Automatika
Journal for Control, Measurement, Electronics, Computing and Communications

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/taut20

A novel framework for an intelligent deep learning based product recommendation system using sentiment analysis (SA)

Roshy Thomas & J. R. Jeba

To cite this article: Roshy Thomas & J. R. Jeba (2024) A novel framework for an intelligent deep learning based product recommendation system using sentiment analysis (SA), Automatika, 65:2, 410-424, DOI: 10.1080/00051144.2023.2295148

To link to this article: https://doi.org/10.1080/00051144.2023.2295148

Published online: 10 Jan 2024.

AUTOMATIKA
2024, VOL. 65, NO. 2, 410–424
https://doi.org/10.1080/00051144.2023.2295148

A novel framework for an intelligent deep learning based product recommendation system using sentiment analysis (SA)

Roshy Thomas and J. R. Jeba

Department of Computer Applications, Noorul Islam Centre for Higher Education, Kumaracoil, India

ABSTRACT
Social media and e-commerce are the two most prominent and quickly expanding industries today. These two areas exhibit the greatest influence on platform users. Numerous new people sign up for these networks on a daily basis. This platform offers extremely quick user networking and communication. These platforms are used to create an online product-based recommender system that will help grow online business by recommending products. Online product recommendations are entirely dependent on the views, feedback, and comments of consumers. Online recommender systems have become a regular part of consumers' everyday routines, with their widespread use observed in e-commerce, social networking platforms, and news websites. This paper offers a novel framework for product recommendation based on sentiment analysis (SA) and collaborative filtering (CF). The SA was performed using an LSTM-based model. On the basis of CF, two distinct recommendation systems were built. The proposed SA model was integrated with the best recommendation system to enhance the recommendations. The experimental findings showed that the proposed system for product recommendation outperformed the existing methods. The outcomes demonstrated the potential of combining CF and SA to improve consumer satisfaction and product recommendation in e-commerce systems.

ARTICLE HISTORY
Received 24 September 2023
Accepted 8 December 2023

KEYWORDS
E-commerce platform; user sentiments; user preferences; sentiment analysis; collaborative filtering; product recommendation;

1. Introduction

The rise of internet usage and the rapid growth of mobile devices have fuelled the widespread adoption and popularity of online shopping, leading to its substantial expansion in recent years [1]. Customers like online shopping because they can make selections about what things to buy based on review comments, product ratings, and technical specifications. Recommender systems encompass software solutions and methodologies that leverage user preferences and historical data to offer recommendations across a range of products or items [2–5]. Users will be assisted in making decisions regarding the products or items by the recommendations made by recommender systems. Recommender systems utilize various types of actively acquired data to analyze and generate recommendations. The type of recommender systems determined the data that was used for information processing. The utilization of the abundant information present on Online Social Networks (OSNs) to offer valuable recommendations on products, items, or other entities is made possible by the significant role played by recommender systems. The cloud platform is used by the automatic recommender system to deliver thoughts or recommendations about the product depending on the user's inquiries. The cloud platform provides a valuable channel for individuals to express their opinions and feelings regarding products and items. The recommender system will function well on the cloud platform provided by online social networks like Twitter and Facebook. Based on user-based and item-based recommenders, the recommendation engines are divided into two categories. Product recommendations through online social networks that offer sentiment data on reviews that users have left about products, items, or anything else. Figure 1 illustrates a visual representation of the recommendation system implemented in an e-commerce platform.

In the e-commerce environment, the recommendation system provides advantages to both the buyers and sellers who participate in the community. In order to cater to diverse product interests and personalized recommendations, recommendation systems play a crucial role by analyzing user purchasing behaviour and preferences from a wide range of available products, ultimately providing relevant recommendations that align with individual needs and preferences [6]. Collaborative and content-based recommendation approaches are the two prevalent types of approaches used in the field of recommendation systems.

The use of SA approach is crucial when creating a recommender system. It is also known as opinion mining. Opinion mining is a technique that utilizes text

CONTACT Roshy Thomas roshythomas.ca@outlook.com Department of Computer Applications, Noorul Islam Centre for Higher Education, Kumaracoil, India-629 180

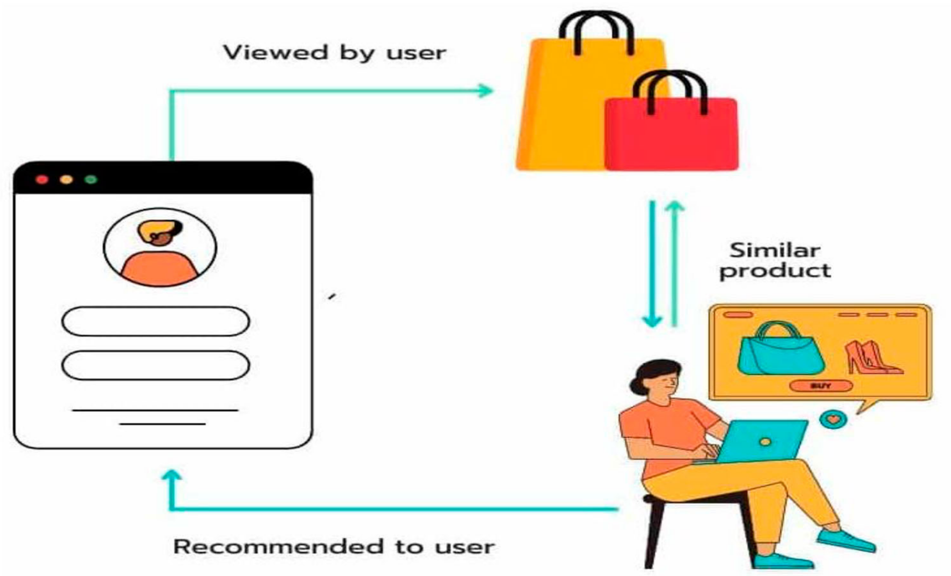

Figure 1. Recommendation system in E-commerce.

mining and natural language processing (NLP) to analyze and extract sentiments or opinions from textual data. The sentiment might be positive or negative [7]. This opinion is sometimes categorized as positive, negative, and neutral. SA offers opinions about the data so that decisions can be made in numerous sectors. SA is a widely utilized approach in NLP that aims to classify sentiments and retrieve subjective insights from the given data. Based on the provided data, the classification of sentiment polarity will take place at three stages of analysis. The fundamental aspect of a recommender system based on SA lies in the utilization of SA techniques within the recommender system. The recommendation system uses SA as a decision support tool. It is intended to give users the most accurate results possible by combining SA with recommender systems. The SA techniques provide the recommender system with information about the sentiment of the subsequent user query, which can be positive, negative, or neutral. This enables the recommender system to make decisions based on the SA results.

