



Article

Advanced large language models for text analytics and consumer opinion analysis

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ARTICLE INFO	ABSTRACT
<i>Article history:</i> Received 25 August 2026 Received in revised form 06 October 2026 Accepted 22 October 2026 Keywords: Sentiment analysis, Product reviews, BERT Model, Text preprocessing, Machine Learning classification, E-commerce *Corresponding author Email address: nileshjainmca@gmail.com DOI: 10.55670/fpjl.fdtai.3.1.1	Large e-commerce sites receive many customer reviews, offering valuable insights into consumer experiences, preferences, and opinions. However, unstructured, high-volume review text makes manual analysis inefficient. This study introduces a Textual Analysis and Consumer Sentiment Classification Approach based on a BERT framework, using the Amazon customer review dataset of 30,841 reviews. The proposed structure handles cleaning, tokenization, feature preparation, class balancing, contextual representations, and BERT-based sentiment classification. The data is first stratified to ensure the two classes are evenly distributed, then split 80/20 into training and testing sets. Then, only the training data is balanced using SMOTE. The BERT model is trained to understand word context and categorize reviews by sentiment. The experimental results show the proposed model has an accuracy (ACC) of 95.94%, precision (PRE) of 95.91%, recall (REC) of 95.97%, and F1 score (F1) of 95.92%. The results show that BERT can model context-aware information in customer reviews and automatically classify sentiment and extract valuable insights from customer feedback in large-scale e-commerce scenarios.

1. Introduction

The rise of online marketplaces like Amazon in the modern digital age has led to a deluge of user-generated content, including reviews and comments on products sold on these sites [1]. Consumer feedback is helpful in determining the product's quality, user satisfaction, experience, and preferences. Sentiment analysis, a branch of NLP sometimes called opinion mining, aims to find, extract, and categorize opinions represented in textual data [2,3]. It helps organizations understand customer satisfaction, public opinion, market trends, and consumer preferences to make informed decisions [4,5]. Product ratings are limited to numerical scores, while product reviews include detailed information about product features, drawbacks, experiences, and expectations in users' natural language [6,7]. Businesses may use these reviews to determine whether a review is positive, negative, or neutral, as well as the reasoning behind the review's attitude. For instance, companies may pinpoint customer complaints about product quality, efficacy, durability, price, and customer service. This data can guide product development, marketing tactics, and consumer satisfaction [8-10].

Demand for efficient, scalable text analytics systems has risen with the growth of user-generated content on blogs, social media platforms, e-commerce websites, and other platforms [11,12]. Lexicon-based techniques, bag-of-words representations, n-gram features, and part-of-speech information have been used to create useful foundations for opinion classification. However, these methods sometimes struggle to capture long-range linkages, semantic ambiguity, denial, sarcasm, and small differences in consumers' expressions. Therefore, advanced natural language processing methods are needed to extract contextual and semantic features from large amounts of unstructured review data and turn them into meaningful consumer insights [13-15].

Advances in ML and DL in recent years have greatly improved text analytics and sentiment analysis. DL and ML models can learn complex representations from text, with the latter especially effective at classifying customer perspectives based on extracted textual attributes [16]. Recent transformer-based architectures and LLMs have enabled approaches that achieve a deeper understanding of complex language [17-19]. This project aims to enhance Advanced LLMs for Text Analytics and Consumer Opinion Analysis to better identify, classify, and understand customer text input.

