SentimentX: Transformer-Driven Embedding Fusion with Rule-Boosted Intelligence for Product Opinion Mining

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To Cite this Article
T. Srilekha, K. Sharmila Reddy, Gandhe Vamshi Krishna, Sripathi Manideep, Dhadi Ram Charan, Konreddy Shivamani, "SentimentX: Transformer-Driven Embedding Fusion with Rule-Boosted Intelligence for Product Opinion Mining", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 511-522, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp511-522

Submitted: 28-02-2026 Accepted: 02-04-2026 Published: 10-04-2026

ABSTRACT

The global e-commerce market is expected to exceed USD 7 trillion by 2030, with over 80% of consumers depending on product reviews to guide their purchasing decisions. However, manual sentiment analysis of these reviews is neither scalable nor consistent, often resulting in inaccurate interpretations and delayed business insights. To address these challenges, this study proposes a robust Natural Language Processing (NLP) framework for automated sentiment analysis using a labeled product review dataset. The proposed methodology begins with comprehensive NLP preprocessing and Exploratory Data Analysis (EDA) to clean, normalize, and understand data distribution. For semantic representation, Sentence Bidirectional Encoder Representations from Transformers (SBERT) is employed to generate context-aware embeddings, capturing deeper linguistic relationships compared to traditional techniques. To handle class imbalance within sentiment categories, the Synthetic Minority Over-sampling Technique (SMOTE) is utilized to generate synthetic samples, ensuring balanced model training. Unlike conventional classifiers such as Random Forest Classifier (RFC), Light Gradient Boosting Machine (LGBM), and Extreme Gradient Boosting (XGBoost), the proposed framework incorporates Deep Neural Network (DNN)-based feature selection combined with a Boosted Rules Classifier (BRC). This hybrid approach enhances both model interpretability and predictive performance. The system classifies customer sentiments into three categories: Negative, Neutral, and Positive. Experimental results demonstrate improved classification accuracy and reduced bias, highlighting the effectiveness of the proposed model.

Key words: Sentiment Analysis, Natural Language Processing (NLP), SBERT (Sentence-BERT), Boosted Rules Classifier (BRC), Deep Neural Network (DNN), SMOTE (Synthetic Minority Over-sampling Technique).

1. INTRODUCTION

Over the past decade, there has been a substantial rise in the availability of product reviews on traditional retail platforms, contributed by both professionals and individual users. To reduce uncertainty in purchasing decisions, consumers increasingly rely on these reviews and associated online content, such as product images. Studies indicate that the majority of users prioritize customer reviews before making a purchase [1], with nearly 90% of consumers consulting reviews prior to buying a product. Consequently, reviews have become highly significant for both consumers and businesses. For consumers, they play a critical role in evaluating whether a product meets their expectations [2], while online retailers recognize that effectively managing reviews and encouraging positive feedback can significantly influence profitability and customer engagement.

Amazon is a multinational technology company specializing in e-commerce, where customer reviews serve as a key factor in purchasing decisions by providing authentic insights. However, manually reading large volumes of reviews can be time-consuming. Reviews are equally valuable for sellers, as they help differentiate products and support marketing efforts. In business growth and customer service contexts, online ratings are essential, enabling customers to quickly evaluate a product's appeal. Purchasing decisions are often influenced by ratings and reviews, which can create either positive or negative perceptions. Prior research has utilized Amazon review data to predict review helpfulness [3], where each review includes feedback on its usefulness from other users.

Figure 1: Product Sentiment Analysis.

In e-commerce, product ratings have gained increasing importance, particularly during the COVID-19 pandemic, which accelerated the shift toward online transactions. This transition resulted in a significant rise in online reviews, with a reported 43% increase that continues to grow. As shown as figure 1 Reviews and ratings provide efficient and reliable guidance for consumers, saving time during decision-making [4]. Meanwhile, sellers leverage review analysis to better understand customer preferences and improve product performance. Researchers have extensively explored predicting review helpfulness using Machine Learning (ML) techniques, which focus on identifying patterns and extracting insights from data.

