classification, sentiment analysis, and language understanding. This technique allows users to produce more accurate, relevant, and personalized recommendations compared to other methods, improving usability and increasing customer satisfaction.

1.1 Contribution of Paper

- Customer reviews for various products make up the data gathered from the Amazon dataset in this suggested method.
- The obtained dataset is pre-processed using the SBWNet technique to eliminate unnecessary language (review) and preserve only the most important information before to calculation.
- The TF-IDF (TF2v) approach is employed to locate the relationship between the words in the review.
- The Amazon product dataset's emoji with text weight were analysed using the RGEWR approach.
- On the collected Amazon dataset, PSO-BERT achieves the highest improvements in training and testing accuracy.
- Compared to other methods, this strategy enables users to generate recommendations that are more precise, pertinent, and customized, enhancing usability and raising customer satisfaction.

## II. LITERATURE SURVEY

The author [6] presented the position that, the chief object of NLP is SA i.e. getting an attitude, idea, opinion or a judgment on a certain topic. In order to realize this goal, long-short-term memory convolutional neural network (CNN-LSTM) method was applied. In the proposed approach, the processing energy and the memory bandwidth are greatly decreased. The Elman Neural Network (LSIBA-ENN) method is adopted to entangle this problem using Local search enhanced Bat Algorithm. As with e-commerce websites, it was utilized to get customer reviews of the goods for which information is gathered. In order to improve the search results, the parameters had to be adjusted. To transition from exploration to exploitation, a better control method is needed [7].

Researchers from a variety of organizations, including academia, the government, and the corporate sector, were drawn to the author's discussion of SA in online reviews [8]. The Deep Learning (DL) methodology hybrid CNN-LSTM approach was recently presented to translate texts into numeric value vectors, with short vector distances between comparable phrases. CNN-LSTM is susceptible to overfitting because of its intricate design and numerous parameters, particularly in situations where training data is scarce. A Recurrent Neural Network with LSTM (RNN-LSTM) approach was used to fix the problem. With the help of SA of text reviews and product ratings from Amazon's dataset was created. when the loss function's gradients with regard to the RNN-LSTM's parameters either get extremely tiny or very large over time [9].

The author cites that the use of DL, combined with NLP and conformal prediction, yields sentiment estimates that are predictive and effective after several years, based on 12 sets of Amazon product evaluations [10]. This is evidenced by the similar outcomes of in- and cross-category predictions, which suggest a high level of generalizability among product evaluation entities. Nevertheless, they may not be able to determine which part of the review they utilized, as this method does not have clearly defined confidence limits for predictions generated in this way. To solve the problem, Group Long Short-Term Memory Networks (GLRNNs) were used. Consequently, this makes the network incapable of detecting long-term dependencies of the data [11].

The author [12] used BERT and its variants based on various word embedding algorithms for basic data augmentation. It was employed to analyses the text's feelings. It might, however, find it difficult to completely understand the context of some reviews. The author suggested an improved LSTM approach to address the problem [13]. When interpreting such data, it was utilised to analyses proper data collection, preprocessing, and classification. Accurately detecting the polarity of customer evaluations is a fascinating and continuous problem because there are still difficulties in handling texts of this scale.

As the author [14] stated, some academics are also concerned with reviewing customer reviews, classifying them into a set of attitudes using text classification methods. To realize the aim, a CNN approach was employed. It is utilized to categorize the views of text reviews as negative or positive. A solution to the problem was offered in the form of a Bidirectional Gated Recurrent Unit (Bi-GRU) approach. It is used to predict the rating of reviews and polarity based on the review text. Nevertheless, most internet review websites do not typically display user-rated star ratings. Due to this reason, one individual does not have the capacity to rate all products [15].

Online reviews are becoming more and more significant when making decisions, according to the author [16]. Before making a purchase, consumers frequently consult internet evaluations to get their thoughts. A unique framework for measuring online review ratings utilizing ML models was offered to achieve the goal. However, anyone wishing to draw a judgement fast finds it difficult due to the vast volume of internet review data and its unstructured form. A DL technique was used to fix the problem. However, user-provided star ratings typically do not correspond with the review's text format. The deployed approach continued to have this issue in spite of numerous attempts to fix it [17].