1.1 Motivation and contribution

The growing volume of consumer evaluations on e-commerce platforms, along with the need for automated techniques to extract insightful comments from unstructured text data, prompted this study. Language nuances can confound traditional sentiment analysis techniques, including complex linguistic structures, semantic ambiguity, and contextual relationships. Accordingly, this work proposes a framework for contextual text analysis and consumer sentiment classification using BERT. This work mostly adds the following:

- The development of an automated framework for analyzing and categorizing consumer reviews using BERT.
 - The review data is improved in quality and consistency by using a text processing system.
 - Class balancing is used to reduce the effect of training-related emotion class imbalance.
 - Semantic and contextual linkages in customer review content may be detected using BERT.
 - The proposed model is evaluated using the following metrics: PRE, ACC, REC, and F1.
 - The efficacy of the suggested technique is compared to that of traditional ML and DL models.
 - A realistic method for extracting customer sentiment from massive e-commerce comment datasets is provided by the framework.
- This study is justified by the need for scalable, automated analysis of the rapidly increasing volume of unstructured customer feedback. The contextual linkages within review text may be difficult for traditional ML algorithms to capture since they rely so much on human-generated or superficial textual representations. This research adds to the literature by analyzing Amazon customer reviews using a BERT-based contextual representation framework that incorporates systematic text preprocessing and class-balancing techniques. The framework aims to improve the accuracy of computer-generated user sentiment categorization and support data-driven decision-making in e-commerce apps.

1.2 Structure of the research

The paper is structured as follows: Section II reviews the literature on text analytics and COVID-19 customer opinion surveys. Section III covers the dataset, preprocessing procedures, data-balancing approach, and recommended BERT-based methodology. Section IV presents experimental outcomes and comparative analysis. Section V concludes the paper with a brief synopsis of the main ideas, a discussion of the study's limitations, and recommendations for future research.

2. Literature review

A comprehensive literature review was conducted to identify key studies, methods, and results on textual analysis and consumer opinion assessment, laying a solid foundation for the current study.

In Dey et al. [20] research, the framework extracts ACOIS and DCOIS sentiment quintuples using transformer-based multi-head attention and part-of-speech tagging to identify product aspects and experiential dimensions. These insights are used to build a consumer brand ranking algorithm that doesn't need labeled training data, a folksonomy approach. Comparative results show F1 improvements of 9%, 6%, and 4% for extracting product aspects, dimensions, and opinions, respectively. When using new and refurbished laptops in the same price range, 40% of refurbished models were among the top 25% of recommendations. The framework proved robust and stable through McNemar's test results, ablation studies, and benchmark comparisons.

T.N.P.Nalini et al. [21] proposed an ML-based approach to customer sentiment analysis of the Lluvia bike products from social media, e-commerce reviews, and customer service data. It integrates TF-IDF, static embeddings, RF, SVM, and transformer-based contextual embeddings, including optimized BERT embeddings. The framework achieves 90.8% ACC, 89.7% PRE, 88.9% REC, and 89.3% F1. It also achieves robustness on positive (93.1%), negative (90.5%), and neutral (91.2%) samples, and performs aspect-level sentiment analysis for performance, pricing, design, and durability. The architecture is data-driven, scalable, and interpretable, which enables product design, consumer loyalty, and strategic business decisions.

Rongala et al. [22] presented an overview of the ML-based and NLP-based techniques for analyzing Amazon product reviews and deriving key attitudes, tastes, and trends. BERT also achieved the best performance in sentiment categorization and review analysis with 89% ACC, 88% PRE, 88% REC, and 89% F1. These results demonstrate sophisticated NLP systems' ability to handle a wide range of complex customer feedback and meet requests and expectations. AI-driven approaches highlight the importance of consumer feedback analysis for business decisions and strategies.

Murugan et al. [23] noted that traditional sentiment analysis methods often fail to capture emotional nuance, sarcasm, and context, and require higher-level methods. A problem with the existing approach is that it cannot handle distorted or noisy data and is not sensitive to small mood changes. The proposed system incorporates a wide range of state-of-the-art DL architectures, including transformer models, LSTM networks, and RNNs. The results highlight advanced sentiment analysis capabilities that surpass existing systems, with an ACC of 94%, 93% PRE, 91% REC, and 93% F1, while improving computational efficiency and emotion classification across sentiments.

