# Context-Aware Product Review Sentiment Analysis with SBERT Representations and Boosted Rules Classifier

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## ABSTRACT

The rapid expansion of the global e-commerce industry, projected to exceed USD 7 trillion by 2030, has intensified the importance of customer reviews in influencing purchasing decisions, with over 80% of consumers relying on online feedback. However, manually analyzing large volumes of product reviews is inefficient, inconsistent, and impractical for timely business insights. Traditional sentiment analysis techniques often fail to capture contextual semantics and struggle with imbalanced data distributions. To address these challenges, this study proposes a robust Natural Language Processing (NLP) framework for automated product sentiment analysis using annotated review datasets. The pipeline begins with comprehensive text preprocessing and Exploratory Data Analysis (EDA) to clean, normalize, and understand review patterns. Context-aware semantic representations are then generated using Sentence Bidirectional Encoder Representations from Transformers (SBERT), which effectively capture sentence-level meaning and relationships compared to conventional feature extraction methods. To mitigate class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is employed to create balanced training samples. Unlike baseline models such as Random Forest Classifier (RFC), Light Gradient Boosting Machine (LGBM), and Extreme Gradient Boosting (XGB), the proposed system integrates Deep Neural Network (DNN)-based feature selection with a Boosted Rules Classifier (BRC), enhancing both predictive accuracy and model interpretability. The framework classifies sentiments into Negative, Neutral, and Positive categories, enabling precise understanding of customer opinions. Experimental results demonstrate improved performance, scalability, and reduced bias, providing actionable insights that support product development, targeted marketing, and customer engagement strategies.

**Keywords:** E-commerce, Sentiment analysis, Natural Language Processing, BERT architecture, Boosted rules classifier.

## 1. INTRODUCTION

The last decade has shown a significant increase in the availability of product reviews on traditional retail sites in both professional and individual formats. To reduce the uncertainty associated with purchasing products, users consult these reviews and pay attention to online information such as images. According to a research study, most users prioritize customer reviews before making a purchase [1]. In other words, nearly 90% of consumers check reviews before buying a product. Reviews are becoming increasingly important for both consumers and businesses. For consumers, online reviews are crucial in deciding whether or not to purchase a product [2]. Exclusive online retailers are focusing on improving the management of reviews, understanding that positive reviews can significantly impact profit gains, and creating an environment where customer reviews are an integral part of the business.

Amazon is a multinational technology corporation specializing in e-commerce, where reviews are crucial for purchasing decisions, providing vital and genuine insights. However, reading through all the reviews of a chosen article can be time-consuming. Reviews are not only important for buyers but also for vendors, who rely on them to differentiate and promote their products. In the context of business growth and customer care, online ratings play a significant role. Customers can easily assess a product's appeal by reviewing its ratings. The decision to purchase a product often depends on its ratings and reviews, which can create a positive or negative impression. Most research in this area has utilized online feedback from Amazon to predict review helpfulness [3], with each review accompanied by data indicating the number of people who found it helpful. In the field of e-commerce, product ratings have become increasingly important. The significance of review ratios has increased during the COVID-19 pandemic, which began in 2020, as commercial transactions have shifted towards being conducted electronically over the internet. This shift has led to a 43% increase in the ratio of online reviews, and it continues to rise over time. Reviews offer a time-saving way to purchase products, as ratings provide helpful and valuable recommendations [4]. On the other hand, sellers are also interested in review analysis to understand customer interests better and achieve successful product sales. Researchers have increasingly focused on predicting the helpfulness of reviews by employing a range of Machine Learning (ML) methods. Machine learning aims to identify significant patterns and gain knowledge from data. Information overload on internet review sites has significantly hindered buyers' ability to assess product or business quality when making purchases. The growth of social media has made it harder to differentiate between genuine content and advertising, leading to a surge in misleading evaluations in the market. The usefulness of a review depends on a voting mechanism. The exponential growth of online shopping has transformed customer behavior, with product reviews serving as a crucial factor in influencing purchasing decisions. Reports show that 95% of shoppers read online reviews before buying, and businesses with higher review ratings experience an average 18% increase in sales [5]. Given the volume of reviews generated daily across platforms, manual sentiment interpretation becomes impractical. Organizations require scalable and intelligent solutions to automatically analyse sentiments, providing insights into customer satisfaction, product performance, and service improvement opportunities. Sentiment analysis has thus become an indispensable tool for e-commerce and retail industries in enhancing decision-making and building customer trust.

