FMDB *Transactions on Sustainable Finance and Data Science*

AI-Based Intelligent Customer Feedback Analyzer with Sentiment Confidence Scoring

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Abstract: To extract insights that can be put into action from the continuously increasing volume of customer-generated content on digital platforms, sentiment analysis has evolved into a vital tool. Within the scope of this research, an artificial intelligence-based customer feedback analysis system is presented. This system combines sentiment categorization with a probability-driven confidence score to generate trustworthy, interpretable predictions of customer opinion. Data collection, text cleaning and normalization, feature extraction using Bag-of-Words and TF-IDF vectorization, and sentiment classification using a collection of deep learning and machine learning models are all included in the proposed framework. These models include Random Forest, Naive Bayes, Logistic Regression, a Feedforward Neural Network, and RoBERTa. This robustly optimized BERT pre-training method estimates the confidence of each prediction and flags ambiguous or borderline reviews for further investigation. The results of an experimental evaluation show that integrating transformer-based contextual representations with probability-based confidence assessment significantly improves the explainability and reliability of automated sentiment analysis. This enables businesses across a wide variety of industries to understand their customers' preferences better, give high-confidence feedback a higher priority, and make well-informed strategic decisions about their products, services, and marketing.

Keywords: Sentiment Analysis; Customer Feedback Analysis; Sentiment Confidence Scoring; Opinion Mining; Machine Learning; RoBERTa and Transformer; Deep Learning; Performance Evaluation.

Received on: 29/07/2025, **Revised on:** 24/09/2025, **Accepted on:** 01/12/2025, **Published on:** 09/06/2026

Journal Homepage: https://www.fmdbpub.com/user/journals/details/FTSFDS

DOI: https://doi.org/10.69888/FTSFDS.2026.000696

Cite as: R. Mohan, B. Rohith, G. Nethaji, R. Angeline, and R. Chauhan, "AI-Based Intelligent Customer Feedback Analyzer with Sentiment Confidence Scoring," *FMDB Transactions on Sustainable Finance and Data Science*, vol. 1, no. 2, pp. 84–92, 2026.

1. Introduction

Opinion mining, another name for sentiment analysis, is an essential part of contemporary data science in terms of determining and understanding customer views and attitudes towards products, services, and brands [1]. As the online platform and social media networking continue growing rapidly, customers can now express their experiences and feedback at will in ways never

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before available to them, resulting in a high influx of user-generated content and creation of a substantial need among users to rely on automated feedback-processing systems that can extract meaningful information out of high volumes of unstructured textual data [2]. Consequently, sentiment analysis has become increasingly significant and is today widely used across fields such as business analytics, business governance, healthcare, and customer relationship management. With the global expansion of the internet, online services have become one of the main sources of information that people worldwide use. People express their opinions on products, services, entertainment, and online experiences, constantly generating enormous amounts of text data that the organization can analyze to assess public perception and support informed decision-making. Sentiment analysis has thus become increasingly popular, and automated opinion-mining techniques are being investigated and applied by researchers, organizations, and businesses more than ever before [3]. The paper is dedicated to the intelligent analysis of customer feedback [4].

It investigates the methodology, applications, challenges, and most recent developments in the field of technology, and emphasizes the inclusion of sentiment confidence scoring to enhance the trustworthiness of the predicted customer opinion [5]. The growing literature on sentiment analysis provides evidence for this, as several studies identify this field across various aspects, with researchers developing computational frameworks to process unstructured customer feedback data to extract opinions, emotional tendencies, and fashion trends [6]. The analysis of customer feedback represents a non-unidimensional area of research encompassing sentiment classification, misleading or spamladen reviews, assessment of the credibility of online feedback, and machine learning due to the content created by customers and some studies are more associated with classification accuracy and others with the influence of online reviews on the purchasing behavior of customers, the perceptions of a brand, and on the performance of organizations. Sentiment analysis can find practical applications by focusing on the real-world usefulness of big data in current society [7]. In the business field, it can be used to evaluate the organization's products, help determine customer preferences, track product development, and identify areas for service enhancement. In contrast, in financial markets, it is used to conduct a higher-quality analysis of market trends and investor sentiment [8]. In healthcare, it can be used to assess customer satisfaction and enhance service delivery. Sentiment analysis use has some limitations, such as the use of informal language, detection of sarcasm, irony, contextual ambiguity, domain language effects despite its prevalence, interpretation of sentiments, as well as the reliability, which is usually determined by the context and the area of application, and this makes sentiment analysis more difficult to interpret the sentiment and determine its reliability.

