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Original Article

Revolutionizing E-Commerce: A Deep Learning-Based Sentiment-Driven Recommendation System

Roshy Thomas[1], J. R. Jeba[2]

[1,2]*Department of Computer Applications, Noorul Islam Centre for Higher Education, Kumaracoil, India.*

[1]*Corresponding Author : roshi.thomas.321@outlook.com*

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Abstract *- The proliferation of the internet and the rising trend of online shopping have contributed to significant changes in consumer behavior. With a vast array of options available, consumers often face decision fatigue and information overload, creating challenges in finding the most suitable products. In response, product recommendation systems have emerged as essential tools of e-commerce, providing customized recommendations to individual preferences. This paper suggests a novel Deep Learning (DL) framework for product recommendation systems, leveraging Sentiment Analysis (SA) to enhance recommendation accuracy and relevance. The proposed framework combines SA with Collaborative Filtering (CF) techniques to provide insightful recommendations based on user sentiments and historical interactions. Specifically, a hybrid model of Bidirectional Encoder Representations from Transformers (BERT) and Gated Recurrent Unit (GRU) is employed for sentiment analysis, offering robust sentiment insights from user reviews. Additionally, CF methods, including user-based and item-based approaches, are utilized to find trends and analogies in user-item interactions, further refining the recommendation process. The efficiency of the suggested framework is demonstrated through comprehensive performance evaluations, including accuracy, precision, recall, and F1-score metrics. The outcomes of the experiment indicate that the integrated SA-CF model performs better than existing methods, achieving superior accuracy and precision in product recommendations. The proposed framework offers a powerful solution to improve the user's experience, engagement, and satisfaction in e-commerce infrastructure by delivering personalized and sentiment-aware product recommendations.*

Keywords *- Collaborative filtering, E-commerce, Product recommendation, Sentiment analysis, User preferences.*

1. Introduction

The internet's quick expansion and the increasing popularity of online shopping have completely changed how customers discover, browse, and purchase items. Online buyers now have an almost limitless selection of products from all over the world at their fingertips, making it easier and more convenient than ever to shop. But as consumers search through an abundance of options to locate the products that best suit their needs and preferences, they experience a demanding process that has led to new challenges including decision exhaustion and information overload [1]. There is a greater demand than ever for efficient methods of product recommendation in this age of Internet commerce. Product recommendation systems, which provide users with customized and appropriate product recommendations, are essential in assisting customers in navigating the broad and always changing world of online products. Utilizing a range of data sources, such as browsing history, purchasing activity, demographic data, and product features, these systems provide personalized recommendations that correspond with the individual's distinct interests and preferences [2].

In today's digital marketplace, product recommendation systems are crucial. They work by using algorithms to assess user data and interests and then recommend products that are specific to each user. These technologies are essential for improving user experience, increasing engagement, and eventually increasing sales for companies. Although the idea of product recommendation is not new, it has seen substantial development with the advent of digital technology. Recommendation systems improve user experience and boost conversion rates by relieving customers of the burden of choice and providing carefully chosen options based on their preferences and historical activity.

Companies gain from increased customer involvement, more relevant services, and insightful data on consumer behavior that helps with product development and marketing initiatives. Recommendation systems in e-commerce platforms encompass diverse categories, including product suggestions based on user behavior, similar items, trending products, personalized recommendations, bundle suggestions, cross-selling, and new arrivals or featured items [3]. These categories are divided into various user preferences, enhancing the shopping experience and driving engagement. Figure 1 represents the recommendation system that withholds in e-commerce.

Recommendation systems in e-commerce platforms use content-based and CF strategies to examine user data and provide customized product recommendations. SA, also called opinion mining, is a vital tool in modern product recommendation systems, providing valuable insights into customer sentiments and preferences. In today's competitive markets, understanding consumer emotions is essential for driving engagement and sales. By automatically analyzing textual data like reviews and social media posts, SA identifies user sentiments, allowing businesses to grasp deeper insights into customer perceptions and attitudes toward products. Integrating SA enhances recommendation systems by adding a layer of personalization and relevance, taking into account both the characteristics of the product and the opinions of users.

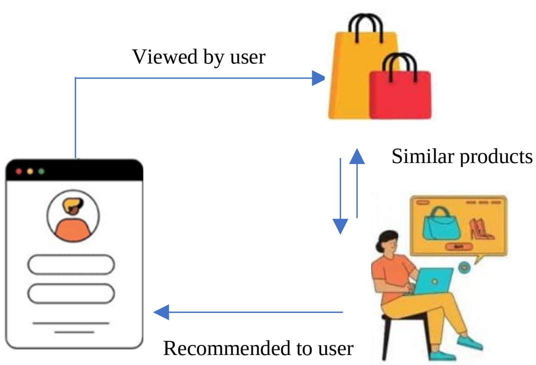


Fig. 1 E-commerce recommendation system

Utilizing Natural Language Processing (NLP) and artificial intelligence, SA identifies emotional complexity, enabling recommendation systems to adjust in real-time to changing consumer sentiments [4]. Traditional recommendation systems, while effective to some extent, often fail to capture the nuanced sentiments expressed by users in reviews and feedback. This oversight limits the ability to deliver personalized and context-aware recommendations. Despite advancements in machine learning and AI, there is a significant gap in leveraging deep learning models to integrate sentiment analysis directly into recommendation systems. Addressing this gap, our research proposes a deep learning-based sentiment-driven recommendation system that enhances the accuracy and relevance of product suggestions by incorporating user sentiment as a core component of the recommendation process. The important objectives of the study are listed below:

- To implement a novel DL-based framework for SA with the help of various data preprocessing techniques.
- To propose a product recommendation system by combining the sentimental analysis model and CF.

The paper is structured as follows: Section two presents a literature review underscoring the necessity for additional research, while Section three outlines the detailed methodology of the proposed model. Section four delves into the discussion based on the model's outcomes, and finally, Section five provides a summary of the overall findings.