## 2. LITERATURE SURVEY

Recent advancements in sentiment analysis (SA) and product quality detection have shifted from traditional machine learning to hybrid deep learning architectures and transformer-based models.

### 2.1 Hybrid and Lexicon-Enhanced Models

Several researchers have sought to overcome the limitations of pure data-driven models by integrating linguistic knowledge. Ullah et al. [5] introduced QLeBERT, which combines an appraisal framework-based lexicon with BERT and BiLSTM to predict product quality, achieving an F1-score of 0.91 on Amazon reviews. Similarly, Mutinda et al. [8] proposed LeBERT, which integrates sentiment lexicons and N-grams with CNNs to address the inability of standard embeddings to capture sentimental orientation. Yuan et al. [12] further enhanced feature extraction through the SAC-BiLSTM model, which utilizes dual-channel character and word-level embeddings alongside self-attention mechanisms.

### 2.2 Comparative Studies and Benchmarking

A significant body of work focuses on benchmarking embedding techniques across diverse architectures. Bellar et al. [6] conducted an extensive comparison of CNN, RNN, and BiLSTM models using BERT, FastText, and Word2Vec embeddings for clothing retail reviews. Sabbeh et al. [7] expanded this by comparing classical (GloVe, Word2Vec) and contextualized (ARBERT) embeddings, noting that BiLSTM generally outperforms CNN on larger datasets, while BERT remains the most robust embedding overall. Ali et al. [9] corroborated these findings through a multi-algorithm study on Amazon reviews, where BERT achieved a superior accuracy of 89% compared to ensemble and traditional ML methods.

### 2.3 Domain-Specific and Multilingual Applications

Research has also branched into specialized domains and languages. In the Arabic context, Almaqtari et al. [11] proposed the Arb-MCNN-Bi model, which leverages AraBERT and BiGRU to achieve high accuracy (up to 96.92%) across multiple Arabic datasets. In the agricultural sector, Cao et al. [13] improved the BERT architecture using speech rules to extract consumer demands, while Liu et al. [15] utilized attention-based LSTM gates to manage the context-sensitive nature of agricultural reviews. Beyond typical commerce, Saxena et al. [10] applied FinBERT and Explainable AI (XAI) to environmental and ESG metrics, achieving 99% sentiment classification accuracy. Finally, Dang et al. [14] demonstrated that integrating these deep learning-based sentiment insights can significantly improve the performance of collaborative filtering in recommendation systems.

## 3. PROPOSED METHODOLOGY

The proposed system transforms raw product review text into accurate, context-aware sentiment predictions using a combination of semantic embeddings, deep feature extraction, and rule-enhanced classification. At a high level, it first preprocesses the data to clean and standardize text, then converts it into dense SBERT embeddings that capture rich contextual meaning. These embeddings are further refined using a deep neural network to extract high-level features, which are subsequently fed into a Boosted Rules Classifier to predict sentiments across multiple categories. The system also balances class distributions to ensure fair predictions and presents results in a web-accessible interface for real-time interaction and visualization.