It is crucial to comprehend the idea of a fundamental recommendation system and the necessity of social media in the modern world. A recommendation system is an online tool or software programme that guides users towards the most suitable products by considering the preferences, rankings, favourites, and evaluations provided by other users according to different criteria. These recommendations may be in the form of many intentions, such as things to purchase, career alternatives for students to consider, friends to add to a social network, films to view, institutions to attend for higher education, or online news to read. In other words, the system provides the customized advice to the user who requests it based on information it has gained from reviews, features, ratings, user feedback, and user-specific data. The framework for recommendations is a crucial tool for effective online interactions between consumers and retailers. The success of sales is greatly influenced by quick and pleasant encounters to identify the perfect product. This paper presented a robust product recommendation system using deep learning (DL) techniques that combine collaborative filtering (CF) and SA, resulting in enhanced performance and accuracy.

2. Literature review

A. Naresha and P. Venkata Krishna [8] introduced a machine learning (ML) based recommender system for SA. Application programming interface is used to collect data from the twitter data source. The collected tweets are preprocessed and classified as either positive, negative, or neutral. Finally, the effectiveness of the three fundamental supervised ML algorithms is evaluated. The framework for SA with recommender systems was developed using supervised learning techniques based on the selected ML models. R.V. Karthik and Sannasi Ganapathy [9] proposed a novel system for product recommendation in online shopping, which utilizes fuzzy logic to dynamically predict the most appropriate products for customers based on their current preferences. The paper introduced an innovative method to compute the sentiment score of a product considering the specific target category associated with end users. The proposed recommendation system, which utilizes fuzzy rules and ontology-based techniques, incorporates ontology alignment to enhance the accuracy of judgments and make predictions that are contextually relevant based on the search context. The outcomes from the experiments indicated that the newly proposed recommendation system outperforms the existing product recommendation systems in terms of accurately predicting relevant products for specific consumers and delivering these recommendations in a more efficient manner. The major limitations of the proposed work are complex to develop and maintain and also sensitive to changes in customer behaviour or preferences. Cach N. Dang et al. [10] proposed and evaluated a recommendation method that combines collaborative filtering (CF) approaches with SA, providing a meaningful integration of these two techniques. The recommender system is constructed using a flexible architecture that integrates advanced DL models for SA and employs improved methods for feature extraction. The outcomes of the empirical investigation conducted with two well-known datasets demonstrate that CF techniques and sentiment-based DL models can greatly improve the effectiveness of the recommender system. But the major limitation is that it is computationally intensive and requires significant computing resources. An intelligent method for product recommendations was proposed by S Parvathi Vallabhaneni et al. [11]. In this work, a structure based on different profound learning models that rely on solo-learning and managed learning methods was introduced. The suggested method used a multilayer perceptron model that makes extensive use of broad learning to apply presumption evaluation to smaller-scale blog literary data using sham variables methodology. According to the experiment results, the suggested bigram-based framework demonstrated superior performance compared to other approaches in the E-commerce field, particularly on the analyzed platform. Fatemeh Abbasi et al. [12] suggested a recommender system that utilizes both explicit and implicit user preferences, aiming to enhance the accuracy of predictions. For user groups, the CF based on DL was merged with sentimental analysis to boost system accuracy. The suggested system utilizes NLP and supervised classification techniques to assess emotions and retrieve underlying attributes from textual data, thereby providing a means to understand sentiments and implicit characteristics. The SVD was utilized to increase scalability when designing the recommender system. The outcomes demonstrated that the suggested strategy enhances CF performance. The limitation of the work is that the time factor to introduce more precision into the recommendation system is not considered.

Abhaya Kumar Sahoo et al. [13] proposed a DL method called the Restricted Boltzmann Machine Convolutional Neural Network. This approach demonstrated the potential of big data analytics in developing a powerful health recommender engine for effective healthcare recommendations. The rise of telehealth offers a major chance for the healthcare sector to shift from a conventional model to a more individualized approach, specifically in the realm of providing remote healthcare services. The experimental outcomes indicate that the DL method proposed in the study exhibits lower error rates compared to previous methods used in the field. The primary drawback of the suggested task is the low level of privacy. Shanshan Yi and Xiao fang Liu [14] employed ML algorithms to acquire knowledge, examine, and categorize consumer experience-based product information and retail information. The data regarding the features and user reviews of the Unifed computing system, a server designed for data-centric computing products, was collected as part of a comprehensive evaluation that included hardware testing, support for visualization, and software management analysis. It has been determined from the findings and comparisons that ML algorithms outperform other methods. However, this paper does not explain why customers are interested in a variety of products in various geographic regions. Maram Almaghrabi and Girija Chetty [15] presented a novel method for forecasting user ratings across various media collections found in online databases and libraries. The method utilizes DL techniques to enhance the Collaborative Filtering (CF) methodology, enabling more accurate predictions for media items like movies, music, and books. The suggested approach was evaluated using four publicly available datasets demonstrated promising results in terms of various performance measures. The experimental evaluation reveals positive outcomes for the proposed method. Sudhanshu Kumar et al. [16] introduced a hybrid recommendation system that integrates content-based filtering, SA of movie tweets, and collaborative filtering. This integrated approach aims to provide more accurate and personalized recommendations by considering the content of movies, analyzing sentiments expressed in tweets related to movies, and leveraging collaborative filtering techniques. To improve this recommendation system, SA is employed. In order to assess current trends and audience reactions, movie tweets have been gathered from microblogging services. A comprehensive study of the proposed recommendation system involves conducting thorough experimentation to provide in-depth insights and analysis. Finally, a comparison with various baseline models is shown using both qualitative and quantitative data. The study does not clarify information on user emotional tones from various social media networks. The proposed framework by I-Ching Hsu and An-Hung Liao [17] is a versatile approach that combines SA and ML to create a recommendation system. The chatbot comprises several modules. The suggested approach was tested by using a sentiment-based article recommendation linebot. This linebot provides an API interface that enables chatbots to activate the system through a webhook mechanism, showcasing the modular functionality of the system. The effectiveness and accuracy of four ML algorithms and two DL algorithms were evaluated in a Spark cloud computing environment. Based on experimental results, the decision tree approach exhibits superior performance in terms of both test accuracy and processing speed when applied to SA tasks. One significant drawback of the proposed work is the absence of any mention regarding the incorporation of decision-making systems that take into account human factors.