2. Literature Review

Latha et al. [5] enhanced e-commerce user satisfaction through Sentiment Analysis (SA) and product recommendations using Modified Convolutional Neural Networks (MCNNs) on Amazon reviews, achieving a mean accuracy of 97.40%. Reliance on a single dataset limits generalizability despite high performance. Vatambeti et al. [6] applied a ConvBiLSTM framework to analyze tweets related to app-based meal delivery businesses. Zomato received the highest positive feedback. The study underscored the importance of Twitter for business insights but noted limitations due to the exclusive focus on this platform. Abubakar et al. [7] used Naive Bayes (NB) and Support Vector Machine (SVM) classifiers for sentiment analysis of product reviews, discovering that SVM outperformed NB in accuracy. Manual annotation of data posed limitations and was time-consuming.

Hasan et al. [8] developed a hybrid movie recommendation system combining cosine similarity and Alternating Least Squares (ALS), achieving high accuracy in predicting user preferences. Serrano-Guerrero et al. [9] utilized fuzzy linguistic models to evaluate hospital opinions, achieving better performance than existing techniques. Interval-valued Pythagorean fuzzy sets and intuitionistic fuzzy sets were employed. The fuzzy term sets used might not adequately reflect complex user attitudes. Kaur & Sharma [10] created a hybrid model for summarizing customer reviews using LSTM networks, achieving high precision, recall, and F1-score across multiple datasets. Dependence on specific datasets limited applicability to other domains. Bhaskaran & Marappan [11] implemented a hybrid e-learning recommender system combining Trust-based SVM (TSVM) and DBSCAN algorithms, showing high accuracy and discovering clusters of various sizes and shapes. Validation on real-world datasets and scalability issues were noted as limitations. Suresh et al. [12] used non-negative matrix factorization and GRU within a BFGS algorithm framework for product recommendations. Effectiveness in predicting long-term product preferences was demonstrated, but further validation in real-world contexts was necessary to confirm generalizability.

Li et al. [13] applied aspect-based SA to restaurant reviews to improve survival prediction accuracy, finding aspect-based sentiment more effective than overall sentiment. Limitations included the availability of data to analyze additional influencing factors. Pavitha et al. [14] used SVM and NB classifiers alongside cosine similarity for movie recommendations, with SVM proving more accurate than NB. The system was constrained by its dataset, limiting its ability to suggest films outside of it. Liu et al. [15] integrated SA and matrix factorization in a recommendation system using LDA and BERT, showing excellent performance compared to traditional algorithms. Dang et al. [16] combined collaborative filtering and SA in a flexible recommendation framework, significantly improving system effectiveness. However, substantial computational resources were required. Naresha and Venkata [17] proposed a Twitter-based SA recommender system using supervised learning, evaluating multiple ML algorithms for sentiment classification. The system demonstrated the workflow of SA in recommendation contexts but focused only on Twitter data. Karthik and Ganapathy [18] employed fuzzy logic and ontology-based techniques for personalized product recommendations, achieving superior accuracy in predicting suitable items. Complexity in development and maintenance and sensitivity to changes in customer behavior was noted.

With the vast array of choices, users often struggle to discern the most pertinent content to meet their needs. Consequently, there is a need for a practical system to assist users in navigating this wealth of information. Traditional methods of recommendation, such as word-of-mouth, have long been relied upon for decision-making, but the rise of social media has transformed the landscape, offering a more interactive and user-driven approach to recommendations. However, the effectiveness of recommendation systems utilizing social media data, which includes reviews, comments, and opinions, relies heavily on sentiment analysis. Yet, obtaining sufficient and accurate data, especially for newer or specialized products, can be challenging, potentially impacting the reliability of recommendations. Therefore, there is a demand for an effective product recommendation system that leverages SA while addressing these limitations.

3. Materials and Methods

The increasing volume and diversity of user-generated data on social media platforms highlight the necessity of an efficient Product Recommendation System capable of sorting through the stream of data and offering precise recommendations based on user preferences. Thus, a DL based framework for product recommendation using SA is proposed in this paper. The whole workflow is depicted in Figure 2.

3.1. Dataset

The data was sourced from Kaggle [25], containing upwards of 30,000 reviews spanning various products, with over 200 individual products represented therein, as given in Figure 3. These reviews and corresponding ratings were contributed by a user base exceeding 20,000 individuals. The dataset encompasses various attributes related to user feedback on products. Each review is distinguished by a unique Identification number (ID). Users rate and review products from different brands across a wide array of categories, including household essentials, books, personal care items, and electrical appliances.