Because reviews have a significant impact on consumers, spammers utilize phone reviews to promote their businesses and products and denigrate rivals, according to the author [18]. To fix the problem, a hybrid LSTM-CNN approach was used. Biases in user reviews may be reflected in DL models, which may then pick up and magnify these biases to produce unfair or distorted sentiment predictions. An approach known as Multiscale Semantic and Visual Analyses (MSVA) was used to fix the problem. Several features of review documents were subjected to semantic analysis using word-aware and scale-aware attention methods. It takes a lot of resources to acquire and label big datasets of Amazon reviews, and sometimes the labelled data is insufficient to train very complicated models [19].

The author [20] addressed the application of sentiment-based methods in recommender systems to overcome the sparsity issue in traditional recommender systems' data. A hybrid recommendation system (SA + collaborative filtering). It may not be able to deal with such noise without proper preprocessing; therefore, the pipeline may become more complex. A more effective LSTM method was also employed to address the problem. By providing summarized statistics, the author aims to enable organizations to gain a deeper understanding of their customers' behavior and purchasing decisions. This is because an LSTM model might fail to understand the application of domain-specific jargon in a specific review unless it is trained on a substantial number of such reviews [21].

To the author, a single score based on all the evaluations will be used to derive a sentiment score that will help consumers and sellers make a better decision [22]. The desired objective was met using a hybrid LSTM encoder-decoder model. Amazon user feedback and any other user-generated material may be noisy, with errors in typing, grammar, the use of emoticons, and abbreviations. A Bi-LSTM - CNN technique was employed to address the issue. Besides the automatic classification feature learning, it was also used in recording contextual and semantic information required to identify the field of sentiment polarities. Amazon reviews can vary significantly in terms of tone, style, and structure, and, depending on the type of product, these differences may not be accurately captured by DL models [23].

An intelligent approach to identify attitudes from consumer evaluations under particular product attributes posted on online shopping sites is highly desired, according to the author [24]. A fuzzy logic approach using an LSTM was used to achieve the goal. It is employed to categories customer review sentences using four distinct labels: negative, positive, very positive, and severely negative. Nonetheless, customers still struggle to comprehend aspect-based views expressed by other customers, and the current model's accuracy remains unsatisfactory. A DL Recommendation Cross-Grained Sentiments (DRCGS) technique was used to fix the problem. The rating-based matrix factorization model was utilised to map the latent factor to the retrieved feature vector. However, the DRCGS is either coarse- or fine-grained, but not both, which makes it unclear how accurate and thorough it is in terms of user preference [25].

Table 1. Different Techniques for Sentimental Analysis on Amazon Product reviews

| Author/Year | Used Methodology | Accuracy | Limitations |
|---|---|---|---|
| Arif, M et al., (2024) | RepTree | 94.03% | It frequently suffers from a class imbalance, with fewer impartial ratings and a preponderance of either extremely good or negative evaluations. |
| Gang Chen et al., (2023) | DL methods | 92.6% | Minority class prediction may become more difficult as a result of this imbalance, which can distort DL models. |
| Anisa Falasari et al., (2022) | Naïve Bayes (NB) | 82% | However, its accuracy is low due to its high sensitivity and excessive feature set. |
| Nassera Habbat et al., (2023) | XLNet | 89.6% | Compared to simpler models, this results in a more costly and time-consuming operation. |
| Muhammet Sinan Başarslan et al., (2021) | BERT | 90% | Reviews with complicated language patterns, slang, or irony, for example, may cause the machine to incorrectly categories the sentiment. |

Table 1 describes the reviews of various methods for SA on Amazon products. However, the previous methods had some limitations for SA classification.

## III. PROPOSED WORK

This section provides an overview of the proposed PSO-BERT, including details on the dataset preparation, identifying the connection, emoji with text review weight analysis, and ranking the product steps. Figure 1 presents the complete process of the proposed model. The PSO-BERT approach has four stages. The first step is preprocessing to eliminate inconsistent text using the SBWNet technique.