Padate et al. [24] proposed a new method for identifying the emotional content of WhatsApp messages using unsupervised ML. It uses NLP to preprocess the text and the PMI algorithm to categorize messages into six main emotions: joy, anger, sorrow, fear, disgust, and surprise. When evaluated on a batch of WhatsApp messages, the model achieved a PRE rate of 92.75%. This method works well with informal language and slang and demonstrates real-world emotional detection from text.

Abraham et al. [25] suggested aspect-based sentiment analysis to guide consumers' purchasing decisions and help manufacturers understand consumer needs. It focuses on identifying and extracting specific review aspects for feature-based opinion analysis. We identify the required features using a DT classifier, a supervised ML method. Next, several ML techniques are used to perform sentiment analysis on these elements. With this plan, we can achieve an ACC of 85-93%. Table 1 summarizes recent research on textual analysis and consumer opinion evaluation, including the models employed, the data used, the conclusions drawn, and the limitations of past work.

Table 1. Previous research on LLM models for textual analysis and consumer opinion evaluation

Author	Proposed Work	Dataset	Key Findings	Limitations & Future Work
Dey, Jenamani and De [20]	Transformer-based multi-headed attention framework for extracting product aspects, dimensions, opinions, irrealis, and sentiment using ACOIS/DCOIS quintuples and brand ranking.	Curated a new and refurbished laptop review dataset within the same price segment.	Improved F1-score by 9%, 6%, and 4% for product aspects, dimensions, and opinions; 40% of refurbished brands appeared in the top 25% recommendations.	Requires further validation across broader product domains and datasets to establish wider generalization.
T. N. P. Nalini, N. Sathiyendran and S. [21]	ML-based customer sentiment analysis using SVM, Random Forest, and fine-tuned BERT with TF-IDF, embeddings, and contextual representations.	Lluvia Bike data from social media, e-commerce reviews, and customer-service sources.	Achieved 90.8% accuracy, 89.7% precision, 88.9% recall, and 89.3% F1-score; strong aspect-level sentiment detection.	Future work can investigate more advanced LLMs and larger multilingual consumer-review datasets.
Rongala et al. [22]	NLP and ML framework for extracting consumer attitudes, preferences, and trends from Amazon product reviews using BERT and other approaches.	Amazon product review dataset.	BERT achieved 89% accuracy, 88% precision, 88% recall, and 89% F1-score, outperforming other approaches.	Further improvement is required for complex, heterogeneous, and domain-specific consumer opinions.
Murugan et al. [23]	Advanced sentiment-analysis framework integrating RNN, LSTM, and transformer architectures for contextual emotion and sentiment identification.	Diverse textual sentiment/emotion data.	Reported 94% accuracy, 93% precision, 91% recall, and 93% F1-score, demonstrating improved sentiment classification.	Better handling of sarcasm, noisy text, subtle emotions, and contextual variations is needed.
Padate et al. [24]	Unsupervised NLP-based emotion detection using a PMI-based approach to classify six basic emotions in informal messages.	WhatsApp text-message corpus.	Achieved 92.75% precision and demonstrated effectiveness for informal language and slang.	Limited focus on consumer opinions and advanced transformer/LLM-based analysis.
Abraham, Udaya Kumar Reddy and Abraham [25]	Aspect-based sentiment analysis using decision-tree-based aspect selection and machine-learning techniques for opinion analysis.	Consumer review text.	Reported accuracy ranging from 85–93% for sentiment/opinion analysis.	Greater contextual understanding and improved aspect extraction using transformer-based/LLM approaches are potential future directions

Research gaps: Previous research has applied ML and transformer-based models to sentiment analysis. However, challenges remain in handling the complex contextual links in customer reviews. Most current methods are limited in scope, i.e., specific to a particular domain or analysis level, such as aspect-level. Advanced contextual modeling, along with systematic preprocessing and proper class balancing, is also not yet widely used. To overcome these shortcomings and derive useful insights from Amazon customer evaluations, we developed a BERT-based framework.