Sentiment analysis, especially aspect-based sentiment analysis, has recently attracted significant interest among natural language processing scholars, as it aims to recognize and assess sentiment regarding particular aspects or features of objects such as products or services, enabling fine-grained opinion analysis to monitor customer reviews, examine market research, and analyze digital media [9]. Earlier methods of sentiment analysis relied on lexicon- and rule-based approaches [10]. However, more recent methods have adapted to deep learning and machine learning models because of the availability of large volumes of data, better NLP algorithms, and easily accessible, powerful computing tools that allow researchers to face complex problems such as context dependency, aspect extraction, sentiment polarity detection, and cross-domain adaptation [11].

Even though conventional machine learning methods can still be effective with a variety of applications, the accuracy of the sentiment prediction is also of critical importance to the practical implementation of the approach; thus, the incorporation of sentiment confidence scores in sentiment analysis tools will allow the estimation of the confidence of the prediction and the confident interpretation of customer feedback [12]. By balancing conventional classification algorithms with transformer-based contextual language models such as RoBERTa and a confidence assessment based on probability, the new smart customer feedback analyzer will deliver accurate, interpretable, and decision-supporting sentiment analysis results that can be used across a variety of organizational contexts.

2. Literature Review

Many methods have been proposed over the past few years to build robust sentiment analysis systems, especially for analyzing customer feedback in business and e-commerce contexts. Sentiment analysis is a complex research field that includes sentiment classification, opinion mining, aspect extraction, confidence estimation, and review analysis. Early studies were mainly focused on lexicon-based approaches and the calculation of sentiment scores, laying the foundation for automated customer feedback analysis, but lacking in context understanding and semantic sensitivity.

Moreover, Zhang et al. [1] proposed a Fourier Graph Transformer Network that effectively captures long-range contextual relationships in customer reviews and achieves superior sentiment classification performance compared to conventional approaches. Despite these great advances, several open challenges remain, including sarcasm detection, context sensitivity, domain adaptation, multilingual sentiment interpretation, and confidence estimation. Such limitations indicate the need for intelligent hybrid frameworks that combine transformer-based language models with classical machine learning algorithms and confidence-aware prediction mechanisms to provide reliable, accurate, and actionable insights for business decision-making.

Kim [15] highlighted the importance of online customer reviews for understanding consumer opinions and the growing role of sentiment analysis in business intelligence. Similarly, Kumara et al. [14] reviewed the sentiment analysis techniques used in e-commerce platforms and discussed the limitations of traditional techniques in handling contextual and domain-specific information. These studies motivated researchers to investigate more sophisticated machine learning and deep learning approaches. With advances in research, machine learning techniques have significantly improved the performance of sentiment analysis systems. Wulandari et al. [13] showed that sentiment classification accuracy can be significantly improved through parameter optimization and intelligent techniques. It has been shown that machine learning algorithms can effectively identify customer needs by analyzing product reviews through contextual feature extraction.