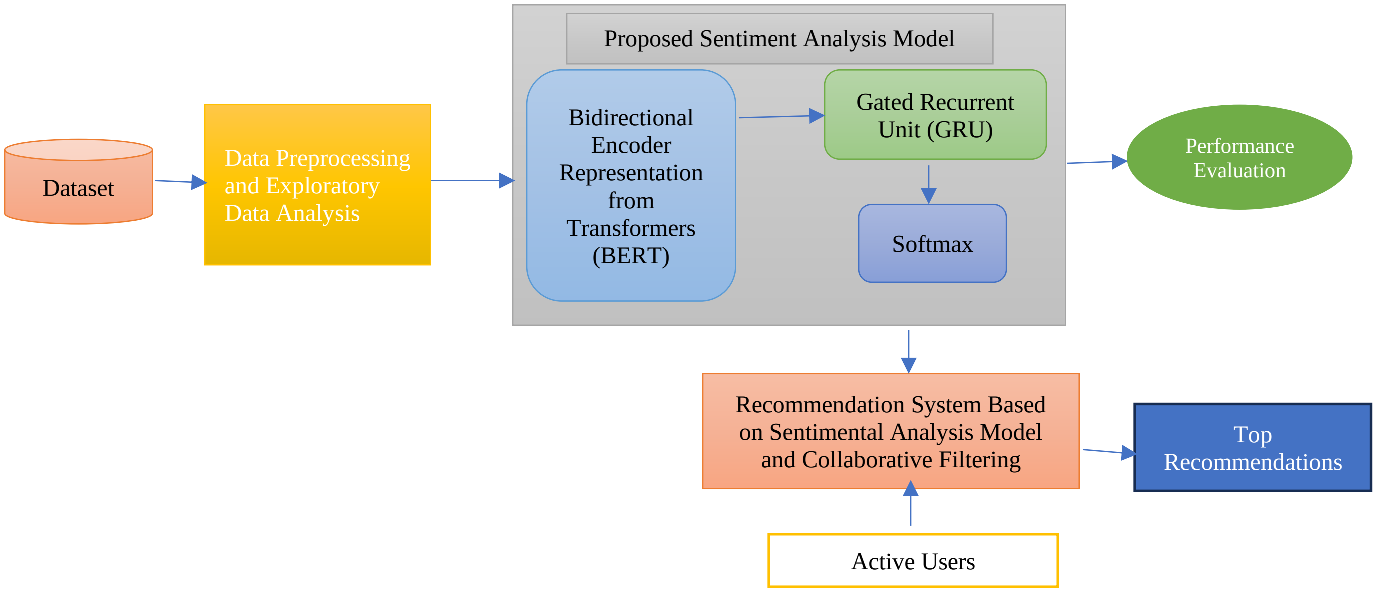


Fig. 2 Block diagram of the suggested model

	name	reviews_rating	reviews_text	reviews_title	reviews_username	user_sentiment
6102	Red (special Edition) (dvdvideo)	5	Enjoyable, my wife loves watching this movie. Fun, some violence, language not over done in swearing. We watch it again and again.	Fun	xyoung	Positive
2539	Mike Dave Need Wedding Dates (dvd + Digital)	5	Funniest movie ever found right away at Best Buy very good deal	Dvd	envygirl	Positive
21576	Nexxus Exxtra Gel Style Creation Sculptor	1	I have been using this product for 20 years and recently went into a store to buy it. I noticed that they had changed the look of the bottle and thought nothing of it. I took it home and used it as I normally would but I noticed that my hair did not stay and it broke half way through the day. This used to be the best gel on the market and now Im not sure what they have done. Also it has a terrible smell like a perfume. I would not recommend buying this product.	Extra Gel	rusty022	Negative
19574	Clorox Disinfecting Bathroom Cleaner	5	I have terrible asthma and allergies and on the occasions that I cannot handle the strong smell of cleaners these wipes work great.	Great for asthma allergies!	yoko76	Positive
12804	Clorox Disinfecting Wipes Value Pack Scented 150 Ct Total	5	Love these wipes especially during this time of year This review was collected as part of a promotion.	CLOROX WIPES	couponingnurse82	Positive

Fig. 3 Dataset samples

	reviews_text	user_sentiment
28208	My family and I love the Disney line movies especially since Cars. This movie is no different in the entertainment area. A must watch for the Kids or the "Kid" in you. Great movie	Positive
3780	This window/door alarm is effective and easy to use. The chime and alarm features are both appropriately loud and will immediately gain one's attention. Installation is easy IF your door is flush with its surrounding framing. If not, you will need to figure out a way to make the alarm and the sensor even with each other. Overall, this is a good, inexpensive alarm. Inexpensive peace of mind	Positive
14296	anything by clorox brand I trust I like the fact that I'm disinfecting my home This review was collected as part of a promotion. clorox a brand I trust	Positive
12231	Love to grab one and wipe off the door knobs throughout the house. This product is quick and easy to use	Positive
5386	Works great and holds all day. I wish it was easier to remove. Mona	Positive

Fig. 4 Data followed by duplicate checking and missing value handling

Additionally, information about the manufacturer's name and the product title is included, along with details like the review date, the user's purchasing status, and their recommendation of the product. The dataset also contains user-specific information such as their city and province of residence. Users provide textual reviews and titles, which are utilized to determine the overall sentiment of each product, classifying it as either positive or negative based on user sentiment.

3.2. Data Processing

Refining raw data to make it suitable for analysis entails several steps within the data preprocessing phase. These steps typically include tasks such as cleaning data to remove duplicates and handle missing values, standardizing text, normalizing words, correcting misspellings, and transforming text to numerical features. This study employs a range of preprocessing techniques to cleanse and standardize the dataset before analysis, ensuring the accuracy and reliability of the results.

3.2.1. Duplicated Data Checking

Duplicated data checking is a crucial procedure primarily focused on identifying and eliminating redundant entries from a dataset. This process involves scrutinizing each data point to detect any instances that exhibit identical or remarkably similar characteristics. Duplicates often arise due to errors in data collection, system malfunctions, or the merging of multiple datasets. By eliminating duplicate entries, data quality is enhanced, ensuring that subsequent analyses are based on accurate and reliable information. Additionally, this step streamlines the dataset, making it more manageable and conducive to efficient analysis.

3.2.2. Handling Missing Values

Handling missing values is a fundamental aspect involving various techniques to address the absence of data in a dataset. Missing values can occur due to a range of reasons, such as human error during data entry, equipment malfunction, or intentional omissions. The primary objective of handling missing values is to mitigate their impact on subsequent analyses and ensure the integrity and reliability of the dataset. Depending on the significance and randomness of these missing values, it may be appropriate to eliminate associated occurrences or variables from the dataset. Once duplicate data checking and handling of missing values are completed, a data frame is constructed for the SA, comprising essential attributes such as "reviews_title," "reviews_text," and "user_sentiment." Additionally, the "reviews_title" and "reviews_text" attributes can be joined to a single attribute to streamline the dataset and prepare it for further analysis. Figure 4 shows the data subsequent to duplicate checking and missing value handling.