The rapid expansion of online review platforms has led to information overload, making it difficult for consumers to assess product quality effectively. Additionally, the growth of social media has blurred the distinction between genuine opinions and promotional content, increasing the prevalence of misleading reviews. Typically, review usefulness is determined through user voting mechanisms. With the continued growth of e-commerce, product reviews have become a central factor influencing consumer behavior. Reports indicate that 95% of shoppers read online reviews before making purchases, and businesses with higher ratings experience an average 18% increase in sales. Given the vast volume of daily reviews, manual sentiment analysis is no longer practical. Therefore, scalable and intelligent solutions are required to automatically analyze sentiments, providing valuable insights into customer satisfaction, product performance, and service improvement. As a result, sentiment analysis has become an essential tool in enhancing decision-making and building customer trust in the e-commerce and retail sectors.

2. LITERATURE SURVEY

The rapid growth of e-commerce platforms has led to an increasing volume of user-generated reviews, making sentiment analysis and product quality prediction critical research areas. Traditional approaches relied heavily on basic sentiment classification; however, recent studies have shifted toward advanced deep learning and transformer-based models to capture contextual and semantic information more effectively.

2.1 Product Quality Prediction and Sentiment Modeling

Ullah *et al.* [5] proposed a novel approach for predicting product quality based on customer reviews using Natural Language Processing techniques. Their model, QLeBERT, integrates quality-related lexicons, N-grams, BERT, and BiLSTM to extract meaningful representations from text. They developed a domain-specific lexicon based on the appraisal framework and achieved an F1-macro score of 0.91, outperforming existing models.

Mutinda *et al.* [8] analyzed the limitations of traditional text representation techniques and introduced a hybrid model (LeBERT) combining sentiment lexicons, N-grams, BERT, and CNN. Their work highlighted the importance of incorporating sentiment orientation into embeddings to improve classification performance.

Cao *et al.* [13] proposed an improved BERT-based model with a symmetrical structure to capture sentence-level semantic features in agricultural product reviews. Their method **enhanced** sentiment detection accuracy, achieving an improved F1 score compared to baseline BERT models.

2.2 Deep Learning Architectures for Sentiment Analysis

Bellar *et al.* [6] conducted a comprehensive comparison of deep learning models, including CNN, RNN, and BiLSTM, using various embedding techniques such as BERT, FastText, and Word2Vec. Their study demonstrated that transformer-based embeddings significantly improve sentiment classification performance across multiple datasets.

Sabbeh *et al.* [7] presented a comparative analysis between classical embeddings (GloVe, Word2Vec, FastText) and contextualized embeddings such as BERT. Their findings revealed that contextualized embeddings outperform traditional methods, while BiLSTM models generally provide better performance than CNN in larger datasets.

Yuan *et al.* [12] developed a Self-Attention-CNN BiLSTM (SAC-BiLSTM) model that combines character-level and word-level embeddings. Their approach improved contextual feature extraction and achieved high precision, recall, and F1 scores on e-commerce datasets.

Liu *et al.* [15] proposed an attention-based LSTM model to address challenges in processing long and context-rich agricultural reviews. Their method utilized attention mechanisms to assign weights to key features and achieved superior performance compared to traditional models.

2.3 Hybrid Models and Advanced NLP Techniques

Ali *et al.* [9] conducted an extensive analysis of sentiment classification using machine learning, ensemble learning, and deep learning techniques. Their experiments evaluated multiple algorithms,

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including Naive Bayes, Random Forest, CNN, BiLSTM, and transformer-based models such as BERT and XLNet, concluding that BERT achieved the highest accuracy of 89%.

Almaqtari *et al.* [11] introduced the Arb-MCNN-Bi model, integrating AraBERT with multi-channel CNN and BiGRU for Arabic sentiment analysis. Their model leveraged contextual embeddings and deep feature extraction techniques to achieve high accuracy across multiple datasets.

Dang *et al.* [14] developed a recommendation system that integrates sentiment analysis with collaborative filtering. Their approach demonstrated that combining sentiment-based deep learning models with recommendation systems significantly improves performance.

2.4 Sentiment Analysis in Specialized Domains

Saxena *et al.* [10] studied sentiment analysis in the context of ESG (Environmental, Social, and Governance) metrics. They developed a nested sentiment analysis framework using FinBERT and enhanced model interpretability through explainable AI techniques. Their model achieved high accuracy in both sentiment classification and ESG prediction.

2.5 Research Gap

Although significant progress has been made in sentiment analysis using deep learning and transformer-based models, several limitations still exist. Most existing approaches focus either on sentiment classification or product quality prediction independently, without integrating both aspects into a unified framework. Additionally, many models lack domain-specific adaptability and fail to fully utilize contextual and semantic nuances in diverse datasets. Therefore, there is a need for a comprehensive model that combines advanced NLP techniques, domain-specific knowledge, and efficient architectures to improve both sentiment understanding and product quality prediction.