Marius Andrei Negret et al. [18] introduced a system created for mood enhancement based on a unique SA approach. The Fer2013 dataset is utilized to train a DL model that can accurately identify moods or emotions. Enhancing the ability of the recommendation system to deliver more relevant and accurate recommendations can be easily achieved by refining the tracks obtained from the Spotify API. Various technologies and programming languages were employed during the system development process to enhance user-system interaction and deliver accurate recommendations for optimizing the utilization of limited resources. The evaluation of the system demonstrated that it is reliable and easy for users to interact with. The trained model achieved a high degree of accuracy, and the validation process was conducted under realistic testing conditions, further establishing its credibility and trustworthiness. A novel SNN framework was presented by S. Prasanna Priya and Karthikeyan [19] for an efficient recommendation system. SNN frameworks typically involve two phases in their operation. The initial stage of the SNN framework involved utilizing NLP techniques to convert unstructured data into structured data, providing a method for organizing and extracting meaningful information from the given data. This approach involves several steps, including data preprocessing, extracting relevant features, scoring words, classifying polarity, and conducting SA. In the second stage of the SNN framework, the validation of polarity classes is conducted through their application to real-world examples to ensure their accuracy. SNN structures demonstrate not only high accuracy in predicting outcomes but also incorporate a classifier weighting factor, contributing to reduced training time. For the network to be trained, the model needed a lot of data and processing power. A sentimental analysis-based product recommendation system based on random forest classifier was created by Gayatri Khanvilkar and Deepali Vora [20]. Major product websites use SA to comprehend the product's popularity and issues. The main structure of SA is a problem of positive and negative classification. Utilizing ordinal classification in SA offers a more comprehensive insight into the range and nuances of sentiments, providing a deeper understanding of the expressed opinions. The suggested approach employs ordinal categorization to assess the sentiment polarity of user feedback. SVM and Random Forest are ML algorithms that the system used to provide polarity. Jian Yu et al. [21] proposed a recommendation algorithm that utilizes content SA. Their algorithm demonstrates superior performance compared to conventional collaborative filtering-based product recommendation algorithms. This study maximizes the utilization of SA technology and proposes a holistic approach that integrates both user sentiment similarity and user score similarity, providing a comprehensive measure of similarity. The collaborative filtering (CF) recommendation algorithm leverages user shopping comments from e-commerce websites to evaluate a comprehensive similarity between users. By combining sentiment similarity and score similarity, the algorithm generates a predictive score for products, enabling effective recommendations. Jinming Zhang et al. [22] developed an algorithm called Aspect Sentiment Collaborative Filtering (ASCF) that integrates SA and a fuzzy Kano model. This integration allows for a meaningful fusion of SA and the fuzzy Kano model in the algorithm. By performing a fine-grained SA on the user's purchase history, ASCF is able to ascertain the different attitudes that users have towards various aspects of the product. Subsequently, the fuzzy Kano model is employed to analyze the user's preferences and perceived importance for each feature. Based on this analysis, a novel method is proposed to measure similarity, incorporating user preferences, for a CF algorithm. Research conducted on Amazon datasets has shown that applying Association Rule-based Collaborative Filtering (ASCF) significantly improves the accuracy of item-level recommendation systems and opinion-enhanced collaborative filtering. ASCF results in higher precision in recommending items and reduces the number of product recommendations while maintaining precision in similarity calculations. One drawback of the proposed approach is the absence of a dedicated optimization solution for sparsity, which could potentially impact the effectiveness and efficiency of the recommendations.

The Internet offers a wide range of data sets, making it a vast resource for users. However, due to the overwhelming amount of information available, users may struggle to navigate through it and find the most suitable and definitive solution to their information needs. Users lack confidence and find it challenging to choose the most important information on the web because of the varied nature of web data. Therefore, a practical system must be created to deal with this problem. The advice of various services, including the choice of appropriate items, getting information on career counselling, films, and books that the users need. The older version of the recommendation system is propagated through "word of mouth", which is frequently utilized by many people to buy a new product or to select the internet information by examining the opinions and feedbacks of the various users. In recent years, social media has become a primary source of data for online recommendation systems, allowing them to present users with recommendations that are more participatory and practical. The vast number of data from various social media networks and other e-commerce sites has also been brought about by the expansion of social

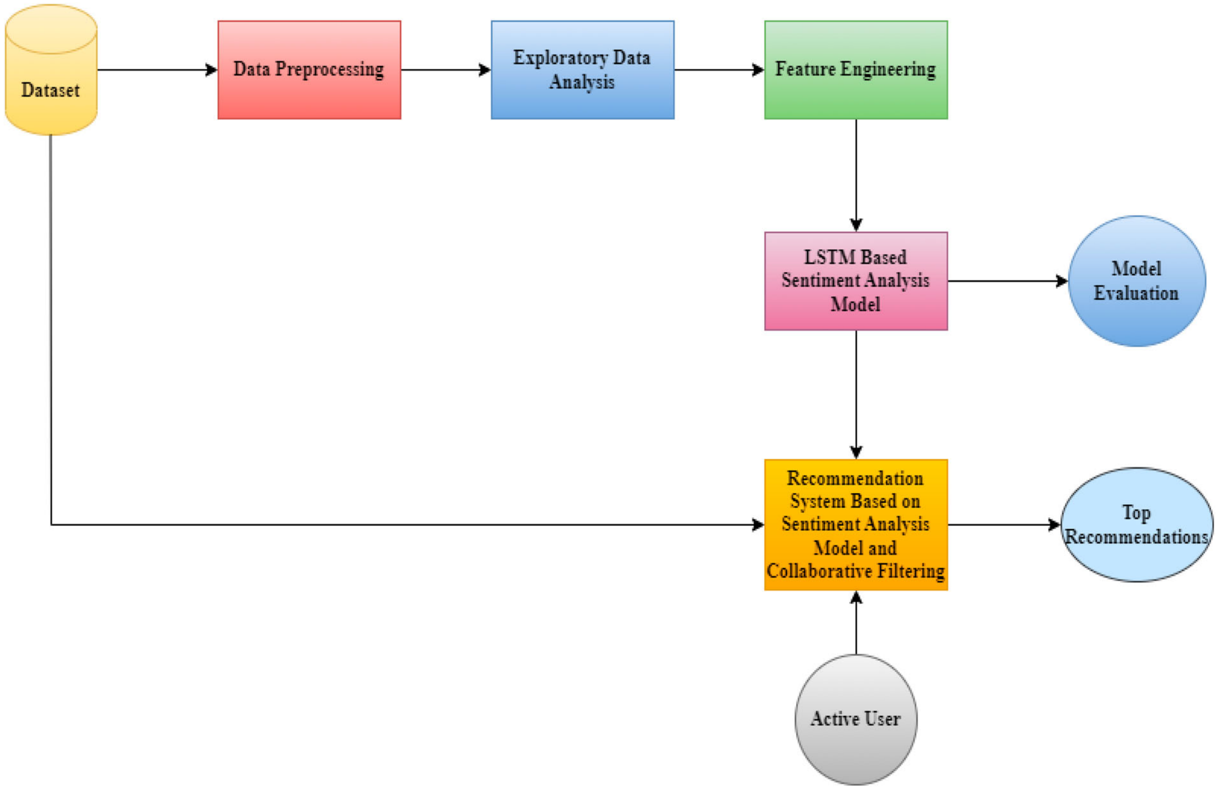

Figure 2. Block diagram of the proposed methodology.

media. This data includes reviews, comments, posts, tweets, tags, and opinions. User-generated material, such as product evaluations or social media remarks, is primarily reliant on SA. But it can be difficult to find a significant amount of good, useful data, particularly for newer or specialized products. The accuracy of the recommendations may be impacted by SA that is incomplete or biased due to a lack of data. So, an effective product recommendation system using SA is required.