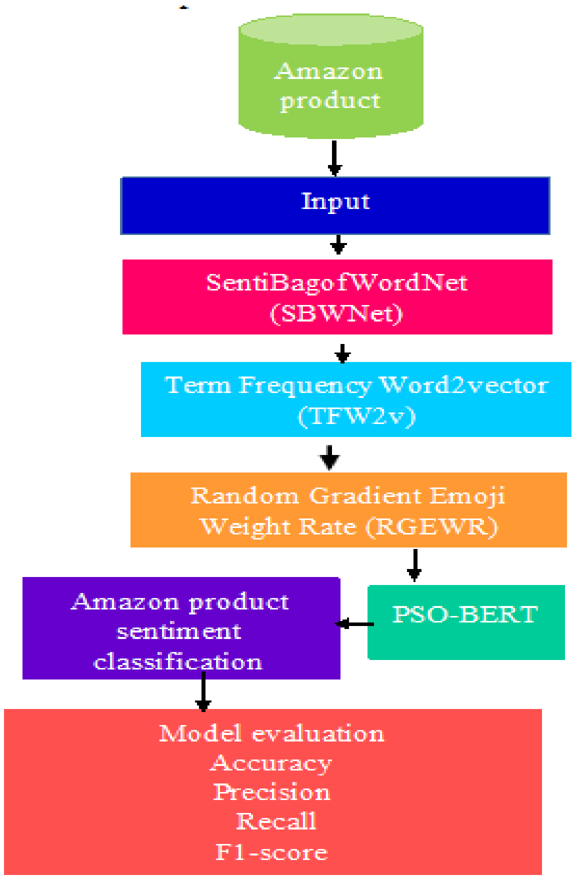


Figure 1: Block diagram for product recommendation

The extracted data, along with the necessary reviews, are fed into the TFW2v technique in the second step. This process analyzes the text connection in the product review. The third step involves examining the Emoji with text weight in the Amazon product dataset. Finally, the product review weights obtained in the third step are ranked according to the users' positive and negative emotional criteria using PSO-BERT.

3.1 SentiBagofWordNet (SBWNet) method

The SBWNet is a sentiment analysis that uses the BoW technique together with the WordNet which filters out irrelevant reviews allowing only important information in the text. The rest of this paper explains how the method could be conceptualized and possibly written in equation form. In equation 1 we split the text in individual tokens,

$$T = \{u_1, u_2, \dots, u_n\} \quad (1)$$

Let, $T$ as token, and $u_x$ as the each word in review. In equation 2 we compute the BoW,

$$BoW = \{(u_1, f_1), (u_2, f_2), \dots, (u_n, f_n)\} \quad (2)$$

Let, $f_x$ as the frequency of $u_x$. The BoW model represents text by counting the occurrence of each word without considering grammar or word order. In equation 3 we classify the sentiment using WordNet,

$$S(u_x) = \begin{cases} +1 \; if \; u_x \; is \; P \\ -1 \; if \; u_x \; is \; N \\ 0 \; if \; u_x \; is \; NU \end{cases} \quad (3)$$

Let, $S$ as Sentiment, $P$ as positive, $N$ as negative, a $NU$ as neutral. In this equation we can enhance the sentiment analysis. For each word $u_x$ WordNet helps find its S. By following we analyze the S score through the review level $R$,

$$R = \sum_{x=1}^{n} S(u_x) \times f_x \quad (4)$$

Once all words of a given review have been classified for sentiment, then add all individual word sentiment scores to come up with the overall sentiment score of the entire review. In equation 5 we filter the insignificant reviews based on Threshold $D$,

$$Z = \begin{cases} T \; if \; Z \geq D \\ F \; if \; Z < D \end{cases} \quad (5)$$

Let, $Z$ as Retain Review, $T$ as True, and $F$ as False. This equation 5 identifies the minimum sentiment score necessary to sustain a review in the system. Hear, squealer below this sentiment lower number scores, the reviews are deemed insignificant and thus rejected. In the following equation 6 we perform the final representation of SBWNet $G$,

$$G = \{(u_1, S(u_1) \times f_1), \dots, (u_n, S(u_n) \times f_n)\} \quad (6)$$

After filtering, a final Bag of Words is constructed for each retained review. This is referred to as the $G$, which contains only the necessary sentiment-laden words. This approach is helpful in discarding any review that has minimal sentiment contribution thus minimizing the number of reviews required in building up a fast and accurate sentiment analysis model.