3. PROPOSED METHODOLOGY

In the current digital ecosystem, large volumes of product reviews and user-generated content are continuously generated across online platforms. Extracting meaningful insights from this data is essential for understanding customer sentiment and improving business strategies. As shown as figure 2 the proposed system integrates NLP with advanced embedding techniques to automate sentiment analysis. It leverages SBERT to capture contextual semantic relationships within textual data. A DNN is used for feature refinement, enhancing representation quality. Finally, a Boosted Rules Classifier ensures accurate and interpretable sentiment prediction.

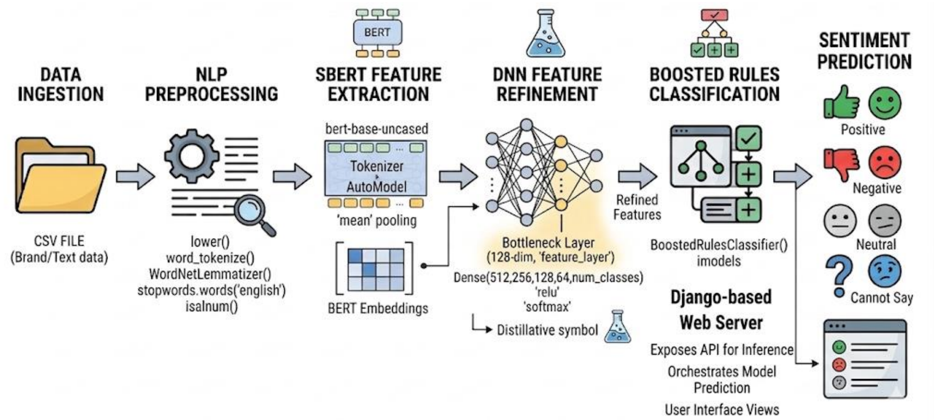

Figure 2: System Architecture of Product Sentiment Analysis with SBERT Word Embeddings.

Product Sentiment Analysis Workflow

Step 1: Data Ingestion

- Collect product review data from sources such as e-commerce platforms, social media, or surveys.
- Store the data in structured formats like CSV files containing review text and related attributes.

Step 2: NLP Preprocessing

- Convert text to lowercase and remove punctuation and special characters.
- Perform tokenization and lemmatization to normalize text.
- Remove stop words and filter irrelevant tokens to prepare clean input data.

Step 3: SBERT Feature Extraction

- Apply SBERT to transform preprocessed text into dense vector embeddings.
- Use mean pooling to generate sentence-level semantic representations.
- Capture contextual meaning and relationships between words and sentences.

Step 4: DNN Feature Refinement

- Pass embeddings through a Deep Neural Network (DNN).
- Use dense layers with activation functions such as ReLU and Softmax.
- Introduce a bottleneck layer to reduce dimensionality and improve feature quality.

Step 5: Handling Class Imbalance

- Apply Synthetic Minority Over-sampling Technique (SMOTE).
- Balance sentiment classes such as Positive, Negative, Neutral, and Cannot Say.

Step 6: Boosted Rules Classification

- Train the Boosted Rules Classifier using refined feature vectors.
- Generate interpretable rules for sentiment prediction.
- Improve classification accuracy compared to traditional models.

Step 7: Sentiment Prediction

- Input new or unseen reviews into the trained model.
- Predict sentiment labels: Positive, Negative, Neutral, or Cannot Say.

Step 8: Model Deployment

- Deploy the system using a web framework (e.g., Django).
- Provide API-based access for real-time predictions and user interaction.

Step 9: Result Visualization and Evaluation

- Generate evaluation metrics such as Accuracy, Precision, Recall, and F1-score.

- Visualize outputs using confusion matrices and graphical representations.