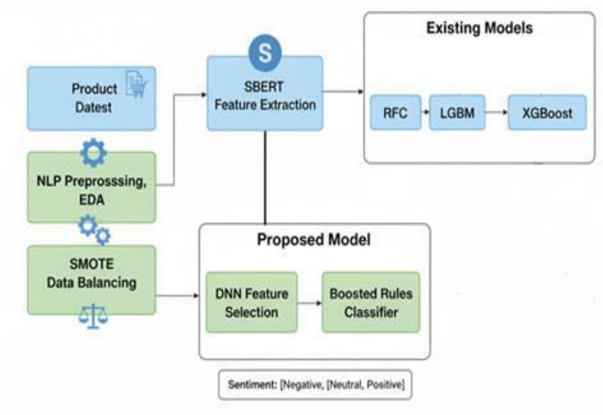


Fig. 1: System architecture of product sentiment analysis with SBERT word embeddings.

**Step 1: Data Ingestion and Upload:** The system begins by allowing users to upload product review datasets through a web interface. Users can provide CSV or Excel files containing textual reviews along with optional sentiment labels. Upon upload, the system validates the dataset to ensure proper formatting, checks for missing or inconsistent values, and confirms the presence of all required columns. This step ensures that the input data is clean, complete, and ready for further processing.

**Step 2: Data Preprocessing:** Once the da is uploaded, the raw text undergoes extensive preprocessing to standardize and clean the content. Each review is converted to lowercase, stripped of special characters, and tokenized into individual words. Stopwords, which do not contribute meaningful sentiment information, are removed, and the remaining words are lemmatized to reduce them to their base forms. If sentiment labels are present, they are encoded numerically to facilitate supervised learning. This preprocessing ensures that the textual data is structured, normalized, and suitable for embedding and downstream modeling.

**Step 3: Embedding Generation using SBERT:** The cleaned reviews are then passed through a Sentence-BERT (SBERT) model to generate dense vector representations for each text input. SBERT captures both semantic and contextual nuances, encoding the meaning of the entire review into a fixed-length vector. Pooling strategies such as mean or CLS token pooling are applied to produce consistent embeddings for all inputs. These embeddings serve as the primary feature set, ensuring that subtle contextual differences in reviews are preserved and ready for deep feature extraction.

**Step 4: Handling Class Imbalance:** To address the common issue of class imbalance in sentiment datasets, the system applies oversampling techniques like SMOTE. Minority sentiment classes, such as “Cannot Say” or “Neutral,” are synthetically augmented to match the distribution of majority classes. This step ensures that the model does not bias toward dominant classes, enabling fair and reliable prediction performance across all categories. Both the embeddings and the corresponding labels are resampled to produce a balanced training dataset.

**Step 5: Deep Feature Extraction via DNN:** The SBERT embeddings are fed into a deep neural network designed to extract high-level semantic features. Multiple dense layers transform the embeddings into refined feature representations, capturing complex relationships and patterns in the text. A dedicated mid-layer serves as a feature extractor, producing a compact yet expressive feature set. These extracted features enhance the predictive power of the downstream classifier and are saved for both training and testing, ensuring reproducibility and efficiency in future predictions.

**Step 6: Sentiment Classification using Boosted Rules:** The extracted features are input into a Boosted Rules Classifier, which combines multiple weak decision rules into a robust, rule-enhanced predictive model. This classifier leverages the DNN-derived features to produce sentiment predictions for each review, handling nuanced and ambiguous cases effectively. Probabilistic outputs or confidence scores are generated when supported, providing interpretable insights for each prediction. This step ensures that the final sentiment classifications are accurate, context-aware, and resilient to challenging examples.

**Step 7: Evaluation and Metrics Calculation:** After predictions are made, the system evaluates model performance by comparing predicted labels against ground-truth annotations. Metrics such as accuracy, precision, recall, and F1-score are calculated for each sentiment category, providing a comprehensive view of the model’s performance. Visualizations like confusion matrices, bar charts, and class-level performance plots are generated to facilitate interpretation. This step supports model validation, tuning, and reporting for stakeholders.