3. Research methodology

The proposed methodology begins by downloading Amazon Customer reviews from Kaggle, then preprocessing the text by removing special characters, URLs, hashtags, and stop words, and by stemming and tokenizing. The next step is to balance the emotion classes after normalizing the features using Min-Max. To split the dataset for training and testing, stratified sampling is used. To assess performance, the proposed BERT model performs sentiment classification and contextual text analysis. It then uses ACC, PRE, REC, F1, and ROC analysis. Figure 1 illustrates the proposed technique for textual analysis and evaluation of consumer opinion. The following section thoroughly describes each step of the proposed methodology.

3.1 Data gathering and analysis

This study used datasets collected from Amazon reviews on Kaggle, covering customer reviews across various product categories. The dataset included 30,841 reviews rated as either good or bad. The sentiment distribution, with bar plots, and the relationships among the extracted features, with correlation heatmaps, were analyzed. The corresponding visualizations are presented below in Figure 1.

Figure 2 shows the sentiment distribution of the customer review dataset, with negative and positive sentiments shown in red and blue, respectively. The bar chart shows a clear difference in the number of reviews across the two sentiment categories. Overall, the visualization highlights the sentiment distribution of the collected customer reviews. Figure 3 is a word cloud displaying the cleaned text's most frequent terms, including "item," "amazo," "delivery," "service," and "order". It suggests that the reviews are largely product, order, delivery, refunds and customer service related. Other terms such as "return", "seller", "money", "problem", and "received" also reflect customers' perception of buying and services.

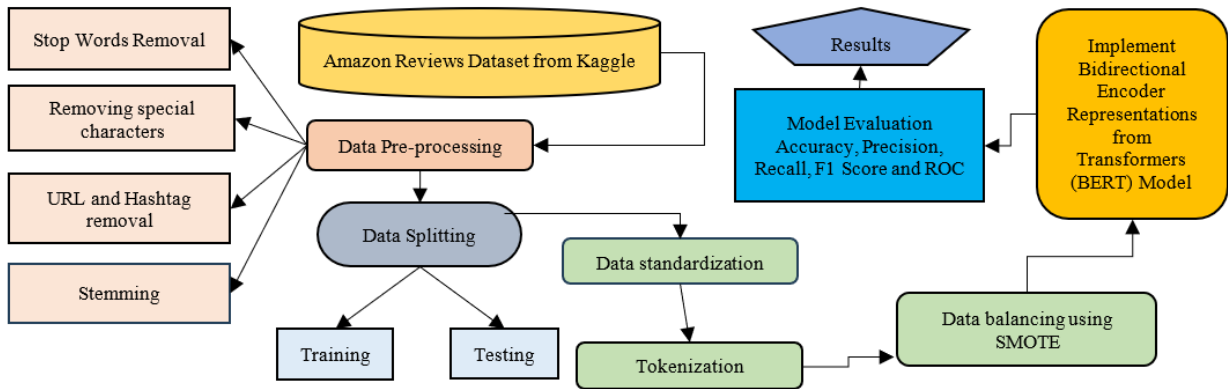


Figure 1. Workflow of the proposed text-based consumer opinion analysis framework

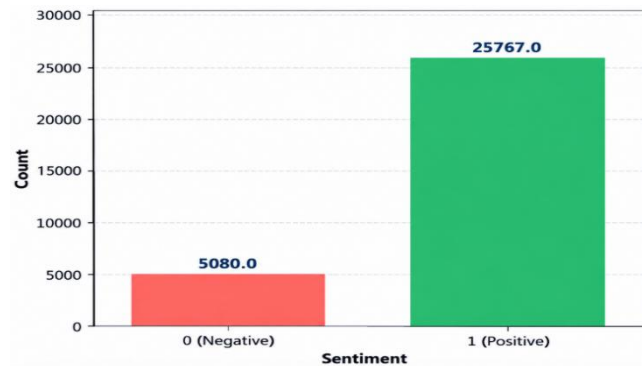


Figure 2. Bar graph of the sentiment distribution of customer reviews



Figure 3. Word cloud of the reviews

3.2 Data pre-processing

Data preparation involved cleaning and removing extraneous material from raw text data to make it usable. The preprocessing methods included URL filtering, hashtag removal, special character removal, stop word removal, stemming, and tokenizing. Lastly, data standardization was implemented to ensure uniformity and improve the quality of the processed data for subsequent analysis. The main preprocessing procedures are summarized as follows:

- **Stop Words Removal:** The process of removing stop words is doing just that: removing terms like "is," "am," "a," "an," etc., from search queries.