3.2.3. Unwanted Text and Unwanted Characters Removal

During text preprocessing, it is crucial to eliminate unwanted text and characters to ensure that the text data is cleaned and prepared for the procedure. This process helps in removing unnecessary material and background noise that could hinder further investigation or analysis. Unwanted elements such as special characters, punctuation marks, apostrophes, whitespace, and any characters other than lowercase letters are often irrelevant for text analysis and can be safely removed. By performing this removal, the preprocessed data becomes more streamlined and suitable for subsequent analysis or modeling. Figure 5 represents the data following the removal of unwanted text and characters.

	reviews_text	user_sentiment
17774	the smell is very clean very nice and simple however it does not last as long as i personally like being diabetic i perspire and suffer from bo more than the average person mainly through my feet but also my underarms so i look for deodorants and anti persperant that last long with a clean sent other than that i have only good reviews of this product it does not streak my black under armor it's a solid stick so my armpits don't feal weard after application i would continue use of this product for casual every day use but not for days i know i will be working hard and perspiring as i like to feel and smell as fresh after a hard day of work as when i got out of the shower that morning so to review sent pass clean and not overpowering duration needs improvement does not last as long as i like for a hard labor intensive day application pass goes on easy does not streak and does not iratate the skin or feel awkward great but not perfect	Positive
2189	not only is this movie outrageous and hilarious but the k looks incredible worth it	Positive
11530	a product that truly works on surfaces such as the kitchen bathroom white painted walls etc its so easy when company is coming over just whip out the clorox wipes and its a fast clean up on counter tops bathrrooms and because it is made whith a product that can be trusted it is unbeatable product that is trusted	Positive
15878	excellent for when you still want the bright freshness of the peppermint lip balms but also a little bit of color these are grand in the cold weather months especially it applies smoothly with even color and is rich and plentiful not quite as longlasting as other lipsticks but i still like it the best of both worlds	Positive
25732	great action sequences and plenty of excitement loved it awesome movie	Positive

Fig. 5 Data followed by the removal of unwanted text and characters

	reviews_text	user_sentiment
7029	I love these handy for disinfect just about everything especially during the sick disinfect	Positive
2026	buy this as a for the be a predictable but it be so funny that you just go with it get ready to laugh	Positive
23151	be a little at but it manage to lay all of the for future not just future but other connected as well get to love and kind of slow but a great	Negative
8340	I only use because they work great on all work great	Positive
8602	I use these at and at my at I be impressed with the disinfect and great	Positive

Fig. 6 Data after lemmatization

	reviews_text	user_sentiment
5750	give find get blueray cheap entertaining	Positive
14906	I love disinfect wipe quick convenient quick	Positive
29222	I use along I like leave feel without saturate do not feel extremely moisturizing I give however do not dry anymore already keep clean enough I do not wash everyday do say	Positive
9632	I like wipe smell feel free fresh	Positive
14775	good quick easy clean I always well	Positive

Fig. 7 Data after stop word removal

3.2.4. Lemmatization

Lemmatization is a linguistic procedure that reduces words to their most fundamental or root form, or lemma, for text preprocessing purposes. The lemma is a representation of a word's canonical or dictionary form that conveys its essential meaning. By converting words to their base form, lemmatization facilitates word normalization and vocabulary reduction, making it easier to analyze and interpret text data. Additionally, lemmatization takes into account the Part of Speech (POS) of each word, which helps determine the proper lemma, as different POS groups may have distinct standards for deriving the base form. After lemmatization as in Figure 6, the data is transformed to reflect these simplified and standardized word forms, enhancing the quality and consistency of textual analysis.

3.2.5. Stop Word Removal

Stop word removal is a widely used technique in text preprocessing aimed at eliminating common words that are not significant to the overall sense of the text. These commonly encountered words, such as articles, prepositions, and pronouns, are referred to as stop words. While removing stop words can streamline the text and improve computational efficiency, it is crucial to exercise caution, especially with nuanced cases like negations ("do not"). By carefully selecting which stop words to remove, text preprocessing can enhance the quality of subsequent NLP tasks such as text classification and SA. However, improper removal of stop words may inadvertently alter the intended meaning of the text, underscoring the importance of thoughtful consideration in the preprocessing stage. The data following the elimination of stop words is given in Figure 7.

3.3. Exploratory Data Analysis

A key component of data exploration is Exploratory Data Analysis (EDA), which is carefully examining data to draw important conclusions, find trends, and make connections between various variables. A key component of EDA is data visualization, which aids in interpreting complex datasets more intuitively. The provided visualizations include word clouds representing positive and negative sentiment in Figure 8 and the distribution of classes in Figure 9.

3.4. Proposed SA Model

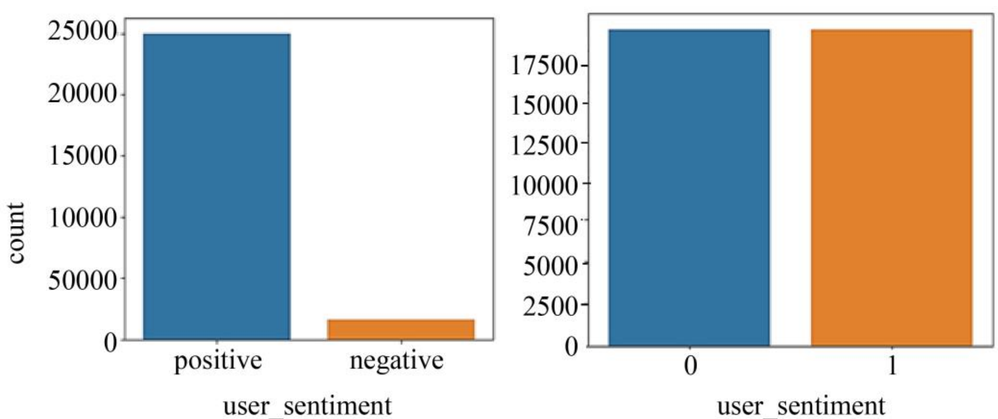
SA was performed using a hybrid model of Bidirectional Encoder Representations from Transformers (BERT) and GRU. The SA model receives preprocessed data after exploratory analysis. Figure 10 shows the structural diagram for the SA model.