4. RESULTS AND DISCUSSION

The SBERT-based Product Sentiment Analysis system is implemented as a modular pipeline covering dataset ingestion, preprocessing, feature extraction, model training, evaluation, and prediction. Text data is cleaned through lowercasing, stop word removal, tokenization, and lemmatization, while target labels are encoded and pre-processed datasets can be saved for reuse. Exploratory Data Analysis (EDA) generates insights via word clouds, frequent words, bigrams, and POS tag distributions. SBERT embeddings are used to create dense contextual feature vectors, optionally refined through a Dense Neural Network, and SMOTE handles class imbalance. Model training integrates conventional classifiers (Random Forest, LightGBM, XGBoost) and the proposed Boosted Rules classifier, with evaluation using accuracy, precision, recall, and F1-score. Trained models and artifacts are stored, and the prediction module applies preprocessing, feature extraction, and classification to new data. This workflow combines transformer embeddings, deep learning, and ensemble methods to deliver flexible, reproducible, and accurate sentiment analysis.

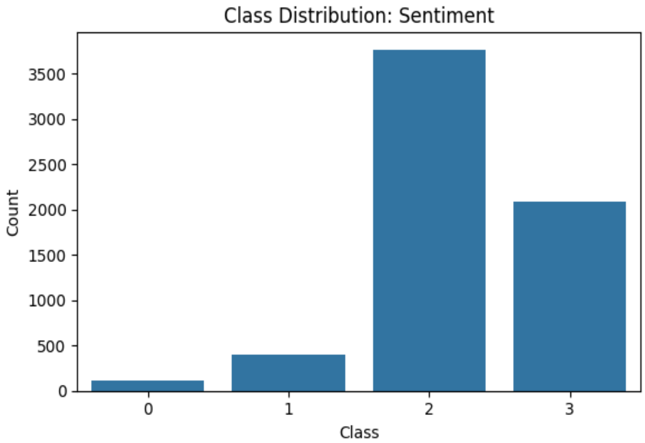

Figure 3: Class Distribution: Sentiment.

Figure 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.

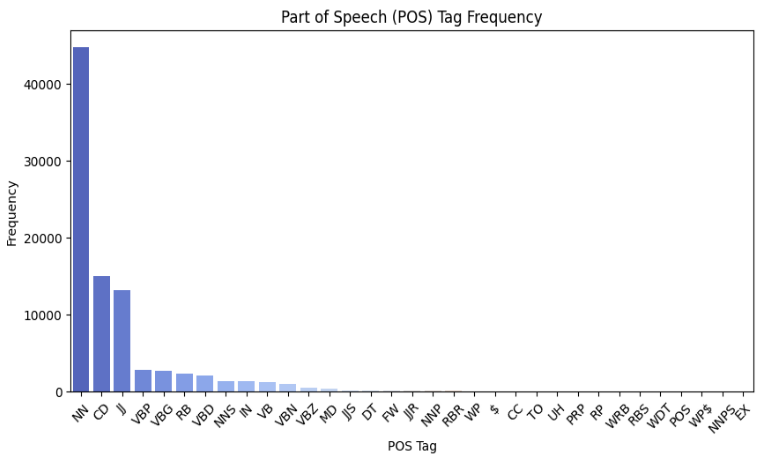

Figure 4: Part of Speech (POS) Tag Frequency

Figure 4 bar chart 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.

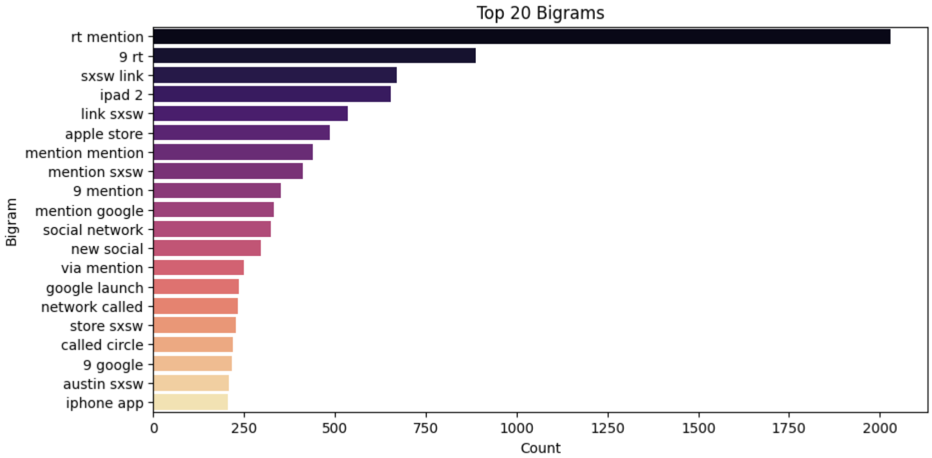

Figure 5: Top 20 Bigrams

Figure 5 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.