**Step 8: Web Integration and Result Visualization:** The system provides an interactive web interface where users can view predictions and associated metrics. Detailed visualizations, including word clouds, frequent word distributions, bigrams, and POS tag frequencies, offer context-aware insights into the dataset and model decisions. Users can also download predictions and reports for further analysis. This integration ensures that advanced NLP modeling is accessible, interpretable, and actionable in a real-world setting.

**Step 9: Deployment and Reusability:** Finally, the system saves trained models, extracted features, and preprocessing pipelines to enable future reuse and batch prediction. The architecture is modular, allowing individual components such as embeddings, DNN layers, or the classifier to be updated or replaced without disrupting the overall workflow. This design ensures scalability, reproducibility, and continuous improvement of the sentiment analysis system for large-scale product review datasets.

**Boosted Rules Classification**

The BRC is a hybrid, rule-based ensemble method designed to enhance classification performance, particularly for imbalanced datasets. In the proposed methodology, it is applied to the DNN-extracted features to improve sentiment prediction by combining interpretable rules with boosting techniques.

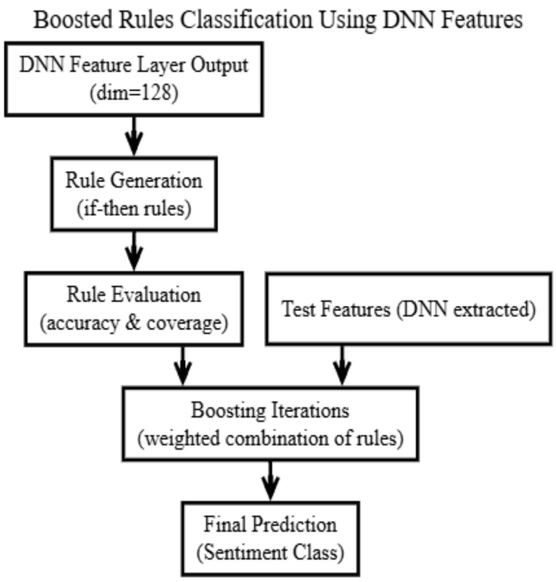


Fig. 2: Internal operations of BRC on DNN-extracted features.

**Internal Operation**

1. **Input Features:** Receives 128-dimensional features extracted from the DNN feature_layer. These features are compact, discriminative, and optimized for sentiment classification.
2. **Rule Generation:** The algorithm automatically generates a set of if-then rules from the input features. Each rule identifies patterns in the feature space that correspond to specific sentiment classes.

   Example: "If feature_12 > 0.5 and feature_45 < 0.3 → class = Positive."
3. **Rule Evaluation:** Each generated rule is evaluated based on its classification accuracy and coverage over the training data. Only rules meeting minimum thresholds for support and confidence are retained.
4. **Boosting Iterations:** Weak rules are combined into a strong classifier using boosting. Misclassified samples in each iteration are given higher weight, guiding the generation of new rules in subsequent iterations. This iterative process continues until the ensemble achieves optimal performance or reaches a predefined number of boosting rounds.
5. **Prediction:** For each test sample, all rules in the ensemble are evaluated. Each rule casts a weighted vote for a class based on its boosting score. The final class label is assigned based on the aggregated weighted votes.

## 4. RESULTS AND DISCUSSION

The dataset used for this research consists of product-related textual data collected from online platforms, encompassing a total of 6,364 records**.** Each record corresponds to a single product review or post and contains multiple attributes relevant for sentiment analysis. The primary columns in the dataset are Text_ID, Product Description, Product Type, and Sentiment**.** The Text_ID serves as a unique identifier for each record, ensuring traceability and proper indexing of the dataset. The Product Description column contains the actual review text or description of the product, which can range from a few words to multiple sentences. This textual data forms the core input for natural language processing and is used to generate embeddings for model training. The Product Type column categorizes products into different classes, which can be leveraged for downstream analysis such as product-specific sentiment trends. Finally, the Sentiment column encodes the sentiment associated with each review, with numeric labels representing categories such as Positive, Negative, Neutral, or Cannot Say. This column serves as the target variable for supervised model training. The dataset is rich in real-world textual variations, including abbreviations, mentions and special characters, which require careful preprocessing. It is structured to support both exploratory data analysis and feature extraction workflows, making it ideal for testing both existing machine learning models and the proposed BRC driven by SBERT embeddings.