3.4.1. BERT

BERT employs a specialized tokenizer to convert input text into tokens, which are then transformed into corresponding token IDs. Operating on the transformer architecture, BERT utilizes self-attention mechanisms to identify relationships amid the words of a sentence or sequence. This architecture comprises multiple layers of self-attention and feedforward neural networks stackable to create a deep model capable of understanding complex patterns in text data as in Figure 11. BERT's bidirectional nature allows it to consider context from both directions, enabling a richer understanding of semantic information [20]. Pre-trained on extensive text data using unsupervised learning tasks like Next Sentence Prediction (NSP) and Masked Language Modeling (MLM), BERT comes in various sizes, each offering different numbers of layers and hidden units. As each tokenized user review passes through BERT, it obtains high-dimensional contextual embeddings representing the meaning of each word within the entire review. To condense these embeddings into a fixed-size representation, aggregation strategies like mean pooling or max pooling can be applied over the token embeddings.

(a) (b)

Fig. 8 Word cloud of (a) Positive sentiment (b) Negative sentiment



(a) (b)

Fig. 9 Word cloud of (a) Positive sentiment (b) Negative sentiment

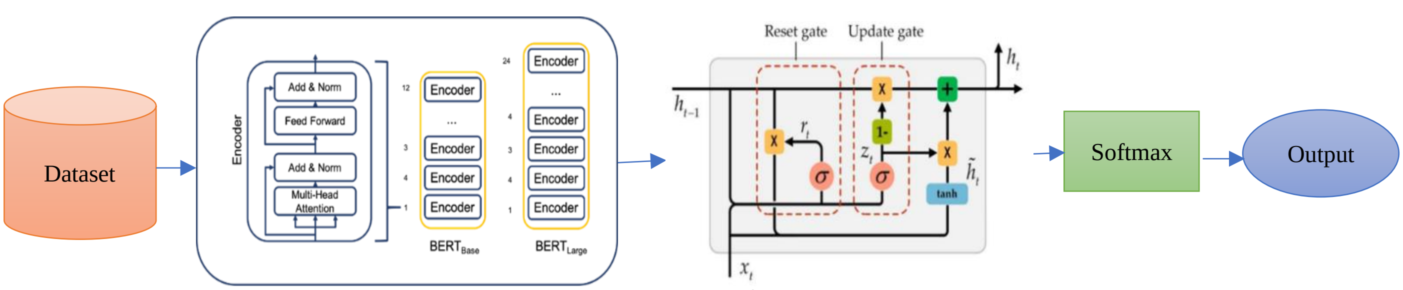


Fig. 10 Block diagram of the SA model

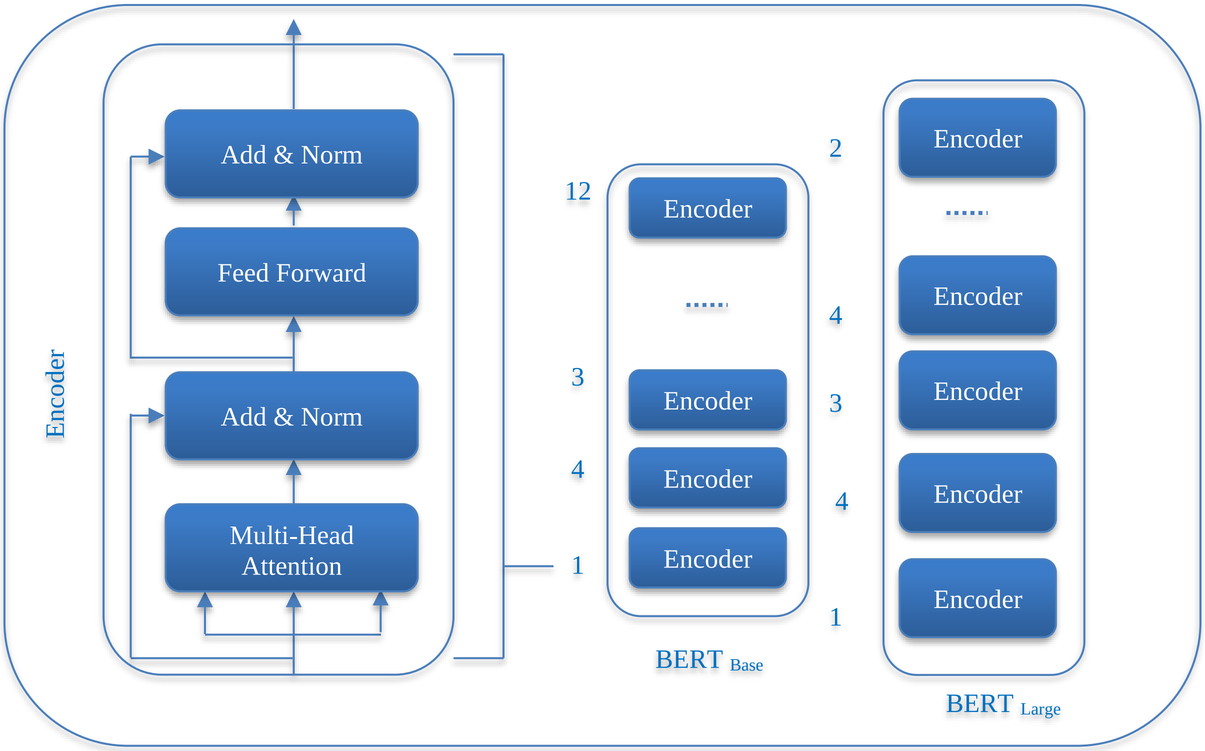


Fig. 11 Basic architecture of BERT

Mathematically, the self-attention mechanism in BERT can be expressed as: Given a sequence of input tokens $x_1, x_{2,.....,} x_n$, BERT computes the attention score α_{ij} between each pair of tokens x_i and x_j. This attention score is calculated using (1)

$$\alpha_{ij} = softmax\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right) \tag{1}$$

Where $Q_i$represents the query vector for the token x_i, $K_j$represents the key vector for the token x_j, d_k is the dimensionality of the key vectors and softmax function applied to normalize the attention scores across all tokens. BERT computes attention scores for each token and uses them to calculate a weighted sum of all token values, producing context-aware representations for each token and capturing their meaning within the input sequence [22]. The representation of feed forward neural network is given in (2)

$$FFN(x) = ReLU(xW_1 + b_1)W_2 + b_2 \tag{2}$$

where W_1 and W_2 are weight matrices for the first and second layers of feed forward network and b_1 and b_2 are bias vectors, and the layer normalization is expressed by (3)

$$LayerNorm(x) = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}} \tag{3}$$

Where μ is the mean and σ^2 is the variance of the input vector, and ϵ is a constant.