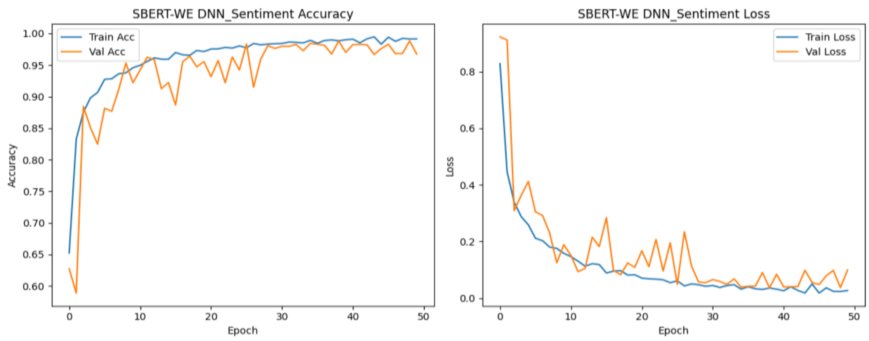

Figure 6: SBERT-WE DNN Sentiment Accuracy and Loss

Figure 6 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.

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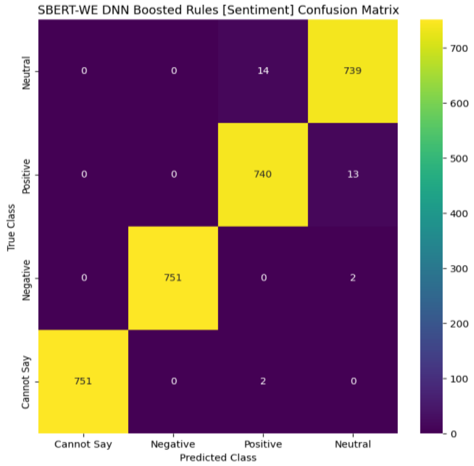

Figure 7: SBERT-WE DNN Boosted Rules (Sentiment) Confusion Matrix.

Figure 7 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.

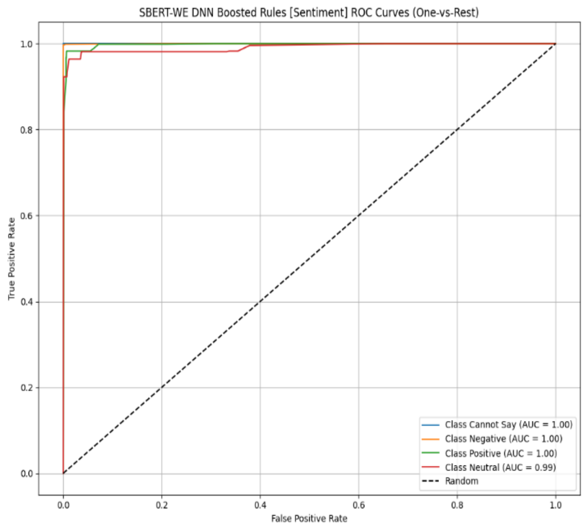

Figure 8: SBERT-WE DNN Boosted Rules (Sentiment) ROC Curves (One-vs-Rest)

Figure 8 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.

Figure 9 bar chart compares the performance of different algorithms across accuracy, precision, recall, and F1-score. All algorithms (SBERT-WE RFC, LGBM, XGB, DNN, DNN Boosted Rules) achieve scores around 92-99%, with DNN Boosted Rules slightly leading in most metrics, showing consistent high performance across the board.