3.2 Term Frequency Word2Vector (TFW2V) method

After successful pre-processing on Amazon dataset, we check the word co-occurrence through TFW2V method. TF provides the fraction of terms in specific reviews. Despite the model, W2V is capable of capturing the semantic relations between words in the whole dataset. In equation 7 we perform the Term Frequency $H$,

$$H(q, p) = G\left(\frac{f_{q,p}}{n_p}\right) \quad (7)$$

Let, $q$ as frequency of word, $p$ as the document a single review of the preprocessed dataset, $f_{q,p}$ as the raw frequency, $n_p$ as the total number of terms in document. It is used to identify the relevance of a word with the review (document) and this is due to the frequency of the specific word. In perspective of the context of the Amazon dataset, high value of H for a word such as ''great'', ''quality'' could be considered as positive whereas ''bad'', ''poor'' as being negative. W2V is a neural network model that learns about words embeddings. These embeddings preserve semantic similarity of the words, and words that are semantically related, or which occur in similar context, are therefore close in the vector space. In equation 8 we perform the word embedding,

$$Y(\theta) = -\sum_{w=1}^{W}\sum_{-q\le y\le q, y\ne 0} \log S(u_{w+y}|u_w;\theta) \quad (8)$$

Let, $W$ as the total number of words in corpus, $q$ as the context window size, $u_w$ as the current word, $u_{w+y}$ as the context word surrounding$u_w$, and $\theta$ for the parameters of the model. The equation 8 looks for relations by placing the words in high-dimensional space and operation related words are gathered closer to each other in this model either in terms of context or meaning.

3.3 Random Gradient Emoji Weight Rate (RGEWR)

In this case, we analysed text-weighted emojis in the Amazon product dataset using the RGEWR method, which assigns an emoji value to each emoji in the attached text.

$$\mathrm{W_v} = 1 - \frac{\sum \mathfrak{D}(\mathcal{E}_{\mathrm{wi}},\mathrm{T})\mathrm{X}(\mathrm{Tw})}{\mathrm{T_{words}}} \quad (9)$$

From equation 9 estimate the emoji and text weight rate in the review. Here, Tw text weight $\mathfrak{D}(\mathcal{E}_{\mathrm{wi}},\mathrm{T})$ lies the distance among emoji & text and $\mathrm{T_{words}}$ lies the total words.

3.4 Product recommendation using PSO-BERT approach

This subsection employs the PSO-BERT approach to categorize SA by ranking products and recommending them to the customer. The BERT approach interprets language specifics and tries to categorize the reviews according to their utility to customers. The dataset of Amazon products in customer reviews is most suitable for use with the BERT model to identify the main features that can aid in rating review effectiveness.

Ranking of products is determined by utilizing the PSO approach. The flocking behavior of birds inspires the approach and will be described in a more formal, dictionary-like manner with more appropriate labels. The potential solutions are referred to as particles and are part of the population. The optimum resolution of each particle is known as Lbest, and the optimum obtained for the whole population is known as Gbest. The two components of the PSO are the modification of the velocity and position. The first step involves changing the velocity of each particle in its Lbest and Gbest directions. In the second phase, particles undergo amelioration. The new position is determined based on the previous position and the new speed. A particle is depicted as a vector in the D-dimensional space.