3.4.2. GRU

The GRU architecture is designed to address the issue of vanishing gradients commonly encountered in traditional Recurrent Neural Network (RNN), as given in Figure 12.

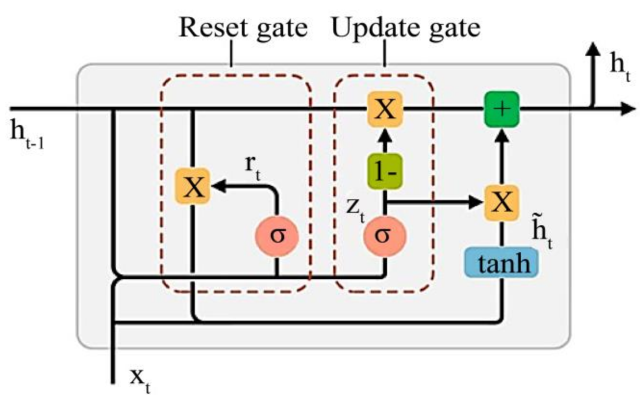


Fig. 12 GRU basic architecture

It achieves this by employing gating mechanisms to better capture long-range dependencies within the network [23]. Unlike traditional RNNs, GRUs utilize a hidden state instead of a separate cell state, generating a new hidden state at each time step by combining input and the previous hidden state. The process involves two key gates: the reset gate r_{ti} and the update gate z_{ti}.The reset gate controls how much of the previous state is forgotten, as in (4),

$$r_{ti} = \sigma(W_r.\left[h_{ti-1,}x_{ti}\right] + b_r) \tag{4}$$

While the update gate manages how much of the prior state is retained, as represented by (5).

$$z_{ti} = \sigma(W_z.\left[h_{ti-1,} x_{ti}\right] + b_z) \quad (5)$$

The candidate activation h_{ti} captures new data and integrates it into the hidden state expressed as (6)

$$h_{ti} = (1 - z_{ti}) * h_{ti-1} + z_{ti} * \overline{h_{ti}} \quad (6)$$

The process starts with the aggregated features extracted from BERT being input into a GRU layer, which handles the sequential information in the user reviews. The GRU layer's hidden states encode the sequential relationships and context within the reviews, serving as representations of each review [24]. These representations then undergo a softmax activation function for classification, generating likelihoods of each sentiment class (e.g., positive, negative). The sentiment class with the highest probability is assigned to the review. Finally, by combining the SA model with CF, the product recommendation system is formed, utilizing sentiment insights to refine the recommendation process.

3.5. Product Recommendation System

A product recommendation system filters and recommends products to users according to their opinions, their prior acts, and pertinent data, aiming to enhance user experience, engagement, and revenue generation in various online platforms like e-commerce. In the proposed system, SA and CF are integrated. CF includes both user-based and item-based recommendation systems, identifying similar users or items based on past interactions to make personalized recommendations. The SA model enhances the recommendation system's predictions by analyzing sentiments associated with user reviews. CF is a recommendation method that indicates a user's choice of items by analyzing the preferences of similar users. It also operates under the assumption that users who possess preferred similar products from the past are probably going to have comparable tastes in the future. CF does not require explicit information about the items or users; instead, it relies on historical user-item interactions to identify patterns and similarities. CF can be implemented using two main approaches: user-based and item-based. In the user-based approach, recommendations are made by identifying users with similar preferences and suggesting items that these similar users appreciate. In contrast, the item-based approach determines the similarity between items based on user interactions and recommends items that are similar to those previously interacted with by the user. CF is a powerful recommendation method commonly used in various online platforms to provide personalized recommendations to users. Here, it computes similarities between users or items using cosine similarity, which measures the cosine of the angle between two vectors, giving a value between -1 and 1. A cosine similarity of 1 indicates identical vectors, 0 denotes no similarity, and -1 implies complete dissimilarity. The cosine similarity is expressed as below in (7)

$$Cosine\ Similarity\ (M, N) = \frac{(M \cdot N)}{(\|M\| * \|N\|)} \quad (7)$$

Here, M·N is the dot product of M and N vectors, while ‖M‖ and ‖N‖ are the Euclidean norms of M and N vectors, respectively. User-based CF implies analyzing user interactions and preferences towards various items to determine similarity, enabling recommendations based on similar user behavior.

In contrast, item-based CF assesses item similarity by examining user engagement with those items, allowing for recommendations of similar items based on user interactions. After determining similarity, a neighborhood selection process chooses a subset of similar users or products to generate recommendations, with the neighborhood size influencing both computational complexity and recommendation quality.

Recommendations are then generated according to the interests of users or similar items. Following a thorough evaluation, the best recommendation system is chosen to generate 20 products likely to be purchased by a customer, factoring in their ratings. Lastly, the recommendation system is enhanced by integrating the SA model.

4. Results and Discussions

4.1. Hardware and Software Setup

Following dataset preparation, the dataset was partitioned into two subsets for model implementation: a training set comprising 75% of the data and a separate test set containing the remaining 25%. The BERT-GRU model was then constructed, trained, and assessed using Google Collaboratory, utilizing TensorFlow and Python throughout the entire process. The hyperparameters that are set prior to the training of a model and remain constant during the training process that are utilized in the study are detailed in Table 1.

4.2. Performance Parameters

Performance parameters are essential for evaluating the effectiveness of the suggested DL model, providing measurable insights into its predictive accuracy. These metrics serve as valuable indicators of the model's performance and its capability to generate accurate predictions. Table 2 shows the analysis of performance indicators.