3. Materials and methods

SA and CF constitute the core of the proposed product recommendation system. The primary objective is to provide a vital instrument for facilitating efficient interactions between customers and retailers in the realm of e-commerce. Figure 2 presents the visual representation of the proposed method in the form of a block diagram. The proposed strategy is categorized into two distinct sections. The first one is a SA model based on LSTM. It is followed by the product recommendation system. The SA model was trained using preprocessed data. Then user- based and item- based recommendation systems are developed using CF. The most suitable recommendation system has been chosen and utilized to suggest 20 products to a user based on their ratings, aiming to identify the products that they are highly likely to purchase. Finally, the recommendation system is linked to the sentimental analysis model to improve the recommendations. The model selects the top five products by analyzing the sentiments expressed in the reviews of the 20 recommended products.

3.1. Dataset

The sample dataset [23] was gathered from Kaggle. The dataset provided comprises over 30,000 reviews, encompassing a wide range of products, with more than 200 products included in the dataset. The reviews and ratings are given by more than 20,000 users. The attribute description of the dataset is tabulated in Table 1. The SA model can utilize only the chosen attributes for analysis. The sample data used for the SA model is illustrated in Figure 3.

3.2. Data preprocessing

Data preprocessing aids in enhancing data quality, reducing noise, standardizing text, normalizing words, addressing misspellings, converting text into numerical characteristics, and ensuring that the data is prepared for analysis. The various data preprocessing methods used in this study are mentioned below.

- Duplicated Data Checking

When two or more identical or nearly similar data points emerge in the dataset, it is said to have duplicate values. Dealing with duplicates is crucial since they can result in biased or incorrect analysis. Compare each data point to the full dataset to find exact or nearly exact

	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

Figure 3. Sample data for dataset.

duplicates. Once the duplicate values have been located, they can be deleted to leave only the unique instances. This makes sure that each data point is only displayed once in the dataset.

- Handling Missing Values

Missing values refer to situations when specific variables or attributes have no data or have partial data. There can be various reasons for the occurrence of missing values, such as data entry errors, technical issues, or when participants choose not to provide a response. Examine each variable or attribute in the dataset and check for null, NaN (Not-a-Number), or other indicators of missing values. It may choose to eliminate the associated occurrences or variables if the missing values are insignificant and arise randomly. After duplicate data checking and handling missing values, a data frame was created for the SA model using only three attributes, "reviews_text, reviews_title, user_sentiment". Then reviews_text and reviews_title can be combined into a single attribute. The data after duplicate checking and missing value handling is shown in Figure 4.

Table 1. Dataset attributes.

Attributes	Attribute description
Id	Unique identity number to identify each unique review given by the user to a particular product in the dataset
brand	Name of the brand of the product to which user has given review and rating
categories	Category of the product like household essentials, books, personal care products, medicines, cosmetics items, beauty products, electrical appliances, kitchen and dining products, health care products and many more.
manufacturer	Name of the manufacturer of the product
name	Name of the product to which user has added review or rating
reviews_date	Date on which the review has been added by the user
reviews_didpurchase	Whether a particular user has purchased the product or not
reviews_doRecommend	Whether a particular user has recommended the product or not
reviews_rating	Rating given by user to a particular prodcut
reviews_text	Review given by the user to a particular product
reviews_tittle	The title of the review given by the user to a particular product
reviews_userCity	The residing city of the user
reviews_userProvince	The residing province of the user
reviews_username	The unique identification for individual user in the dataset
user_sentiment	The overall sentiment of the user for a particular product (Positive or Negative)

- Removal of Unwanted Text and Unwanted Characters

Unwanted text and characters must be removed during text preprocessing in order to clean up the text data. It assists in removing unnecessary material and background noise that could obstruct further investigation. Special characters and punctuation are often unnecessary in text analysis and can be eliminated. Apostrophes, whitespace, and any characters other than lowercase letters can also be eliminated. The preprocessed data after the removal of unwanted text and characters are shown below (Figure 5).

- Lemmatization

The goal of the lemmatization approach is to break down words into their basic or root form, or lemma. The canonical or dictionary form of a word, which embodies its fundamental meaning, is the base form of the term. Lemmatization aids in word

	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

Figure 4. Data after duplicate checking and missing value handling.

	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

Figure 5. Data after removal of unwanted text and characters.

normalization and vocabulary reduction. Lemmatization considers the word's part of speech (POS). The POS tag aids in determining the proper lemma since many POS categories have different criteria for deriving the base form. Below is a display of the data after lemmatization (Figure 6).

- Stop Word Removal

Stop word removal is a popular text preprocessing technique used to get rid of words that are seen as common and don't significantly add to the text's overall meaning. Articles, prepositions, pronouns, and other commonly used words are referred to as stop words. Stopwords like "don't", which are used with certain words such as "don't buy", "don't try", and "don't like", among others, should not be eliminated (Figure 7).

3.3. Exploratory data analysis

Exploratory Data Analysis (EDA) plays a vital role in data analysis as it involves examining the data to gain valuable insights, identify patterns, and establish relationships or connections between different variables. EDA seeks to enumerate the primary traits of the dataset, reveal any underlying structure, and produce hypotheses for more research. An important EDA approach is data visualization. The below figure displays the visualization of the preprocessed data. Figures 8 and 9 depict the word clouds representing positive and negative sentiment, respectively. Figure 10 displays the distribution of classes.

3.4. Feature engineering

The feature engineering process involved three steps, feature extraction using TF-IDF, handle class imbalance, perform train and test split. The preprocessed data were divided into test data and train data prior to feature extraction. 25% of the data were utilized for testing, and the remaining 75% for training.

The process of feature extraction using TF-IDF transforms the original texts into a matrix of TF-IDF features. A feature extraction method called TF-IDF vectorizer is used in natural language processing to transform text data into numerical feature vectors. Term Frequency-Inverse Document Frequency (TF-IDF), is a numerical representation that measures the importance of a term within a particular document in relation to the entire collection of documents [24].

	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

Figure 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

Figure 7. Data after stop word removal.

Figure 8. Word cloud for positive sentiment.

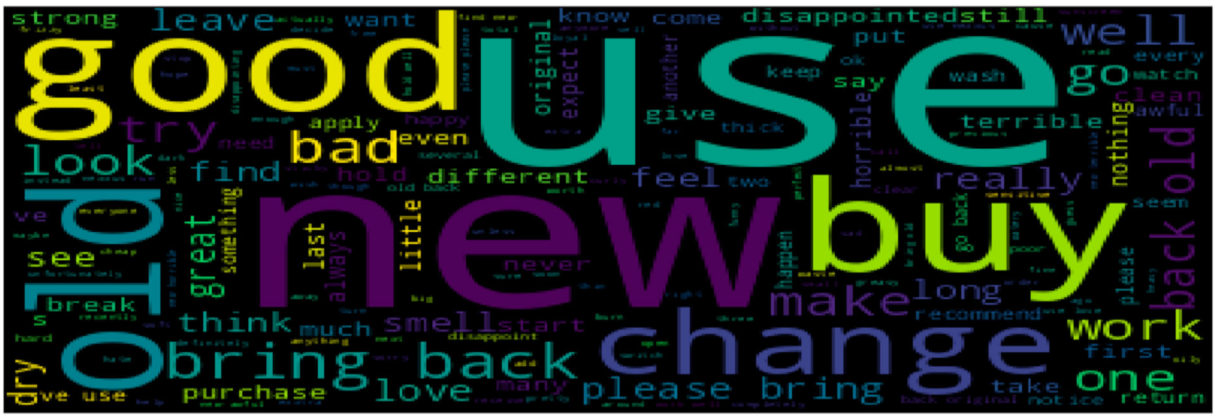

Figure 9. Word cloud for negative sentiment.