Similarly, Godia and Tiwari [11] highlighted the importance of natural language processing and feature engineering for better classification of product reviews. Vanshika et al. [10] provided a comprehensive survey of available datasets, algorithms, limitations, and future research opportunities in sentiment analysis. Also, Khanum et al. [9] showed that integrating natural language processing with machine learning and deep learning techniques significantly improves sentiment prediction accuracy, and Aydoğan and Okay [8] confirmed the usefulness of these techniques for analyzing customer reviews in e-commerce applications. Deep learning architectures revolutionized sentiment analysis by allowing automatic feature extraction and context-aware learning.

In sentiment classification tasks on e-commerce product reviews, Paul et al. [7] showed that a hybrid CNN-LSTM architecture outperformed many traditional machine learning models. Similarly, Tripathy et al. [6] demonstrated the capability of deep learning models to simultaneously analyze customer sentiment, forecast business growth, and predict product defects from consumer feedback. More recent work has focused on transformer-based architectures that provide richer contextual representations. Triawan et al. [5] compared various natural language processing algorithms and reported that transformer-based models achieve higher accuracy in sentiment classification and greater computational efficiency.

In a similar vein, the work of Liang et al. [4] has shown that transformer architectures are effective at generating context-aware textual representations, thereby enabling more accurate language understanding and sentiment prediction. Recent advances in sentiment analysis have focused on transformer- and graph-based learning frameworks that can model long-range semantic dependencies. Nawrocka et al. [3] review the evolution of machine learning techniques from traditional classifiers to sophisticated deep learning architectures that can be applied in both social media and e-commerce. Markande et al. [2] highlighted the importance of natural language preprocessing, polarity analysis, and visualization techniques for analyzing customer satisfaction in product reviews.

3. Proposed Method and System Architecture

3.1. Data Collection

Various sources are available for collecting data, such as online databases, customer reviews on different platforms, and social media commentary, including tweets. The dataset used for this work is Amazon product reviews. Information about customer reviews and rating scores is open data available on Kaggle.

3.2. Preprocessing of Data

The data should be decontaminated and well-supported, then sent to the model for further calculations. Prior data processing is necessary to improve ML model performance. Tokenization, stop-word removal, and stemming are among the preprocessing techniques used in this work:

- Duplicates and rows having null values are removed. A target column is formed using three sentiment classes, which include positive, neutral, and negative, based on the Score feature present in the dataset.
- Class imbalance: the neutral and negative classes have considerably smaller samples than the positive class. To overcome this imbalance problem among classes, neutral and negative classes are oversampled. The distribution of the samples after oversampling is shown in Figure 2.
- Tokenisation: Each assessment in the gathered data is processed into a separate file, composed mostly of sentences. The tokenization process is a mechanism for breaking text into small units called tokens.
- Stop-word Removal: To simplify the process, those words that are within the text, which may occur multiple times, and, at the same time, do not carry much semantic meaning, are removed.
- Stemming: Words are transformed into their root forms after stopping words are removed from the tokenized data. An example of this is that playing becomes play (Figure 1).

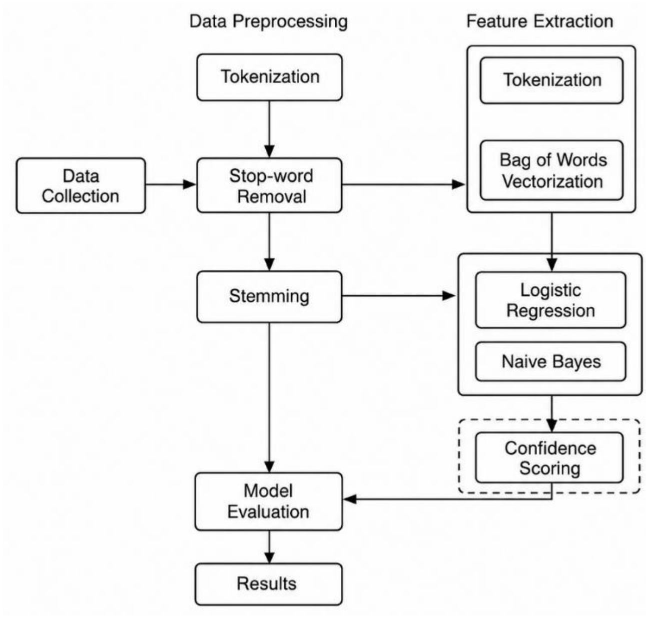

Figure 1: Workflow

Amazon reviews may contain spelling mistakes, typos, and unwanted symbols. Therefore, additional preprocessing steps, such as removing HTML tags, emojis, digits, and extra white spaces, and converting all characters to lowercase, are performed to improve data quality.