Table 1. Hyperparameter specifications

Hyperparameters	Values
Activation function	Softmax
Loss	Mean Squared Error
Number of Epochs	300
Optimizer	Adam
Batch size	64

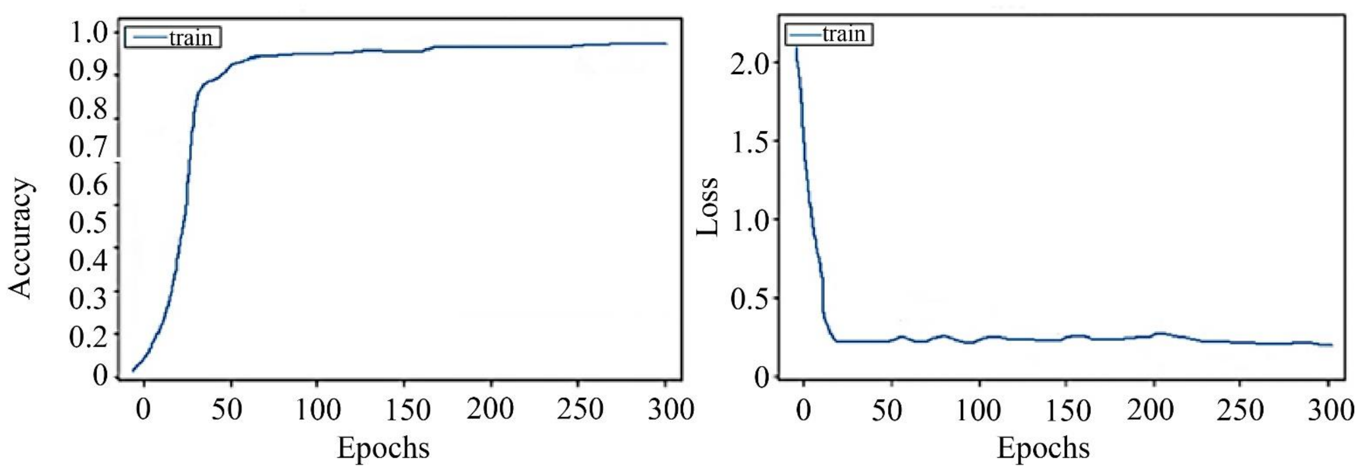
Table 2. Performance parameters

Performance Metrics	Equations
Accuracy	$(TP + TN) / (TP + TN + F + FN)$
Precision	$TP / (TP + FP)$
Recall	$TP / (TP + FN)$
F1 Score	$2 * (Precision * recall) / (Precision + recall)$
where TP-True Positives, FP-False Positives, TN-True Negatives and FN-False Negatives	

The comprehensive indicator used to assess the efficacy of the model is the classification report, providing essential parameters. The performance of the SA model is given by Table 3 which illustrates the superior execution of the suggested SA model with an accuracy of 98.93%. The accuracy and loss plot offer valuable insights into the performance and convergence of the system during training. The accuracy plot showcases the evolution of system accuracy throughout the training process, reflecting improvements for both training and validation data as the model learns from examples. Conversely, the loss plot demonstrates how the model's loss changes over training epochs, with reduced loss indicating better alignment between predicted and actual values. A decreasing loss trend indicates an improved model fitting to the training data. Figure 13 displays the accuracy and loss plot of the proposed SA model, demonstrating its training dynamics.

Table 3. Performance of SA model

Evaluation Parameters	Results (%)
Accuracy	98.93
Precision	99.35
Recall	98.98
F1-Score	99.32



(a) (b)