Fig. 3 bar chart illustrates the distribution of sentiment classes, with three categories labeled 0, 1, and 2. Class 2 has the highest count, exceeding 3500, indicating a significant prevalence. Class 1 follows with a count around 2000, while Class 0 has the lowest count, just above 0. This suggests an imbalanced dataset with a dominant presence of Class 2.

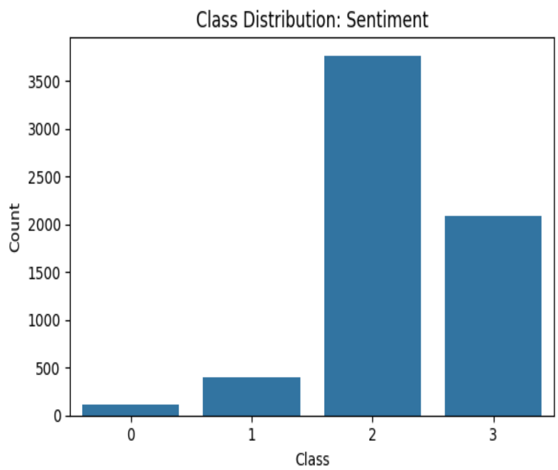


Fig. 3: Class distribution for sentiment attribute.

Fig. 4 showcases word cloud highlights the most frequently occurring words, with size and prominence reflecting their frequency. Words like "sxsw," "link," "mention," "google," "ipad," and "apple" stand out, indicating key topics or entities. The use of various colors helps distinguish the words, with "sxsw" and "link" appearing most dominant. Fig. 5 represents bar chart ranks the top 20 most frequent words, with "sxsw" leading at over 6000 counts, followed by "mention" and "link" with counts around 5000 and 4000, respectively. Other words like "rt," "google," "ipad," and "apple" also show notable frequencies, decreasing gradually, reflecting their relative importance in the dataset. Fig. 6 illustrates histogram, overlaid with a curve, shows the frequency of document lengths in words. The distribution peaks at around 15-20 words with a frequency of over 1200, indicating the most common document length. The curve suggests a roughly normal distribution, with frequencies dropping off on either side, especially beyond 25 words.