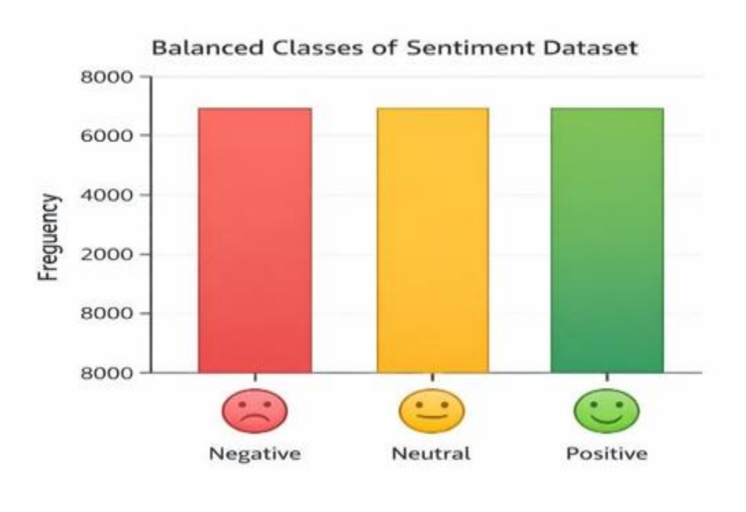

Figure 2: Balanced classes

3.3. Splitting the Data

The processed data is separated into 70:30 training and assessment sets. To assess how well the suggested models perform on data they were not trained on, the models are evaluated on the test set after being trained on the training set.

3.4. Feature Extraction

To put it another way, written consumer input is transformed into numerical data using feature extraction techniques so that machine learning models may use it. Term Frequency-Inverse Document Frequency (TF-IDF) and the Bag-of-Words (BOW) vectorization approaches are used in this work to represent textual data. TF-IDF Vectorization: TF-IDF is a method that illustrates a term's relevance in a document in relation to the corpus overall. It gives instructive keywords more weight and lessens the impact of repetitive words. IDF(t) = log (N/df(t)), where df(t) is the number of documents containing the word, and

N is the total number of documents. TF(t,d) = The frequency of term t in the text d. (t). The textual data is then converted to a sparse feature matrix of weighted word frequencies using TF-IDF.

Bag-of-Words (Bow) Vectorizer: The Bag-of-Words model counts the occurrences of each word in the lexicon to transform text into fixed-length numerical vectors. Each page is represented as a vector of word frequencies, ignoring word order. Despite its simplicity, Bow performs well in many traditional text categorisation applications.

Table 1: Frequency

Words	Document 1	Document 1	Document 1
Image	1	1	1
Augmentation	1	1	1
is	1	1	1
important	1	1	0
and	0	1	0
useful	0	1	0
difficult	0	0	1

According to Table 1, researchers get three vectors with a fixed length of seven:

- [1,1,1,1,0,0,0] is Document 1
- [1,1,1,1,1,1,0] is Document 2
- [1,1,1,0,0,0,1] is Document 3