Fig. 13 Accuracy and loss plot of BERT-GRU based SA model

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Enter user name: zzdiane
Index(['42 Dual Drop Leaf Table with 2 Madrid Chairs"',
       'Mike Dave Need Wedding Dates (dvd + Digital)',
       'D-Con Mice Bait Station - 3ct', 'J.R. Watkins Hand Cream, Lemon Cream',
       'Chex Muddy Buddies Brownie Supreme Snack Mix',
       'Meguiar's Deep Crystal Car Wash 64-Oz.',
       'SC Johnson One Step No Buff Wax',
       'Iman Second To None Stick Foundation, Clay 1',
       'Care Free Curl Gold Instant Activator',
       'Dark Shadows (includes Digital Copy) (ultraviolet) (dvdvideo)',
       'Equals (blu-Ray)', 'Tostitos Bite Size Tortilla Chips',
       'Pleasant Hearth 1,800 sq ft Wood Burning Stove with Blower, Medium, LWS-127201',
       'Boraam Sonoma Kitchen Cart With Wire Brush Gray - Maaya Home',
       'Hawaiian Punch Berry Limeade Blast Juice',
       'Meguiar's Ultimate Quik Detailer 22-Oz.',
       'Jergens Extra Moisturizing Liquid Hand Wash, 7.5oz',
       'Chester's Cheese Flavored Puffcorn Snacks',
       'Stacy's Simply Naked Bagel Chips',
       'Tree Hut Shea Body Butters, Coconut Lime, 7 oz'],
      dtype='object', name='name')
```

Fig. 14 Recommendation of top 20

Two recommendation systems were crafted using CF and assessed through Root Mean Square Error (RMSE) metrics, which are used to measure the average deviation between predicted values and actual values in a dataset. The user-based approach obtained an RMSE of 1.32, and the item-based one scored 2.46. Despite the slightly higher RMSE, the item-based system prevailed due to dataset characteristics. With 20,000 users predominantly rating only one product, the user-based matrix became vast and sparse, offering fewer valuable recommendations. Conversely, the dataset's 200-item count made the item-based matrix more condensed and practical. Hence, the item-based method was deemed superior, furnishing the top 20 probable product purchases. The recommendation output is given in Figure 14.

Following the SA of the reviews for the 20 recommended products, the top 5 products with predominantly positive feedback were isolated using the integrated sentimental analysis model given in Figure 15.

The comparison of the suggested methodology with existing techniques is given in Table 4.

	Product Recommendations
0	42 Dual Drop Leaf Table with 2 Madrid Chairs
1	Hawaiian Punch Berry Limeade Blast Juice
2	Stacy's Simply Naked Bagel Chips
3	SC Johnson One Step No Buff Wax
4	Chester's Cheese Flavored Puffcorn Snacks

Fig. 15 Recommendation of top 5 products

Table 4. Performance comparison with current methods for SA

Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Modified CNN [5]	98.85	96.13	96.30	96.2
CNN-BILSTM [6]	93.4	93.5	93.4	93.4
SVM-NB [7]	93.7	94.1	95.2	94.1
LSTM [10]	90.9	94.46	91.63	92.81
GRU [12]	70.52	69.45	68	68.71
Proposed BERT-GRU	98.93	99.35	98.98	99.32

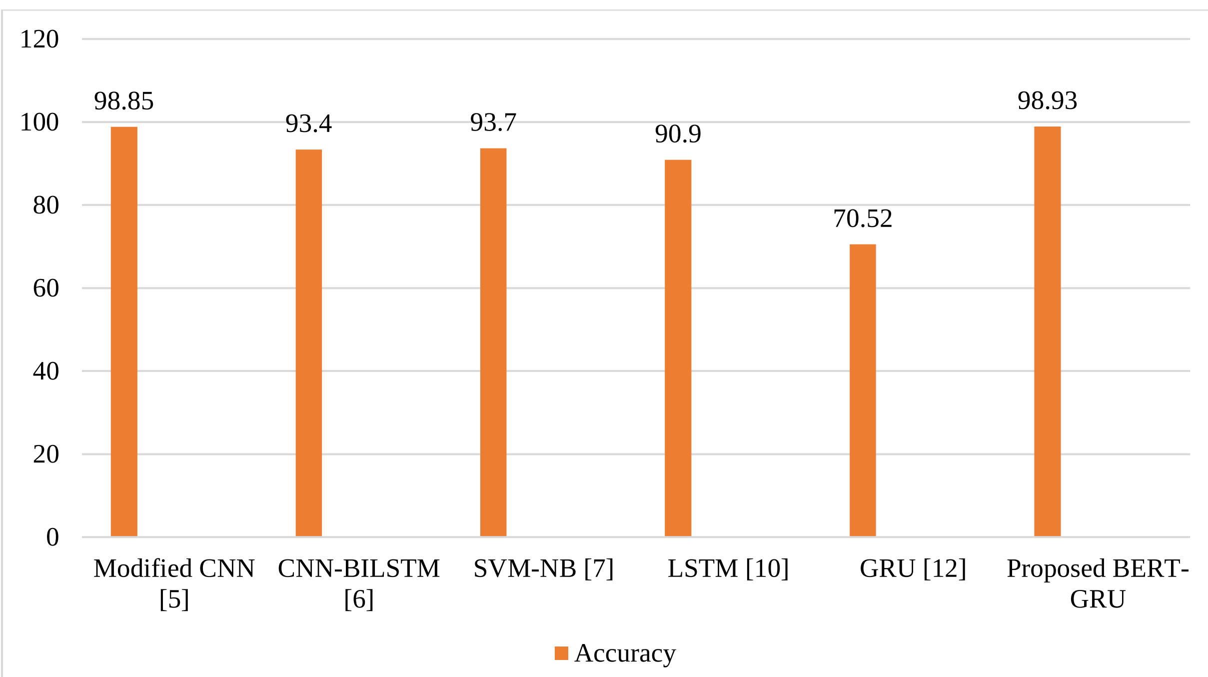

Fig. 16 Graphical representation of accuracy

Table 4 reveals that the proposed BERT-GRU model outperforms existing methodologies for sentiment analysis across all key metrics: accuracy, precision, recall, and F1-score.

With an accuracy of 98.93%, the BERT-GRU model slightly surpasses the Modified CNN, which has an accuracy of 98.85%, showcasing its superior ability to predict sentiments correctly. Additionally, the BERT-GRU model achieves a remarkable precision of 99.35%, recall of 98.98%, and F1-score of 99.32%, significantly outperforming other methods such as CNN-BILSTM, SVM-NB, and LSTM, which have lower scores across these metrics. The comparatively poor performance of models like GRU, with an accuracy of 70.52%, underscores the effectiveness of the BERT-GRU approach in capturing the nuances of sentiment analysis, thereby offering a more robust and reliable solution for e-commerce applications.

The proposed BERT-GRU model achieves superior results in sentiment analysis compared to state-of-the-art techniques due to the synergy between BERT's deep contextual understanding and GRU's ability to capture sequential dependencies. BERT's bidirectional nature allows it to comprehend complex language patterns by considering the full context of a sentence, which is critical for accurate sentiment interpretation. When these rich embeddings are processed through a GRU, which efficiently manages sequential data and retains relevant information across long text sequences, the model becomes highly effective at understanding and predicting sentiment. Additionally, the fine-tuning of BERT on the specific sentiment analysis task further enhances its ability to capture subtle nuances, leading to higher precision, recall, and overall F1-score compared to traditional models like CNNs or LSTMs. This combination of advanced language representation and sequential learning is what enables the BERT-GRU model to outperform existing methods in accuracy and consistency.

5. Conclusion

In e-commerce systems, a crucial element for enhancing user satisfaction, increasing consumer engagement, and ultimately driving sales revenue is a product recommendation system. By efficiently navigating through vast product selections, such systems offer recommendations based on user preferences and behaviors, thus facilitating personalized shopping experiences. This study introduces an innovative approach by integrating SA and CF techniques into the product recommendation system. SA enables the system to analyze user sentiments expressed in reviews or textual data, discerning preferences and attitudes toward specific products. Utilizing the BERT-GRU model as the foundation for SA, the system can accurately capture sentiment information. On the contrary, CF utilizes user-item interactions or item-item similarities to identify trends and provide personalized recommendations by analyzing similar user behaviors. By combining SA and CF, the proposed system aims to take advantage of the strengths of both approaches, enhancing user engagement and satisfaction levels through more precise and emotionally resonant product recommendations customized to individual preferences. This integration is poised to enhance the overall effectiveness of the recommendation system and foster more meaningful interactions between users and the platform.

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