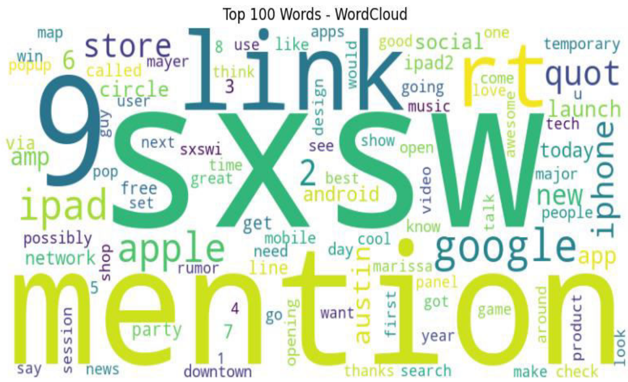


Fig. 4: Top 100 Words – WordCloud

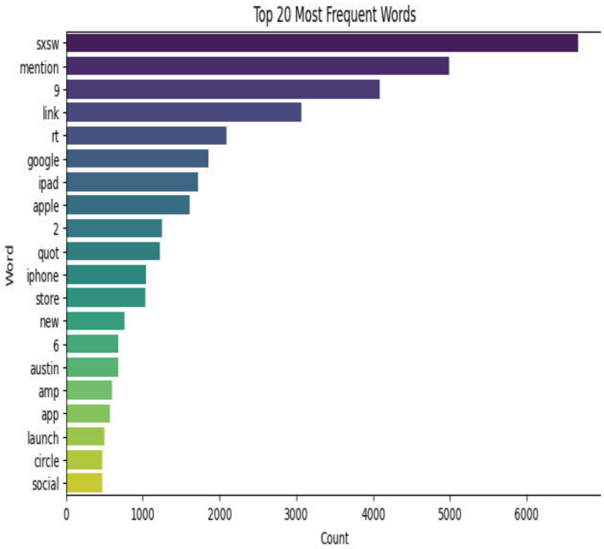


Fig. 5: Top 20 most frequent words.

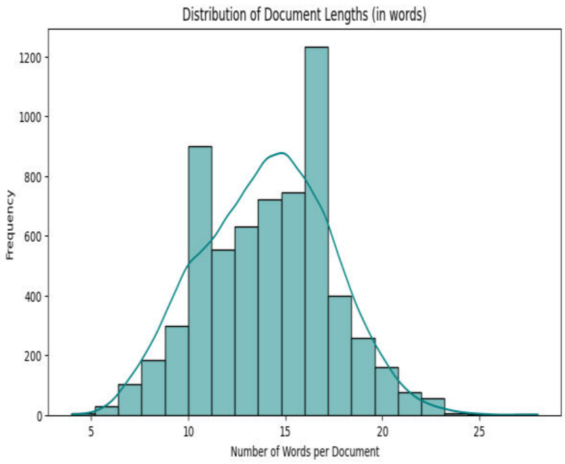


Fig. 6: Distribution of document lengths (in words).

Fig. 7 displays the frequency of different parts of speech tags. The tag "NN" (noun) dominates with a frequency above 4000, followed by "CD" (cardinal number) and "VB" (verb) with frequencies around 2000 and 1000, respectively. Other tags have significantly lower frequencies, showing a skewed distribution favoring nouns. Fig. 8 displays the bar chart lists the top 20 most frequent bigrams, with "rt mention" leading at over 2000 counts, followed by "9 rt" and "sxsw link" with counts around 1500 and 1200, respectively. Bigrams like "ipad 2," "apple store," and "mention mention" also appear frequently, indicating common word pairs in the dataset. Fig. 9 represents dual-plot chart tracks training and validation accuracy (left) and loss (right) over 50 epochs. Accuracy rises sharply to around 0.95 and stabilizes, while loss drops from 0.8 to below 0.2, with both training and validation curves converging, indicating a well-fitted model with high performance.