3.5. Classification Model

The resulting feature vectors are fed into various classification algorithms to predict sentiment. This research compares the performance of various techniques, ranging from lightweight statistical classifiers to cutting-edge contextual deep learning architectures using conventional machine learning models. Logistic Regression: To determine whether an instance belongs to a particular class, a probabilistic classification model known as logistic regression is used. Both Bag-of-Words and TF-IDF feature representations employ it for sentiment categorization. Naive Bayes Classifier: It is a classifier based on independence and the Bayes theorem. Because of its simplicity and effectiveness, it is frequently utilized for text classification and high-dimensional sparse data, including TF-IDF and Bag-of-Words features. Random Forest Classifier: This is a group of learning techniques that uses random code sets from the training data and feature space to construct multiple decision trees. The ultimate prediction, which increases classification accuracy and resilience, is the majority vote of the trees. Feedforward Neural Network: Another neural network implementation used for sentiment classification is the feedforward neural network.

A dense hidden layer made up of 128 neurons with ReLU activation is applied to the input feature vectors. To avoid overfitting, a dropout of 0.5 is used. The output layer, which employs a SoftMax activation function to produce scores interpreted as likelihoods, consists of three neurons corresponding to the classifications of positive, neutral, and negative attitudes. This includes training on larger corpora, removing the next-sentence prediction objective, using dynamic masking, and training with larger mini-batches over more iterations. Compared to traditional machine learning models, these improvements allow RoBERTa to capture deeper bidirectional contextual representations of text. The suggested approach uses the Amazon product review dataset to refine a pre-trained RoBERTa-base model for three-class sentiment categorization. The tokenizer transforms each review into subword token sequences with positional embeddings, and a classification head consisting of a linear layer applied to the [CLS] token output produces the final probability distribution over positive, neutral, and negative sentiment classes. RoBERTa is intrinsically compatible with the confidence scoring structure of the suggested system, as its softmax output probabilities are used immediately as the sentiment confidence score.

3.6. Sentiment Confidence Scoring

In addition to sentiment classification, the proposed system provides a sentiment confidence score for each prediction. Confidence score is the likelihood of the predicted sentiment class, and it shows the level of certainty of the classifier. The classification models' probability outputs are used to obtain confidence values using the predict_proba() function. The overall level of confidence of each review is calculated as:

Confidence Score = max (Ppositive, Pneutral, Pnegative)

The mechanism enables organizations to obtain the highest-confidence sentiment predictions first, enhancing the effectiveness of automated analysis of customer feedback and enabling more informed decision-making.

3.7. Performance Evaluation

- The accuracy of the proposed sentiment classification models, as measured by the correctness of the projected classifications, is evaluated using a confusion matrix. There are four fundamental components to the confusion matrix.
- Instances that have been expected to be positive are known as True Positives (TP).
- True Negative (TN): The negative predictions were accurate.
- False Positives (FP) are cases that were incorrectly classified as positive.
- Positive instances mislabeled as negative are called false negatives (FNs).
- The following assessment metrics are ultimately computed from these values to assess performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

The percentage of correctly predicted favorable outcomes among all positively anticipated decisions is known as precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: It is defined as the proportion of correctly anticipated positive events to all actual positive events:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score: An equal indicator of categorization performance, the F1-score represents the harmonic mean of recall and precision:

$$\text{F1-Score} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

These evaluation metrics will give a thorough assessment of the efficacy and dependability of the proposed sentiment classification system.

4. Results and Discussion

The learned classification models' ability to predict sentiment was evaluated. Five classifiers, Feedforward Neural Network, Naive Bayes, Logistic Regression, Random Forest, and RoBERTa Transformer, were tested using Bag-of-Words (BoW) and TF-IDF feature representations. Additionally, RoBERTa used refined contextual embeddings.