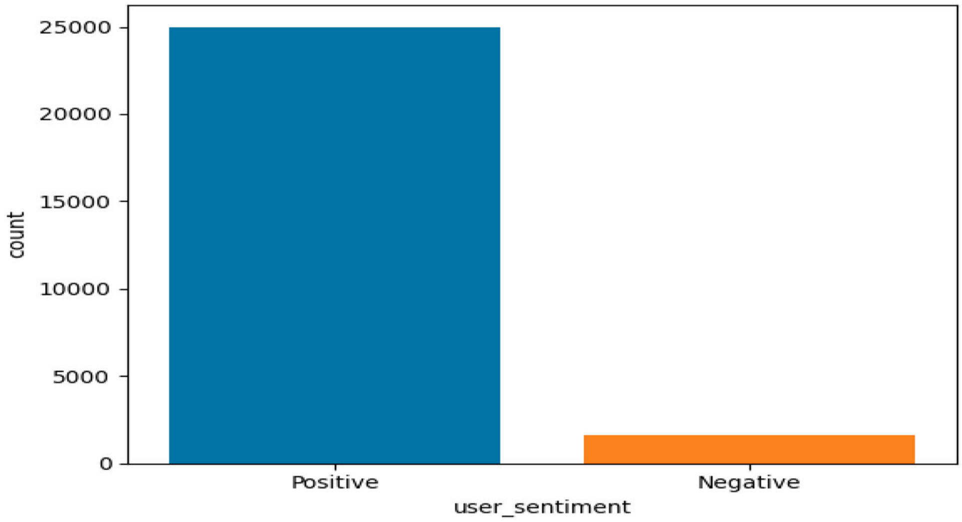

Figure 10. Class distribution.

The term frequency (TF) component measures the frequency of occurrence of a specific term or word within a document. The frequency of a given term in a document is evaluated by dividing the total number of terms in the document by how often that specific term appears in the document. If a term occurs more often in a document, TF will give it a higher value since it believes it to be of more significance. The IDF component determines how uncommon a term is across the entire collection of documents. It is evaluated by dividing the total number of documents by the number of documents that contain a specific term. IDF assumes that uncommon terms in the corpus are more informative and gives them higher ratings. The TF and IDF values for each phrase in a document are multiplied to provide the TF-IDF score. The resulting TF-IDF score represents the significance of a term in a particular text in relation to the entire corpus. The process involves converting a collection of textual documents into a matrix of TF-IDF features using the TF-IDF vectorizer. Each document in the corpus is represented as a numerical feature vector, where every feature corresponds to a term within the document.

It is clear from the class distribution that the given data is highly imbalanced. In imbalanced data sets, one class has a disproportionately smaller number of instances than the other class, which can affect model performance and produce false predictions. So, random oversampling was used to address the class disparity. The objective of random oversampling is to enhance the representation of the minority class by increasing its proportion, thereby achieving a more balanced distribution of classes. In order to attain the appropriate balance, samples from the minority class are repeatedly duplicated at random. Using this method, both classes are given equal representation and weight during model training. Figure 11 displays the class distribution after correcting class imbalance.

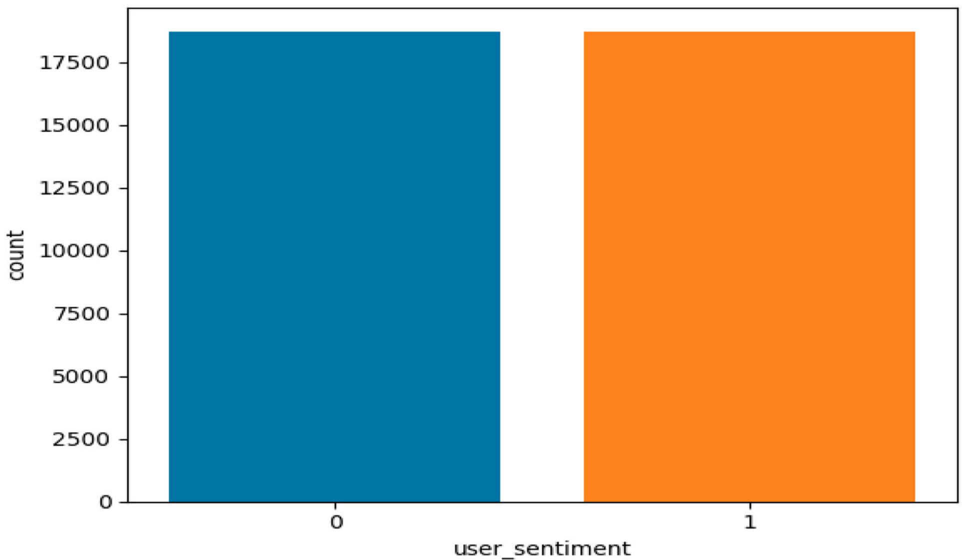

Figure 11. Class distribution after handling class imbalance.

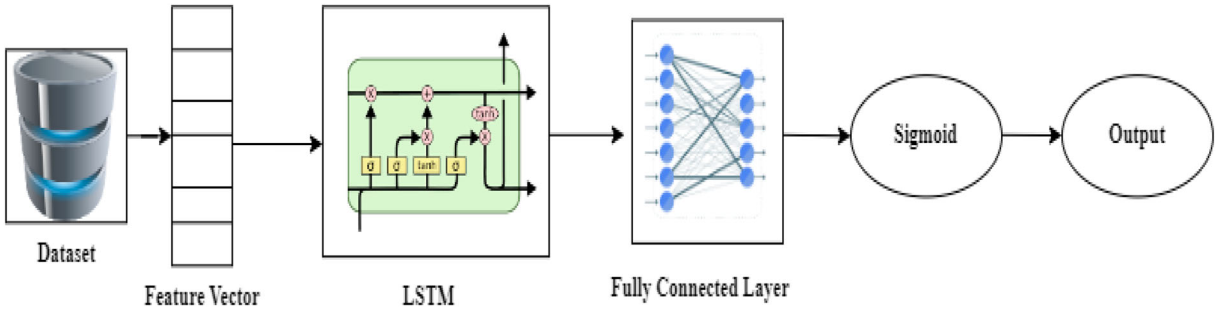

Figure 12. Block diagram of the suggested SA model.

3.5. Long Short-Term Memory (LSTM) for SA

SA was performed using the LSTM model. The SA model received the generated feature vector as input. The classification task is carried out by the LSTM model. Figure 12 illustrates the block diagram for the SA model.

Long Short-Term Memory is a type of recurrent neural network structure that is developed to effectively capture and understand the relationships and patterns present in sequential data [25]. Because of its unique capacity to store information over extended periods of time, LSTM is particularly well suited for modelling and predicting sequences with long-term dependencies. This is accomplished by the network using memory cells, which give it the ability to selectively recall or forget information at each time step. Figure 13 illustrates the LSTM framework. LSTM unit is comprised of three essential elements: the input gate, the forget gate, and the output gate. The gates present in the LSTM cell regulate the flow of information, enabling it to selectively process and retain important information while discarding redundant or irrelevant information.