- **Removing special characters:** To ensure accurate categorization, special characters like \$ should be removed from feelings. If they aren't removed, special characters could blend in with the text, making them indistinguishable.
- **URL removal:** Since URLs are not useful for determining the tone of data, they are removed from the data.
- **Hashtag removal:** Removing the hashtag from the data and saving it separately improves feature extraction. At a later stage, you may use the hashtag's weight.
- **Stemming:** The stemming process simplifies and expedites the process by reducing words to their root words. Examples include quick, quick, and faster.

3.3 Data Splitting

A stratified partition with an 80:20 ratio was used to split the dataset into training and testing sets. This preserved the relative class distribution between the two subsets, so the class proportions were the same in both subsets as in the total dataset.

3.4 Data standardization

The feature scales of the accident data vary; hence, standardizing the data is crucial. The feature values may be transformed to a range between [0,1] using min-max normalization. This lessens the effect of outliers and makes the data comparable across datasets. Using min-max normalization to standardize feature data improves the stability and ACC of several ML methods. This is how min-max normalization is calculated:

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

The normalized data point is denoted by X_{new} , where the value usually falls between 0 and 1. X is the original data value. X_{min} and X_{max} are the minimum and maximum values of the feature, respectively.

3.5 Tokenization

Tokenization is a method for analyzing and evaluating customer opinions by dividing text into individual words or meaningful subword units. Splitting a long word string into its component parts—keywords, phrases, words, symbols, and so on—is known as de-structuring. Anyone can call software that does tokenization a tokenizer, lexer, or scanner.

3.6 Data balancing using synthetic minority over-sampling technique (SMOTE)

Data balancing is an important data pre-processing strategy used to reduce class imbalance and ensure a fair representation of each class in the data. This research used SMOTE to generate additional synthetic observations for the minority class rather than just replicating the data. Minority samples are the only ones for which the algorithm determines nearest neighbors using Euclidean distance, and it generates new minority samples by interpolating between selected samples and their neighbors. The training data set is then updated to include these observations, leading to a more balanced class distribution and improved learning for the ML model. Figure 4 shows the sentiment dataset's class distribution after SMOTE balancing. Positive and negative feelings have an identical number of sentiment classes (12150). This balanced distribution improves sentiment classification reliability and reduces class bias.