Let us assuming, list of particles denoted as$\mathcal{P}_\mathrm{i} = \{\wp_1, \wp_2 \dots \wp_{\mathrm{nD}}\}$, velocity implies $\mathcal{P}_{\mathcal{V}\mathrm{i}} = \{\wp_{\mathcal{V}1}, \wp_{\mathcal{V}2} \dots \wp_{\mathcal{V}\mathrm{i}}\}$ and previous location expressed as$\mathfrak{P}_{\mathcal{P}\mathrm{i}} = \{\mathfrak{p}_1, \mathfrak{p}_2, \dots \mathfrak{p}_1\}$.

$$\mathcal{P}_{\mathcal{V}\mathrm{i}} = \mathcal{w}\wp_{\mathcal{V}\mathrm{i}} + \gamma1\rho(\mathfrak{P}_{\mathcal{P}\mathrm{i}} - \wp_\mathrm{i}) + \gamma2\rho(\mathfrak{P}_{\mathcal{P}\mathrm{i}} - \wp_\mathrm{i})$$

The above equation is used find the velocity of the particle. Here, γ1, γ2 lies the important parameters, ρ denotes the random number and $\mathcal{w}$ indicates the weight values.

$$\mathfrak{P}_{\mathcal{P}\mathrm{i}} = \mathcal{P}_\mathrm{i} + \mathcal{P}_{\mathcal{V}\mathrm{i}}$$

The above equation is used to estimate the position of particles.

$$\mathrm{U_p} = \begin{cases} \mathcal{P}_\mathrm{i}(\mu,\sigma), & \rho < 0.5 \\ \mathfrak{P}_{\mathcal{P}\mathrm{i}}, & \text{otherwise} \end{cases}$$

The above equation is used find the particle movement based on fitness function for ranking the products. μ Denotes the mean values between Gbest and Lbest. σ lies the standard deviation.

Algorithm steps

Input: Emoji with text weight

Output: Ranking the products and recommendation

Start procedure

Import Emoji with text weight values

Read the weight values

Computing the input layer $\mathrm{I_{Layer}}$

$$\mathrm{I_{Layer}} = \sum \mathcal{w}\mathrm{X}\mathrm{W_v} + \mathcal{B}$$

Computing the hidden layer $H_{Layer}$

$$H_{Layer} = \sum \mathcal{w} X\, I_{Layer}(U_p) + \mathcal{B}$$

Computing the output layer $O_{Layer}$

$$H_{Layer} = A_n \sum \mathcal{w} X\, H_{Layer}(U_p) + \mathcal{B}$$

Return ranking the products with recommendation
Stop procedure

The above algorithm steps efficiently identifies the amazon product SA. Here, $\mathcal{B}$ denotes the bias values and $A_n$ denotes the activation function.

## IV. RESULT AND DISCUSSION

This division describes the experimental assessment of the proposed PSO-BERT methodology. The proposed method is assessed using an Amazon dataset containing various product reviews from multiple brands.

Table 2: Simulation parameters settings

| Constraints | Values |
|---|---|
| Dataset name | Amazon product review |
| Tool | Anaconda/ Jupyter |
| Language | Python |
| Total records | 28333 |
| Testing records | 30% |
| Training records | 70% |

Table 2 defines the simulation parameters settings for sentiment analysis using PSO-BERT method. This proposed methodology evaluate the metrics are accuracy, precision, recall, and F1-score. The comparison methods are Deep Belief Generative Neural Network (DBGN2), XLNet Nassera Habbat et al., (2023) and Bi-LSTM-CNN Bhuvaneshwari et al. (2022).

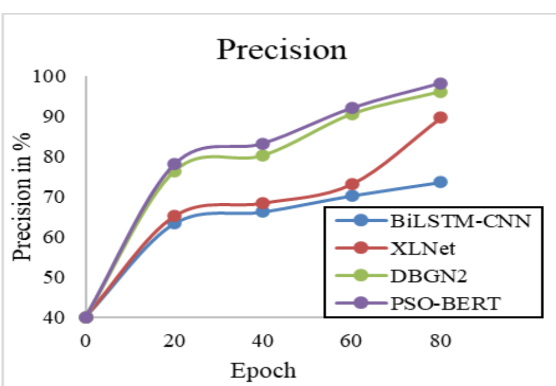


Figure 2: Experimental result for precision performance

Figure 2 describes the comparison of precision performance for sentiment analysis. The proposed method attains the 78.01%, 83.22%, 92.06% and 98.24% for 20, 40, 60, and 80 iterations, correspondingly.