The role of the input gate is to regulate the extent of new information that should be integrated into the cell state. To process the previous hidden state and the current input, the combination of the two is subjected to the sigmoid activation function. The sigmoid activation function plays a crucial role in determining the proportion of newly introduced data that gets incorporated into the cell state. The forget gate in an LSTM network determines which information from the previous cell state should be discarded or forgotten. The combination of the previous hidden state and the current input undergoes the application of the sigmoid activation function. The sigmoid activation function's output determines how much of each component of the cell state should be kept. In order to update the prior cell state, the forget gate is used in conjunction with the new data from the input gate. The responsibility of the output gate is to decide the extent to which information from the current cell state should be revealed as the hidden state. During the implementation of SA, the previous hidden state and the current input are passed through a sigmoid activation function for processing. The sigmoid activation function controls the amount of transformation that occurs from the cell state to the hidden state through the tanh activation function.

There are two LSTM layers in the proposed SA model. There are 128 units in the first LSTM layer. There are 128 units that regulate the quantity of internal memory cells. There are 64 units in the second LSTM layer. The complexity and capacity of the LSTM layer are controlled by the number of units (64). The output sequences from the first LSTM layer are passed onto the second layer, which returns a single output. After the LSTM layers, two additional Dense layers are included in the model. In the dense layer, every input unit is connected to every output unit, forming a FC layer. The dense layer utilizes the sigmoid function as its activation function. Table 2 contains a summary of the suggested model. Figure 14 displays the architecture of the model.

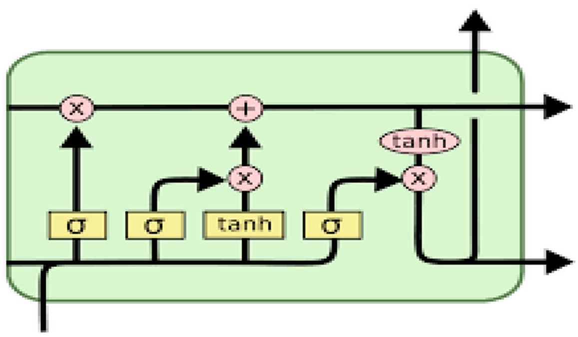

Figure 13. LSTM architecture.

3.6. Product recommendation system

A recommendation system for products is a form of filtering system that offers users product recommendation by taking into account their preferences, previous actions, and relevant data. It is commonly utilized to

Table 2. Model summary.

Total parameters	118,081
Trainable parameters	118,081
Non-Trainable parameters	0

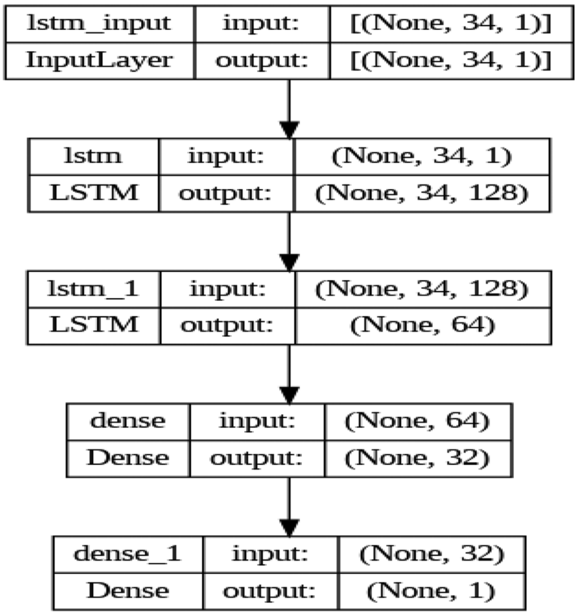

Figure 14. Proposed model architecture.

improve user experience, boost customer engagement, and boost revenues in e-commerce platforms, online marketplaces, and video streaming services. The SA model and CF are combined in the proposed product recommendation system. A user-based and also an item-based recommendation system is developed with the help of CF. User-based CF identifies similar users based on their historical interactions with items. In order to generate recommendations, it looks for people who have reviewed or bought similar things. It is possible to suggest products to a target user that they have not yet consumed but that are appreciated or preferred by users who are similar to them. According to previous user interactions, item-based CF finds similar items. It seeks out items that users have rated or purchased jointly and suggests products that are comparable to those already consumed by the target user. According to the theory, users are more likely to be interested in associated items if they liked a particular item. The SA model was integrated with the best recommendation system to enhance the predictions.

Collaborative filtering is a popular approach that generates personalized recommendations by analyzing the preferences and actions of a community of users. It assumes that individuals who have previously shared similar tastes and preferences will likely continue to do so in the future. In order to find patterns and similarities between users and items, the CF method makes advantage of historical user-item interactions. The CF approach does not require explicit knowledge of the traits or properties of objects or users. It just employs the observable interactions between users and the items. Since item qualities are not always readily available or when users' preferences change over time, it is especially helpful in these situations. The gathered data is used to create the user item matrix. The interactions between users and items are represented by this matrix, where each row is a user and each column denote an item. The elements in the matrix describe how the user interacted with the item, such as a rating or a binary value indicating whether the user interacted with the item or not. The subsequent stage involves determining the similarity between users or items within the user-item matrix by performing a comparison. Here, the similarity is determined using the cosine similarity measure. The cosine similarity of two vectors is calculated by considering the cosine of the angle formed between them. The value ranges from -1 to 1, where 1 means the vectors are the same, 0 means they have no similarity, and -1 means they are completely opposite. The cosine similarity is represented as follows:

$$\text{Cosine Similarity (M,N)} = \frac{(\text{M} \cdot \text{N})}{(\| \text{M} \| * \| \text{N} \|)} \quad (1)$$

where M • N denotes the dot product of vectors M and N. ||M|| and ||N|| represent the Euclidean norms (magnitudes) of vectors M and N, respectively.

The calculation of user similarity in user-based collaborative filtering relies on their interactions and preferences towards different items. One way to provide recommendations is by analyzing the behaviour of users who display similar patterns of interaction. Item-based collaborative filtering determines the similarity between items by considering the manner in which users engage with those items. It is possible to produce recommendations using items that are similar based on how frequently the same users interact with them. A neighbourhood selection stage is carried out after determining how similar two users or items are. This step involves choosing a subset of similar users or items that will be used to generate recommendations. Both the computational difficulty and the quality of the recommendations can be considerably influenced by the size of the neighbourhood. Once the neighbourhood has been chosen, suggestions can be produced based on the interests of users or products that are similar to them.

After careful consideration, the most appropriate recommendation system was selected to suggest 20 products that are highly probable for a user to purchase, considering their ratings. Finally, the SA model is combined with the recommendation system to improve the recommendations.

4. Results and discussion

4.1. *Hardware and software setup*

The suggested model was executed after the dataset has been prepared. The acquired dataset can be split into two distinct sets: a training set comprising 75% of the

Table 3. Hyperparameters.