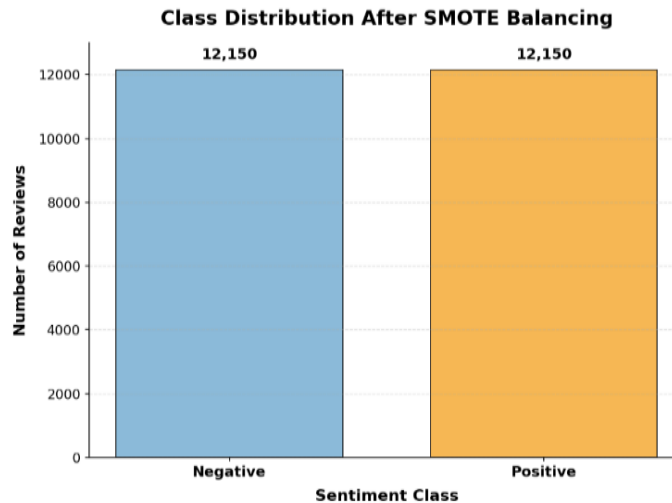


Figure 4. Bar graph of class distribution after SMOTE

3.7 Proposed bidirectional encoder representations from transformers (BERT) model

This study introduces a BERT model to analyze textual opinions and evaluate consumer opinions. To tokenize the input text, BERT uses a specialized tokenizer. BERT creates the token IDs after converting the text into tokens using a unique tokenizer. BERT uses self-attention networks to identify the connections between the words in a phrase or sequence. The design is based on the Transformer architecture. By combining self-attention with many layers of feedforward neural networks, this architecture generates a deep model capable of understanding complex patterns in user-supplied text. Next Sentence Prediction (NSP) and Masked Language Modeling (MLM) are two unstructured tasks that BERT was pre-trained on using a large amount of text. The number of layers and hidden units determine the size, which comes in wide varieties. When each tokenized user review passes through BERT, it produces a high-dimensional contextual embedding that describes each word's meaning in the full review. Aggregation methods such as max pooling and mean pooling can compress the token embeddings into a fixed-size representation. The BERT self-attention mechanism can be mathematically represented as: Each pair of input tokens x_i and x_j is used to calculate the attention score α_{ij} by BERT, which is given as $x_1, x_2, x_3 \dots \dots x_n$. The formula used to determine this attention score is:

$$\alpha_{ij} = \text{softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right) \quad (2)$$

The dimensionality of the key vectors is denoted by dk , the softmax function is used to normalize the attention scores across all tokens, and Q_i is the query vector for token x_i . K_j is the key vector for token x_j . BERT creates context-aware representations of each token and captures their significance inside the input sequence by computing attention ratings for each token and using them to produce a weighted sum of all token values. Equation (3) represents a feedforward neural network.

$$\text{FFN}(x) = \text{ReLU}\left((x)W_1 + b_1\right)W_2 + b_2, \quad (3)$$

Equation (4) provides the layer's normalization, where b_1 and b_2 are the bias vectors and W_1 and W_2 are the weight matrices for the feed-forward network's first and second layers.

$$\text{LayerNorm}(x) = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (4)$$

where μ stands for the input vector's mean, σ^2 for its variance, and ϵ is a constant. With a learning rate of 0.00002, a batch size of 16, the AdamW optimizer, a maximum sequence length of 128, and a dropout rate of 0.10, the suggested BERT model completed 100 training iterations. The model used two warm-up epochs and a weight decay of 0.01 to reduce overfitting and improve training stability. These hyperparameter settings were selected to support effective contextual learning and reliable sentiment classification of Amazon customer reviews.

3.8 Evaluation metrics

The suggested architecture was evaluated using multiple performance metrics. The provided data can be divided into four potential outcomes: TN, FN, TP, and FP. TP data is clearly positive and indicated as such, whereas FN data is clearly negative and marked as such. TN data is marked and classed as negative, whereas FP data is tagged as positive. The following is a breakdown of how these parameters were utilized to calculate the F1, REC, ACC, and PRE, four crucial performance measures in Equations (5 to 8).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (7)$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

The model's performance was evaluated using the ACC, PRE, REC, F1, and ROC curves. ACC measures the percentage of cases in the dataset correctly categorized. The percentage of accurate identifications among all positive instances is the pre-identification rate (RE), and the ratio of accurate positive predictions to all positive predictions is PRE. To get a fair measure of classification performance, F1 takes the harmonic mean of PRE and REC and assigns it a number between 0 and 1. ROC plots the values of TPR (or REC) against FPR (or 1 minus Specificity) to show how well the model performs at various decision thresholds.

4. Results and discussion

This section describes the proposed BERT model for textual analysis and consumer opinion evaluation, along with its experimental design and evaluation. The studies were carried out on a powerful computer system that has an Intel Core i9-13900K CPU (3.0 GHz), 64 GB of DDR5 RAM, and Windows 11 Pro. Tools including Pandas, NumPy, Matplotlib, Seaborn, and Scikit-learn were utilized for data processing, visualization, and assessment. The Amazon Reviews Dataset was used to train the suggested BERT model, which was then assessed using metrics including ACC, PRE, REC, and F1.