Table 2: Accuracy

Vectorizer	Bag of Words Vectorizer	TF-IDF Vectorizer
Feedforward Neural Network	0.9032	0.8975
Logistic Regression	0.7341	0.7418
Naive Bayes Classifier	0.7015	0.6982
Random Forest Classifier	0.7156	0.7193
RoBERTa Transformer	0.9341	0.9287

Table 2 presents the accuracy of all evaluated models using BoW and TF-IDF feature representations. RoBERTa Transformer achieves the highest accuracy at 0.9341 (BoW) and 0.9287 (TF-IDF), demonstrating the clear advantage of contextual pre-trained representations. These findings demonstrate the efficacy of transformer-based models for consumer sentiment categorization and validate that combining RoBERTa with traditional classifiers significantly enhances overall system performance. The model's classification performance in each sentiment category is shown in Figure 3, which displays the best-performing model confusion matrix. The classification report for the top-performing model, RoBERTa, assessed across all three sentiment classes using Accuracy, recall, and F1-Score metrics, is shown in Table 3.

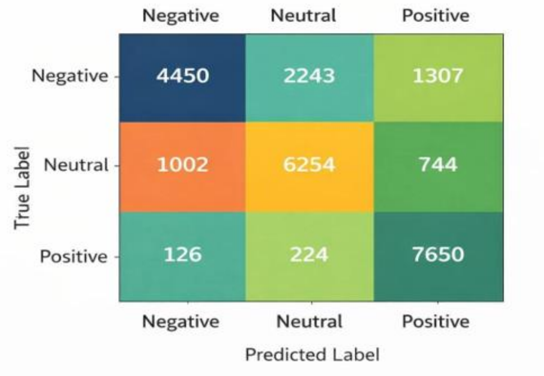

Figure 3: Confusion matrix

All classes perform well with RoBERTa; the Positive class has the greatest F1 rating of 0.96, followed by Neutral at 0.90 and Negative at 0.86.

Table 3: Classification report

Class	Precision	Recall	F1-score
Negative	0.88	0.84	0.86
Neutral	0.91	0.89	0.90
Positive	0.95	0.97	0.96

While the consistently high scores across all classes verify that the contextual representations learned by RoBERTa significantly outperform traditional bag-of-words approaches for customer sentiment analysis, the relatively lower scores for the Negative class reflect the inherent difficulty in identifying nuanced critical language (Table 4).

Table 4: Sample sentiment confidence scores

Review ID	Predicted Sentiment	Confidence Score
R1	Positive	0.91
R2	Neutral	0.79
R3	Negative	0.74
R1	positive	0.91
R2	Neutral	0.79
R3	Negative	0.74

Figure 4 presents the accuracy comparison across all five classification models. RoBERTa clearly outperforms all classical models, achieving 93.41% accuracy with BoW features, confirming the benefit of pre-trained contextual embeddings.

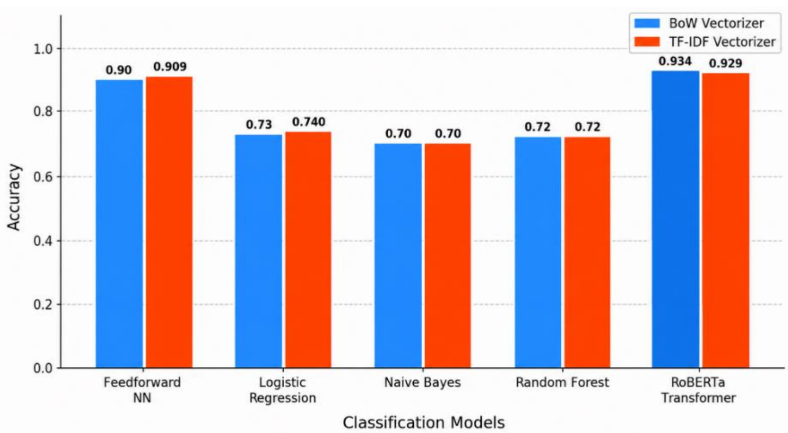

Figure 4: Accuracy comparison of all classification models

The bar chart also shows that the Feedforward Neural Network is the second-strongest baseline at 90.32%, while the traditional models cluster between 69% and 74%. The sentiment confidence score distribution further shows that RoBERTa generates a higher proportion of high-confidence predictions, reducing the number of ambiguous reviews that require manual review. Taken together, the experimental results demonstrate that incorporating RoBERTa, a transformer-based classifier, alongside classical machine learning models substantially increases the overall accuracy, reliability, and interpretability of the proposed intelligent customer feedback analysis system across diverse business domains.