Loss	Mean Squared Error
Optimizer	Adam
Activation function	Sigmoid
Batch size	64
Number of Epochs	300

Table 4. Performance parameters.

Performance metrics	Equation
Accuracy	$\frac{(Tp+Fp)}{(TP+FP+TN+FN)}$
Precision	$\frac{(TP)}{(TP+FP)}$
Recall	$\frac{(TP)}{(TP+FN)}$
F1-Score	$2 \times \frac{(Precision \times Recall)}{(Precision+Recall)}$

Where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

data, and a test set consisting of 25% of the data. The model was created, trained, and evaluated using LSTM on Google Collaboratory. Python and TensorFlow were used throughout the entire process. The Adam optimization method was used for prediction. The model trained for 300 epochs using a 64-batch size. The following Table 3 lists the hyperparameters that were used in this study.

4.2. *Performance parameters*

The effectiveness of the suggested DL model is determined using performance parameters. These metrics offer quantifiable evaluations of the model's effectiveness and assist in determining its ability to produce precise predictions. Below is a discussion of the most popular performance metrics (Table 4).

4.3. *Experimental results*

The model's functionality and convergence during training are revealed by the accuracy plot and loss plot. The accuracy plot provides a visual representation of how the model's accuracy changes throughout the training process for both the training and validation data. The accuracy of the training data often improves over time as the model learns the training examples. A loss plot shows the trend of the model's loss over the course of training epochs. The loss function evaluates the degree of alignment between the model's predictions and the actual values. In order to show that the model is capable of accurate prediction, the purpose of training is to minimize the loss. A declining loss over epochs in the figure indicates that the model is getting better at fitting the training set of data. Figure 15 shows the accuracy plot and loss plot of the suggested SA model.

The classification report serves as a comprehensive evaluation metric employed to assess the effectiveness of the model. It offers a number of crucial parameters, including precision, recall, and F1 score. Table 5 lists the collected performance metrics for the suggested SA model.

The suggested SA model got superior performance compared to existing SA model. The model obtained an accuracy of 98.43%. The graphical representation of the effectiveness of the suggested SA model is illustrated below (Figure 16).

Table 5. Performance of SA model.

Performance metrics	Obtained results
Accuracy	98.43%
Precision	99.27%
Recall	98.12%
F1-Score	98.69%

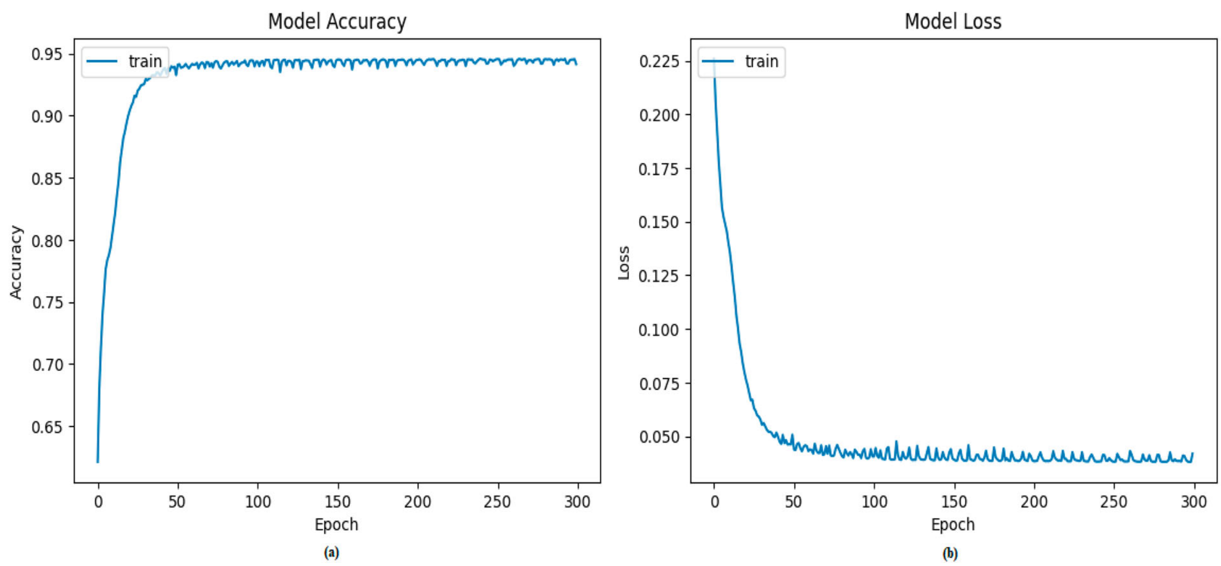

Figure 15. (a) Accuracy plot (b) loss plot of proposed SA model.

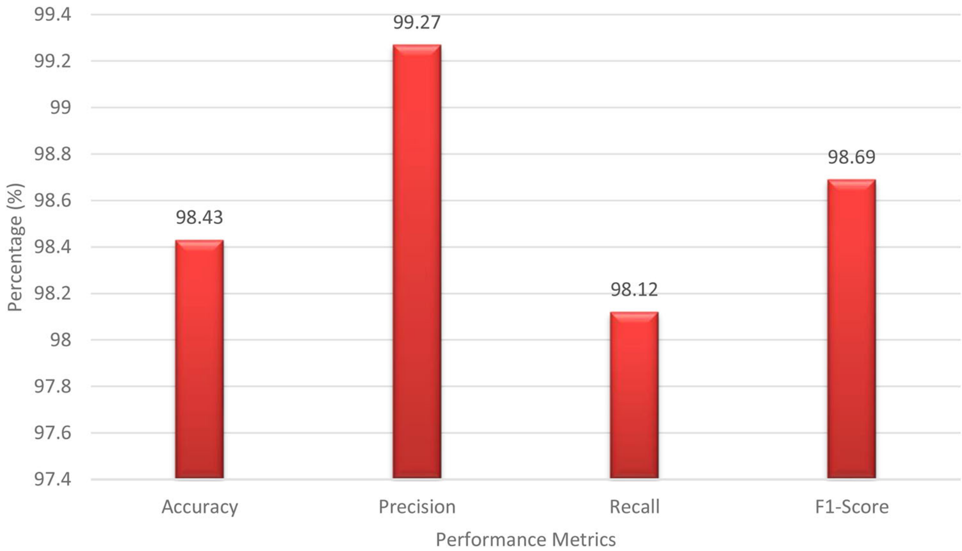

Figure 16. Performance comparison of proposed SA model.

```
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')
```

Figure 17. Top 20 recommendations.

Two different recommendation systems were developed using CF. The effectiveness of recommendation systems is assessed by employing Root Mean Square Error (RMSE) as a metric. The user-based recommendation system achieved an RMSE value of 1.99, while the item-based recommendation system yielded an RMSE of 3.58. It is better to choose the item-based recommendation system despite having a slightly higher rmse. Because there are 20,000 users and most of them have rated only a single product. Because of this, the user-based recommendation matrix is both enormously vast and sparse. Such a recommendation system won't give the user any helpful recommendations. The dataset only contains 200 items. The recommendation matrix was therefore compact and dense. As a result, the item-based recommendation system was chosen as the best one. The item-based recommendation algorithm suggests the top 20 products that are most likely to be purchased by a user. The outputs for recommendations are displayed below (Figure 17).