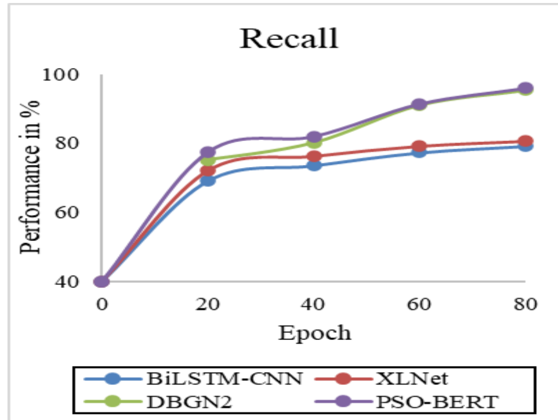


Figure 3: Experimental result for recall performance

Figure 3 describes the comparison of recall performance for sentiment analysis. The proposed method attains the 77.01%, 82.01%, 91.46% and 96.01% for 20, 40, 60, and 80 iterations, correspondingly.

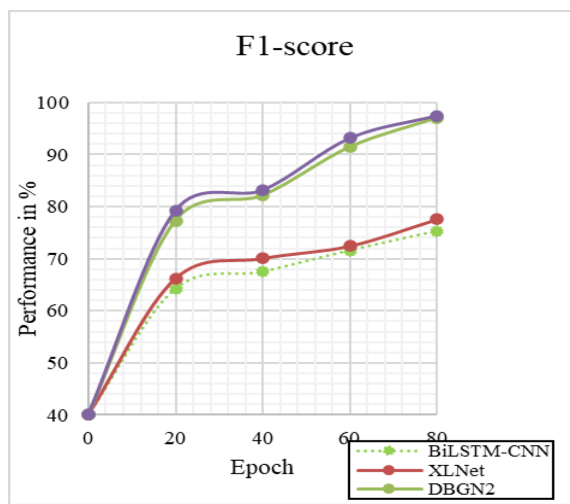


Figure 4: Experimental result for F1-score performance

Figure 4 describes the comparison of F1-score performance for amazon product sentiment analysis. The proposed method attains the 79.24%, 83.16%, 93.16% and 97.48% for 20, 40, 60, and 80 iterations, correspondingly.

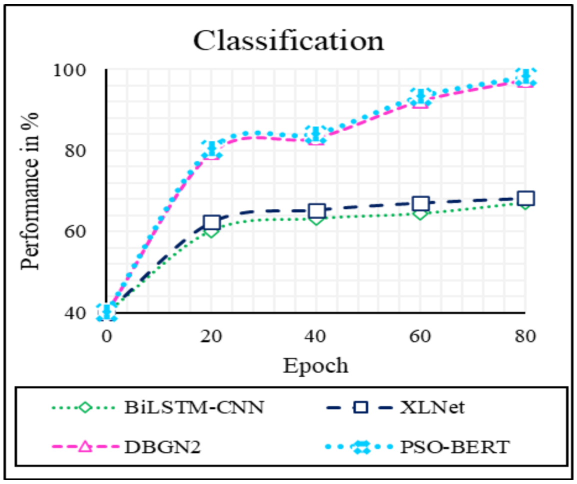


Figure 5: Experimental result for classification performance

Figure 4 describes the comparison of classification performance for amazon product sentiment analysis and ranking the products. The proposed method attains the 80.44%, 84.06%, 93.22% and 98.05% for 20, 40, 60, and 80 iterations, correspondingly.

## V. CONCLUSION

The PSO-BERT technique is introduced in this paper to rank recommended products. The data collected will be preprocessed before the computation to eliminate irrelevant texts (reviews) and retain the required information through the SBWNet technology. We apply the TFW2v algorithm to the reviews to determine links among words. The paper outlines the method of Random Gradient Emoji Weight Rate (RGEWR) for text-weighted emojis analysis on the Amazon products dataset. The suggested PSO-BERT method is effective in ranking products. The accuracy of the proposed simulation was 95.05%, compared to other systems, including DBGN2, XLNet, and BiLSTM-CNN.

## REFERENCES

[1] Z. Liu, H. Liao, M. Li, Q. Yang and F. Meng, "A Deep Learning-Based Sentiment Analysis Approach for Online Product Ranking with Probabilistic Linguistic Term Sets," in IEEE Transactions on Engineering Management, vol. 71, pp. 6677-6694, 2024, doi: 10.1109/TEM.2023.3271597.