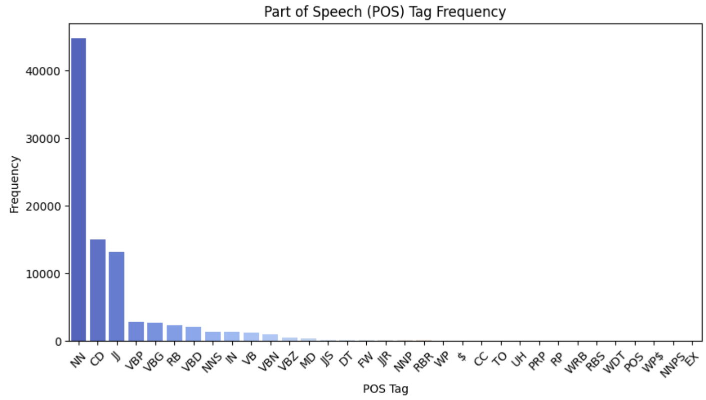


Fig. 7: Part of Speech (POS) tag frequency

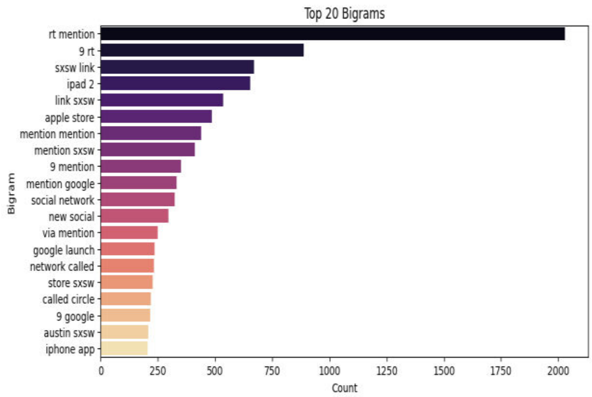


Fig. 8: Top 20 bigrams.

Fig. 10 (left) compares confusion matrix true and predicted sentiment classes. The "Cannot Say" class has 751 correct predictions, "Negative" has 751, and "Neutral" has 740, with "Positive" showing 739 correct predictions. Off-diagonal values (e.g., 14 misclassifications from Neutral to Positive) are minimal, suggesting good classification performance. In Fig. 10 (right), ROC curve plot shows true positive rates against false positive rates for each class. All classes ("Cannot Say," "Negative," "Positive," "Neutral") achieve an AUC of 1.0, indicating perfect classification, while the random guess line (AUC = 0.99) serves as a baseline.

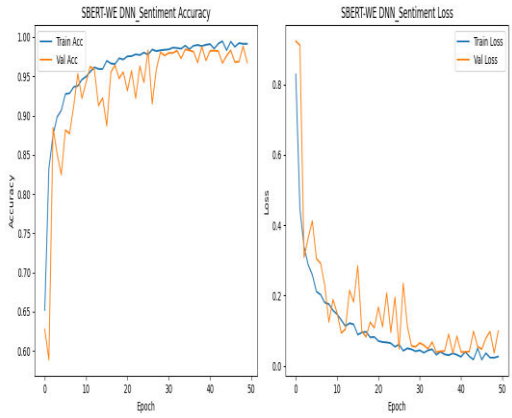


Fig. 9: SBERT-WE DNN sentiment accuracy and loss.