After analyzing the sentiments of the 20 recommended product reviews, the top 5 products have been identified and filtered out based on their positive reviews. The top 5 product recommendation after combined with SA model is tabulated below (Table 6).

The comprehensive summaries of the results attained from the experiments are discussed below.

- A product recommendation system based on SA and CF was introduced in this paper.

Table 6. Top 5 product recommendations.

	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	Chesters Cheese Flavored Puffcorn Snacks

- The collected dataset was preprocessed and converted into feature vector format.
- LSTM model was used as the base of the proposed SA model. The suggested SA model obtained superior performance.
- User-based and item- based recommendation systems was developed using CF.
- Item- based recommendation system was selected as the best recommendation system.
- The item- based recommendation system was combined with the proposed SA model for improving the recommendations.

5. Conclusion

A product recommendation system is essential in e-commerce for optimizing user experience, boosting consumer engagement, and boosting revenues. It aids consumers in navigating the enormous product selection, suggests pertinent products based on their likes and behaviour, and offers personalized recommendations. This paper proposed a SA and CF-based efficient product recommendation system. The system can comprehend and analyze the sentiment indicated in user reviews, feedback, or textual product data using SA. The system is able to determine user preferences and attitudes towards particular products by extracting sentiment information, such as positive or negative emotion. The LSTM model was used as the base of the SA model. CF, on the other hand, uses data about user-item interactions or data about item-item similarity to find patterns and offer recommendations. It examines the choices and behaviour of comparable users or products to create individualized recommendations. The product recommendation system can gain from both techniques by combining SA and CF. SA and CF can be combined to create a more potent product recommendation system that comprehends user sentiments, accurately records user preferences, and delivers personalized recommendations that are in line with users' emotional and practical demands. This combination raises user engagement and satisfaction levels, which eventually raises the possibility of effective product recommendations.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

[1] Olagunju T, Oyebode O, Orji R. Exploring key issues affecting African mobile ecommerce applications using sentiment and thematic analysis. IEEE Access. 2020;8:114475–114486. doi:10.1109/ACCESS.2020.3000093

[2] Ricci F, Rokach L, Shapira B. Recommender systems handbook. Vol. XVIINew York (NY): Springer; 2010. p. 1003. doi:10.1007/978-1-4899-7637-6

[3] McCarthy K, Salamo M, Coyle L, et al. Group recommender systems: a critiquing-based approach. Proceedings of the 11th international conference on Intelligent user interfaces. 2006: 267–269.

[4] Puerta Melguizo MC, Boves L, Deshpande A, et al. A proactive recommendation system for writing: Helping without disrupting. Proceedings of the 14th European conference on Cognitive ergonomics: invent! explore!. 2007: 89–95. doi:10.1145/1362550.1362569

[5] Burke R. Hybrid web recommender systems. In: Brusilovsky P, Kobsa A, Nejdl W, editors. The adaptive web. Lecture notes in computer science Vol. 4321. Berlin, Heidelberg: Springer; 2007. doi:10.1007/978-3-540-72079-9_12

[6] Li M, Wu H, Zhang H. Matrix factorization for personalized recommendation with implicit feedback and temporal information in social ecommerce networks. IEEE Access. 2019;7:141268–141276. doi:10.1109/ACCESS.2019.2943959

[7] Lydia Priyadharsini R, Lovelin Ponn Felciah M. Recommendation system in E-commerce using sentiment analysis. Int J Eng Trends Technol (IJETT). 2017;49(7):445–450.

[8] Naresh A. Recommender system for sentiment analysis using machine learning models. Turk J Comput Math Educ. 2021;12(10):583–588.

[9] Karthik RV, Ganapathy S. A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce. Appl Soft Comput. 2021;108:107396. doi:10.1016/j.asoc.2021.107396

[10] Dang CN, Moreno-García MN, Prieta FDL. An approach to integrating sentiment analysis into recommender systems. Sensors. 2021;21(16):5666. doi:10.3390/s21165666

[11] Devi DGL, Vallabhaneni SP, Singothu DJR. Performance evaluation of DLSARS framework in intelligent product recommendation systems; 2020. Available from SSRN: doi:10.2139/ssrn.3738862.

[12] Abbasi F, Khadivar A, Yazdinejad M. A grouping hotel recommender system based on deep learning and sentiment analysis. J Inf Technol Manage. 2019;11:2.

[13] Sahoo AK, Pradhan C, Barik RK, et al. Deepreco: deep learning based health recommender system using collaborative filtering. Computation. 2019;7(2):25. doi:10.3390/computation7020025

[14] Yi S, Liu X. Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. Complex Intell Syst. 2020;6(3):621–634. doi:10.1007/s40747-020-00155-2

[15] Almaghrabi M, Chetty G. A deep learning based collaborative neural network framework for recommender system. In: Howard D, Bashar MR, Rhee PK, editors. International Conference on Machine Learning and Data Engineering, iCMLDE 2018, Sydney, NSW, Australia; 2019. p. 121–127.

[16] Kumar S, De K, Roy PP. Movie recommendation system using sentiment analysis from microblogging data. IEEE Trans Comput Soc Syst 2020;7(4):915–923. doi:10.1109/TCSS.2020.2993585

[17] Hsu IC, Liao AH. (2022). Sentiment-based chatbot using machine learning for recommendation system.

[18] Negreț MA, Popescu PS, Mocanu M, et al. MusicBud: a music recommendation system based on deep learning algorithms.

[19] Priya SP, Karthikeyan M. Sentiment Neural Network (SNN)-for knowledge based recommender system.

[20] Khanvilkar G, Vora D. Sentiment analysis for product recommendation using random forest. Int J Eng Technol. 2018;7(3):87–89. doi:10.14419/ijet.v7i3.3.14492

[21] Yu J, An Y, Xu T, et al. Product recommendation method based on sentiment analysis. In: Web information systems and applications: 15th International Conference, WISA 2018, Taiyuan, China, Proceedings 15. Springer International Publishing; 2018. p. 488–495.

[22] Zhang J, Chen D, Lu M. Combining sentiment analysis with a Fuzzy Kano model for product aspect preference recommendation. IEEE Access. 2018;6:59163–59172. doi:10.1109/ACCESS.2018.2875026

[23] https://www.kaggle.com/datasets/deepthiar/product recommendation kaggle kernels pull shawamar/product-recommendation-system-for-e-commerce

[24] Liu C-Z, Sheng Y-X, Wei Z-Q, et al. Research of text classification based on improved TF-IDF algorithm. In: 2018 IEEE international conference of intelligent robotic and control engineering (IRCE), Lanzhou; 2018. p. 24–27. doi:10.1109/IRCE.2018.8492945

[25] Sherstinsky A. Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network. Phys D Nonlinear Phenom. 2020;404:132306. doi:10.1016/j.physd.2019.132306