BERT achieved strong, balanced classification performance, as shown in Table 2, with an ACC of 95.04%, PRE of 95.01%, REC of 95.07%, and F1 of 95.22%. These results show that the BERT model is a strong tool for analyzing text and gauging customer sentiment.

Table 2. Classification results of the proposed model for textual analysis and consumer opinion evaluation

Matrix	BERT
Accuracy	95.94
Precision	95.91
Recall	95.97
F1-score	95.92

Figure 5 shows the BERT model's training and testing ACC over 100 epochs. The curves in both graphs show rapid improvement in the first few epochs, then gradual stabilization as epochs increase. The testing curve shows slight fluctuations during training. Figure 6 shows the BERT model's training and testing loss over 100 epochs. The training loss gradually decreases as epochs increase, reflecting ongoing model optimization. The testing loss also declines initially and fluctuates in later epochs. Figure 7 depicts the ROC performance of the BERT model, with the corresponding TPR graph plotted against the FPR. The BERT curve remains in the upper-left corner, indicating strong classification performance. The dashed diagonal line shows random classification, but the BERT curve shows it performs better at discrimination.

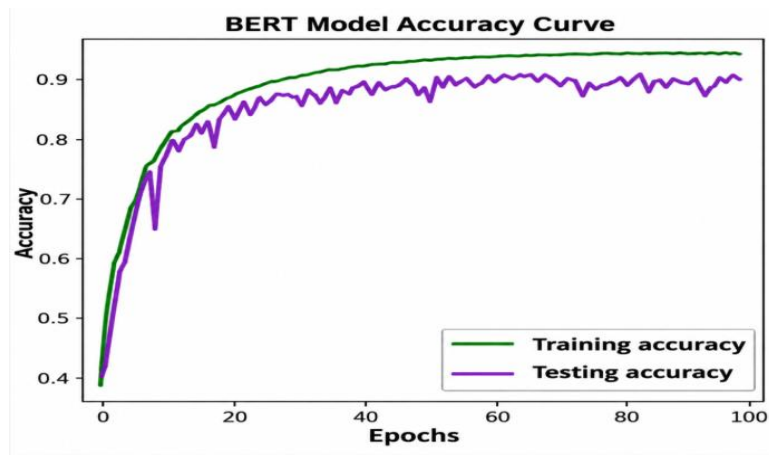


Figure 5. Accuracy curve for the BERT model

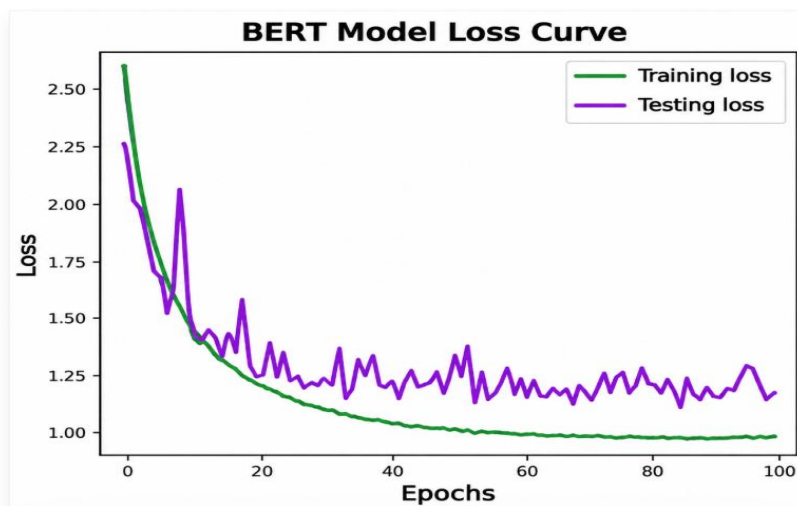


Figure 6. Loss curve for the BERT model

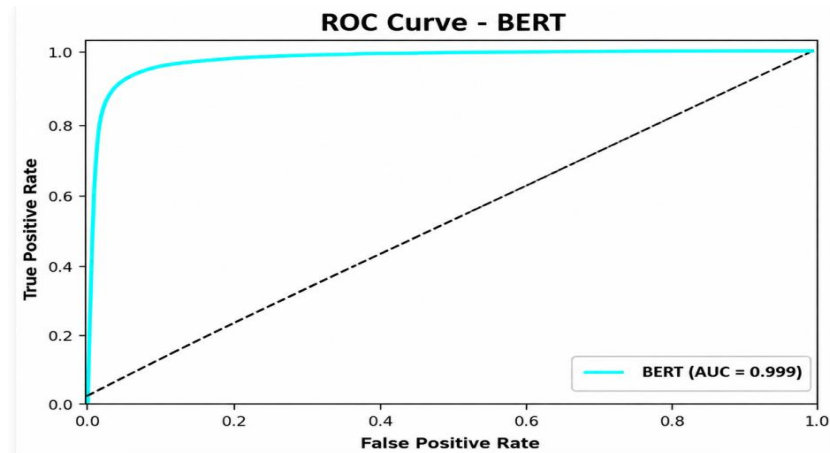


Figure 7. ROC curve for the BERT model

4.1 Comparative analysis

Table 3 evaluates the proposed BERT model's efficacy by comparing its ACC with that of other current models. The findings show that the suggested BERT model has the highest ACC (94.94%), PRE (94.91%), REC (95.07%), and F1 (95.22%). Comparison scores are as follows: RF 93.56% ACC, LSTM 92.90%, AdaBoost 83.43%, and LR 81.90%. The proposed BERT model also achieves better PRE, REC, and F1 values than the existing models, demonstrating its competence in textual analysis and consumer opinion estimation.

Table 3. Performance comparison of machine learning and deep learning models for textual analysis and consumer opinion assessment

Model	Accuracy	Precision	Recall	F1-score
LR [26]	81.9	87	88	88