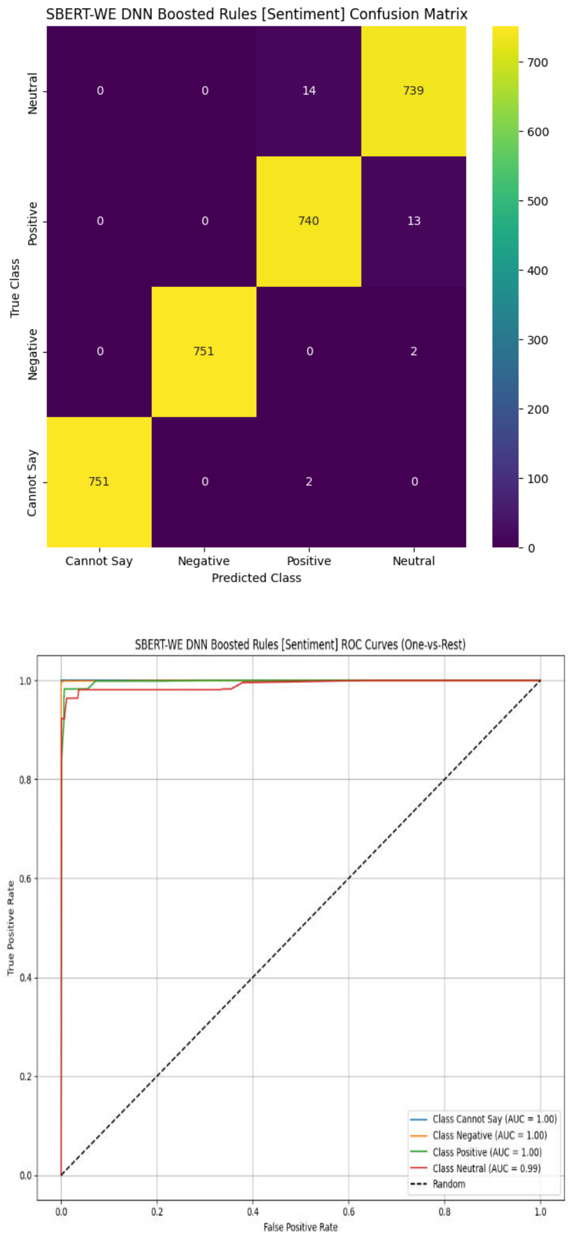


Fig. 10: SBERT-WE DNN boosted rules (Sentiment) confusion matrix (left). ROC curves (One-vs-Rest) (right).

Table 1: Model performance comparison.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| SBERT-WE RFC [Sentiment] | 92.065 | 92.055 | 92.065 | 92.055 |
| SBERT-WE LGBM [Sentiment] | 93.260 | 93.248 | 93.260 | 93.252 |
| SBERT-WE XGB [Sentiment] | 93.526 | 93.481 | 93.526 | 93.482 |
| SBERT-WE DNN boosted rules [Sentiment] | 98.971 | 98.974 | 98.971 | 98.972 |

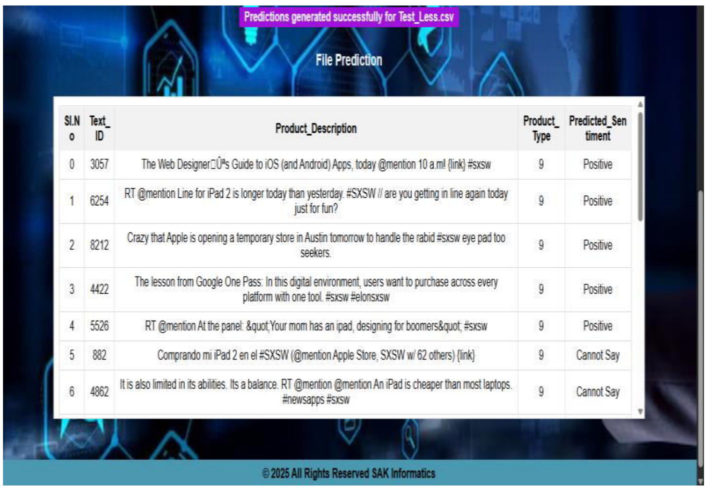


Fig. 11: Real time predictions of Product sentiment analysis.

Fig. 11 illustrates the real-time sentiment prediction interface where users upload or input product-related data to obtain instant sentiment results. The figure presents how the system processes text through the model and displays outputs such as positive, negative, or neutral sentiment. It represents the core analytical feature of the system, showcasing immediate and dynamic prediction capability.

## 5. CONCLUSION

The proposed system demonstrates a powerful and efficient framework for sentiment classification by integrating advanced Natural Language Processing (NLP) and machine learning techniques. Through systematic preprocessing, SBERT-based embedding extraction, deep feature refinement using DNN, and robust classification via ensemble models and BRC, the research achieves significant performance improvements over traditional classifiers. Comparative analysis revealed that the SBERT-WE DNN BRC model outperforms baseline approaches such as RFC, LGBM, and XGB, achieving an outstanding accuracy, precision, recall, and F1-score of 98.971, compared to the 92–93 range achieved by standard ensemble models. This improvement clearly indicates the effectiveness of combining semantic-rich embeddings, deep learning feature extraction, and rule-based boosting to capture both linguistic nuances and decision logic for sentiment classification. The integration of multiple models not only enhanced predictive accuracy but also maintained interpretability, making the approach well-suited for real-world applications where both performance and explainability are critical. The pipeline effectively handles multi-class sentiment categories and provides stable results across all evaluation metrics, demonstrating its scalability and robustness.

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