[2] Alantari, H. J., Currim, I. S., Deng, Y., & Singh, S. (2022). An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews. International Journal of Research in Marketing, 39(1), 1-19. https://doi.org/10.1016/j.ijresmar.2021.10.011

[3] Deniz, E., Erbay, H., & Coşar, M. (2022). Multi-Label Classification of E-Commerce Customer Reviews via Machine Learning. Axioms, 11(9), 436. https://doi.org/10.3390/axioms11090436

[4] Mehbodniya, A., Rao, M. V., David, L. G., Joe Nigel, K. G., & Vennam, P. (2022). Online product sentiment analysis using random evolutionary whale optimization algorithm and deep belief network. Pattern Recognition Letters, 159, 1-8. https://doi.org/10.1016/j.patrec.2022.04.024

[5] Singh, U., Saraswat, A., Azad, H. K., Abhishek, K., & Shitharth, S. (2022). Towards improving e-commerce customer review analysis for sentiment detection. Scientific Reports, 12(1), 1-15. https://doi.org/10.1038/s41598-022-26432-3

[6] Onan, A. (2021). Sentiment analysis on product reviews based on weighted word embeddings and deep neural networks. Concurrency and Computation: Practice and Experience, 33(23), e5909. https://doi.org/10.1002/cpe.5909

[7] Zhao, H., Liu, Z., Yao, X., & Yang, Q. (2021). A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach. Information Processing & Management, 58(5), 102656. https://doi.org/10.1016/j.ipm.2021.102656

[8] Praphula Kumar Jain, Vijayalakshmi Saravanan, and Rajendra Pamula. 2021. A Hybrid CNN-LSTM: A Deep Learning Approach for Consumer Sentiment Analysis Using Qualitative User-Generated Contents. ACM Trans. Asian Low-Resour. Lang. Inf. Process. 20, 5, Article 84 (September 2021), 15 pages. https://doi.org/10.1145/3457206

[9] J. C. Gope, T. Tabassum, M. M. Mabrur, K. Yu and M. Arifuzzaman, "Sentiment Analysis of Amazon Product Reviews Using Machine Learning and Deep Learning Models," 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE),

Gazipur, Bangladesh, 2022, pp. 1-6, doi: 10.1109/ICAEEE54957.2022.9836420.

[10] Norinder, U., & Norinder, P. (2022). Predicting Amazon customer reviews with deep confidence using deep learning and conformal prediction. Journal of Management Analytics, 9(1), 1–16. https://doi.org/10.1080/23270012.2022.2031324

[11] Alharbi, N. M., Alghamdi, N. S., Alkhammash, E. H., & Al Amri, J. F. (2020). Evaluation of Sentiment Analysis via Word Embedding and RNN Variants for Amazon Online Reviews. Mathematical Problems in Engineering, 2021(1), 5536560. https://doi.org/10.1155/2021/5536560

[12] Balakrishnan, V., Shi, Z., Law, C.L. et al. A deep learning approach in predicting products' sentiment ratings: a comparative analysis. J Supercomput 78, 7206–7226 (2022). https://doi.org/10.1007/s11227-021-04169-6

[13] Iqbal, A., Amin, R., Iqbal, J., Alroobaea, R., Binmahfoudh, A., & Hussain, M. (2021). Sentiment Analysis of Consumer Reviews Using Deep Learning. Sustainability, 14(17), 10844. https://doi.org/10.3390/su141710844

[14] Qorich, M., El Ouazzani, R. Text sentiment classification of Amazon reviews using word embeddings and convolutional neural networks. J Supercomput 79, 11029–11054 (2023). https://doi.org/10.1007/s11227-023-05094-6

[15] Ahmed, B.H., Ghabayen, A.S. Review rating prediction framework using deep learning. J Ambient Intell Human Compute 13, 3423–3432 (2022). https://doi.org/10.1007/s12652-020-01807-4