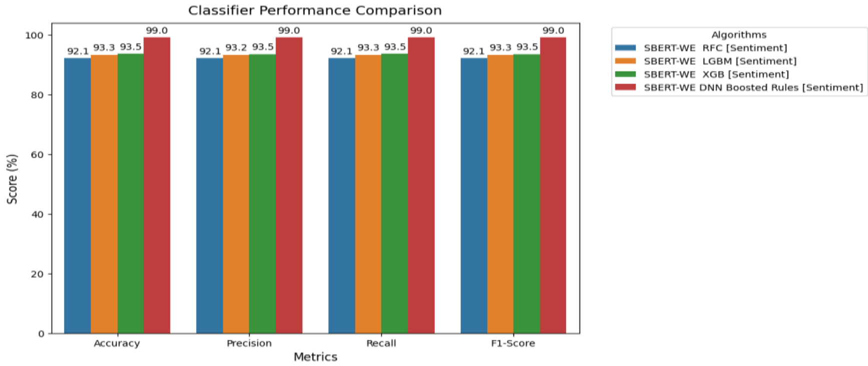

Figure 9: Classifier Performance Comparison

Figure 10 bar chart compares the performance of various algorithms (SBERT-WE RFC, LGBM, XGB, DNN, DNN Boosted Rules) for the "Cannot Say" sentiment class, focusing on precision, recall, and F1-score. All algorithms exhibit near-perfect scores, with precision ranging from 99.5% to 100%, recall from 99.6% to 100%, and F1-score from 99.7% to 99.9%, showcasing exceptional accuracy. The SBERT-WE DNN Boosted Rules model stands out with a 99.9% F1-score, slightly outperforming others like RFC and LGBM, which also perform admirably. The consistent high performance across these metrics highlights the robustness of the models in classifying the "Cannot Say" category with minimal errors.

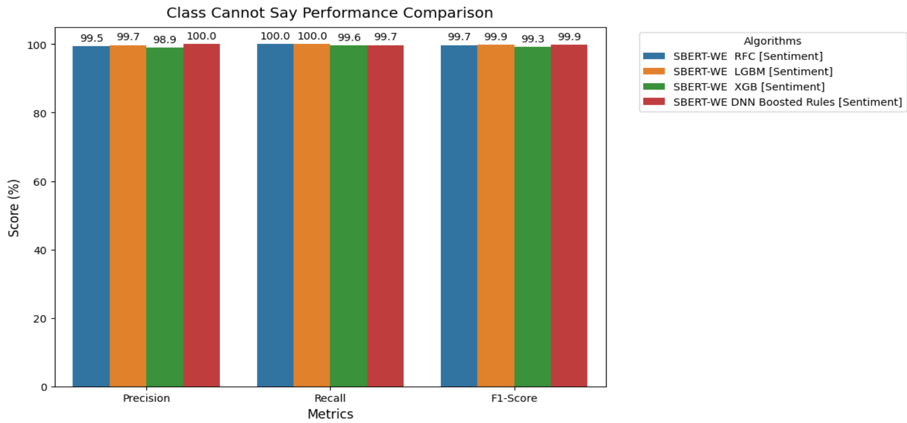

Figure 10: Class Cannot Say Performance Comparison

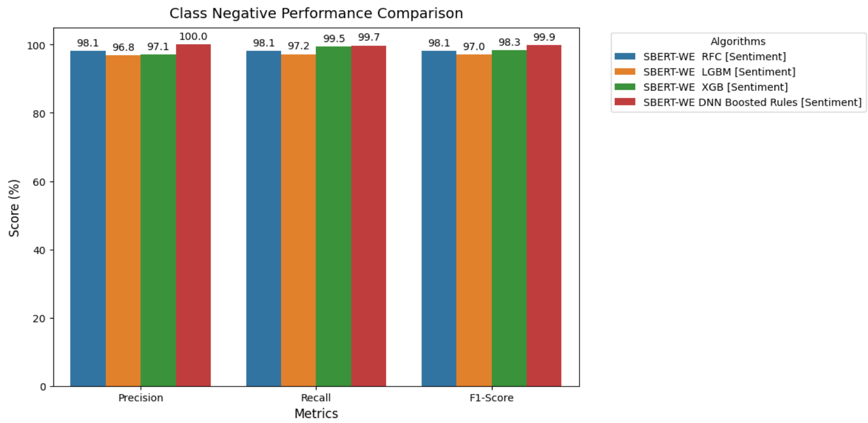

Figure 11: Class Negative Performance Comparison

Figure 11 bar chart evaluates the performance of different algorithms (SBERT-WE RFC, LGBM, XGB, DNN, DNN Boosted Rules) for the "Negative" sentiment class, covering precision, recall, and F1-score. Precision ranges from 98.1% to 100%, recall from 97.2% to 99.5%, and F1-score from 98.1% to 99.9%, indicating strong overall performance. The SBERT-WE DNN Boosted Rules model leads with a 99.9% F1-score, closely followed by XGB and LGBM, demonstrating high accuracy in negative sentiment detection. The high scores across all metrics suggest that the models effectively identify negative sentiments with very few misclassifications.