AdaBoost [27]	83.43	79	84	81
LSTM [28]	92.9	92.5	92.9	92.5
RF [29]	93.56	94.8	99.3	97
Proposed BERT	95.94	95.91	95.97	95.92

The proposed BERT model achieves a remarkable ACC of 95.94%, demonstrating its effectiveness for textual analysis and consumer opinion assessment. Its transformer-based structure is better suited to encoding contextual relationships and semantic meaning than conventional ML methods. BERT is trained to understand complex language structures and variations in consumer reviews, improving sentiment classification accuracy. Thus, the proposed model can be a solid, trustworthy system for extracting useful information from consumer opinions expressed in text.

5. Conclusion

Sentiment analysis uses NLP to extract data, opinions, reviews, or statements and determine the emotion of the statement. Sentiment analysis entails dividing content into three classes: "positive," "neutral," or "negative. It affects many people and businesses worldwide. Sentiment analysis is a vital task in NLP, especially in e-commerce, where insights into customer sentiment can shape business decisions. It explores applying advanced text-processing and DL techniques to extract customer opinions from a dataset of Amazon product reviews. The proposed BERT model achieved the highest ACC of 95.94%, outperforming LR (81.90%), AdaBoost (83.43%), LSTM (92.90%), and RF (93.56%). The results show that BERT outperforms the others by better capturing the context of customer reviews. So, this method offers a solid foundation for e-commerce data-driven decision-making and for gaining valuable customer insights. Future work on the review datasets might include a larger, more multilingual sample from other e-commerce platforms, allowing further expansion of the suggested framework. Future work may explore using sophisticated transformers and LLMs to identify sarcasm, opinions, and complex language structures. Sentiment analysis and Explainable AI can also be applied to improve understanding and application of consumer opinions.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically concerning authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The author declares no potential conflict of interest.

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