[16] Budhi, G.S., Chiong, R., Pranata, I. et al. Using Machine Learning to Predict the Sentiment of Online Reviews: A New Framework for Comparative Analysis. Arch Computat Methods Eng 28, 2543–2566 (2021). https://doi.org/10.1007/s11831-020-09464-8

[17] Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V., & Nappi, M. (2021). Discrepancy detection between actual user reviews and numeric ratings of Google App store using deep learning. Expert Systems With Applications, 181, 115111. https://doi.org/10.1016/j.eswa.2021.115111

[18] Bathla, G., Singh, P., Singh, R.K. et al. Intelligent fake reviews detection based on aspect extraction and analysis using deep learning. Neural Comput & Applic 34, 20213–20229 (2022). https://doi.org/10.1007/s00521-022-07531-8

[19] Zhan, Z., & Xu, B. (2022). Analyzing review sentiments and product images by parallel deep nets for personalized recommendation. Information Processing & Management, 60(1), 103166. https://doi.org/10.1016/j.ipm.2022.103166

[20] Dang, C. N., N., M., & Prieta, F. D. (2020). An Approach to Integrating Sentiment Analysis into Recommender Systems. Sensors, 21(16), 5666. https://doi.org/10.3390/s21165666

[21] Kaur, G., Sharma, A. A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. J Big Data 10, 5 (2023). https://doi.org/10.1186/s40537-022-00680-6

[22] Jain, S., Roy, P.K. E-commerce review sentiment score prediction considering misspelled words: a deep learning approach. Electron Commer Res 24, 1737–1761 (2024). https://doi.org/10.1007/s10660-022-09582-4

[23] Bhuvaneshwari, P., Rao, A.N., Robinson, Y.H. et al. Sentiment analysis for user reviews using Bi-LSTM self-attention-based CNN model. Multimedia Tools Appl 81, 12405–12419 (2022). https://doi.org/10.1007/s11042-022-12410-4

[24] Sivakumar, M., Uyyala, S.R. Aspect-based sentiment analysis of mobile phone reviews using LSTM and fuzzy logic. Int J Data Sci Anal 12, 355–367 (2021). https://doi.org/10.1007/s41060-021-00277-x

[25] Cai, Y., Ke, W., Cui, E., & Yu, F. (2022). A deep recommendation model of cross-grained sentiments of user reviews and ratings. Information Processing & Management, 59(2), 102842. https://doi.org/10.1016/j.ipm.2021.102842

[26] Arif, M., Hasan, M., Al Shiam, S. A., Ahmed, M. P., Tusher, M. I., Hossan, M. Z., … Imam, T. (2024). Predicting Customer Sentiment in Social Media Interactions: Analyzing Amazon Help Twitter Conversations Using Machine Learning. International Journal of Advanced Science Computing and Engineering, 6(2), 52–56. https://doi.org/10.62527/ijasce.6.2.211

[27] Gang Chen, Lihua Huang, Shuaiyong Xiao, Chenghong Zhang, Huimin Zhao (2023) Attending to Customer Attention: A Novel Deep

Learning Method for Leveraging Multimodal Online Reviews to Enhance Sales Prediction. Information Systems Research 35(2):829-849. https://doi.org/10.1287/isre.2021.0292

[28] Falasari, Anisa, and Much Aziz Muslim. 2022. "Optimize Naïve Bayes Classifier Using Chi Square and Term Frequency Inverse Document Frequency for Amazon Review Sentiment Analysis". Journal of Soft Computing Exploration 3 (1):31-36. https://doi.org/10.52465/joscex.v3i1.68.

[29] N. Habbat, H. Anoun and L. Hassouni, "Combination of GRU and CNN Deep Learning Models for Sentiment Analysis on French Customer Reviews Using XLNet Model," in IEEE Engineering Management Review, vol. 51, no. 1, pp. 41-51, 1 First quarter, march 2023, doi: 10.1109/EMR.2022.3208818.

[30] MS Başarslan and F. Kayaalp, "Sentiment Analysis on Social Media Reviews Datasets with Deep Learning Approach", SAUCIS, vol. 4, p. 1, pp. 35–49, 2021, doi: 10.35377/saucis.04.01.833026.