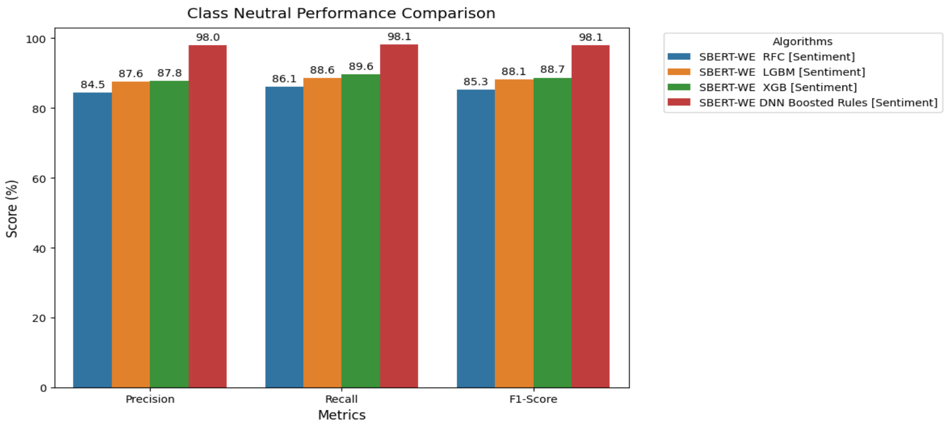

Figure 12: Class Neutral Performance Comparison

Figure 12 bar chart assesses the performance of algorithms (SBERT-WE RFC, LGBM, XGB, DNN, DNN Boosted Rules) for the "Neutral" sentiment class, analyzing precision, recall, and F1-score. Precision varies from 84.5% to 99.0%, recall from 86.1% to 98.6%, and F1-score from 85.3% to 98.1%, revealing some variability in performance. The SBERT-WE DNN Boosted Rules model achieves the highest F1-score at 98.1%, while RFC lags with 85.3%, indicating challenges in consistent classification. The lower precision and recall for certain models suggest difficulties in accurately identifying "Neutral" sentiments compared to other classes.

Comparative Analysis

Table 1 presents a comparative analysis of four sentiment classification models using SBERT word embeddings, evaluating their performance across accuracy, precision, recall, and F1-score. Among traditional machine learning models, the Random Forest Classifier (RFC) achieves 92.07% accuracy, followed by LightGBM at 93.26% and XGBoost at 93.53%, showing incremental improvements in predictive performance. In contrast, the proposed SBERT-WE DNN Boosted Rules classifier significantly outperforms all baseline models, achieving 98.97% across all metrics, demonstrating both high accuracy and balanced precision and recall. This indicates that integrating SBERT embeddings with a deep neural network for feature refinement, combined with a Boosted Rules classifier, provides superior sentiment classification by effectively capturing contextual semantics while maintaining interpretability. The table highlights the advantages of the proposed approach over conventional classifiers in terms of both effectiveness and robustness for product sentiment analysis.

Table 1: Model Performance Comparison

Algorithm	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

Figure 13 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.

Sl.No	Text_ID	Product_Description	Product_Type	Predicted_Sentiment
0	3057	The Web Designer□Ûªs Guide to iOS (and Android) Apps, today @mention 10 a.m! {link} #sxsw	9	Positive
1	6254	RT @mention Line for iPad 2 is longer today than yesterday. #SXSW // are you getting in line again today just for fun?	9	Positive
2	8212	Crazy that Apple is opening a temporary store in Austin tomorrow to handle the rabid #sxsw eye pad too seekers.	9	Positive
3	4422	The lesson from Google One Pass: In this digital environment, users want to purchase across every platform with one tool. #sxsw #elonsxsw	9	Positive
4	5526	RT @mention At the panel: "Your mom has an ipad, designing for boomers" #sxsw	9	Positive
5	882	Comprando mi iPad 2 en el #SXSW (@mention Apple Store, SXSW w/ 62 others) {link}	9	Cannot Say
6	4862	It is also limited in its abilities. Its a balance. RT @mention @mention An iPad is cheaper than most laptops. #newsapps #sxsw	9	Cannot Say

Figure 13: Real time predictions of Product sentiment analysis.

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 boosted rules, the research achieves significant performance improvements over traditional classifiers. Comparative analysis revealed that the SBERT-WE DNN Boosted Rules model outperforms baseline approaches such as Random Forest, LightGBM, and XGBoost, 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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