5. Conclusion

The ability to analyze customer reviews for sentiment has emerged as a critical analytical tool across industries, including retail, e-commerce, media, product evaluation, and market intelligence, because it helps inform customers about products or services and continuously improve them. This work presents an intelligent customer feedback analysis system that combines classical machine learning classifiers with the RoBERTa transformer model and probability-based sentiment confidence scoring to deliver reliable, interpretable, and high-accuracy predictions of customer opinion. By converting unstructured reviews into structured feature representations through Bag-of-Words and TF-IDF vectorization for classical models, and by fine-tuning RoBERTa on contextual subword embeddings, the proposed framework demonstrates the clear benefit of integrating transformer-based deep learning with confidence-aware sentiment prediction for data-driven business decision support. Organizations can measure the strengths and weaknesses of their offerings, monitor changing consumer behavior, and anticipate future behavior through systematic analysis of customer feedback, thereby enabling them to plan their strategies proactively and better serve their consumers. The proposed framework can help service providers and manufacturers in the food, retail, and hospitality industries improve the customer experience, increase customer loyalty, and enhance operational performance and revenue generation.

The addition of sentiment confidence scoring also brings organizations closer to making decisions between high-predictability judgments and guesses, enabling a greater number of more reflective, actionable feedback data points to be prioritized. Even with these developments, sentiment analysis still encounters issues, such as accurately detecting sarcasm, irony, context-sensitive meaning, domain-specific vocabulary, and culturally specific linguistic phrases, which can undermine prediction accuracy. There are more subjective interpretations of experiences, along with variations in language use, which further complicate sentiment evaluation in real applications. Future research directions include extending the framework with larger transformer variants, such as RoBERTa-large or DeBERTa, incorporating aspect-level sentiment analysis, leveraging multimodal and cross-domain feedback sources, and developing real-time sentiment-monitoring pipelines that provide a continuous view of customer opinions across multiple digital platforms. These improvements can greatly increase the scalability, adaptability, and reliability of intelligent customer feedback analysis systems, helping organizations achieve better decision-making, greater customer satisfaction, and continued competitive advantage in highly dynamic business environments.

Acknowledgement: The authors would like to express their sincere gratitude to SRM Institute of Science and Technology at Ramapuram and Fitch Group for their valuable support, encouragement, and assistance throughout this research.

Data Availability Statement: Data supporting the findings of this study are available from the corresponding author upon reasonable request, where permitted and applicable.

Funding Statement: This research was conducted without the receipt of any external financial support or funding.

Conflicts of Interest Statement: The authors declare that there are no conflicts of interest related to this work. All sources utilized in this original study have been properly acknowledged and referenced.

Ethics and Consent Statement: The study was conducted in accordance with established ethical principles, and informed consent was obtained from all participants.

References

1. Y. Zhang, Q. Ma, Y. Zhang, and Y. Liu, "Sentiment analysis for e-commerce product reviews using a Fourier graph transformer network," *IEEE Access*, vol. 13, no. 11, pp. 194127–194138, 2025.
2. S. Markande, S. R. Shree, M. Moharir, and S. Lakhotia, "Customer Sentiment Analysis of Product Reviews," *in Proceedings of the International Conference on Intelligent Computing and Control Systems (ICICCS)*, Erode, Tamil Nadu, India, 2025.

3. A. Nawrocka, M. Nawrocki, A. Kot, and M. Słychan, "The application of machine learning in sentiment analysis of social media and e-commerce: A review of methods and techniques," *in Proc. 26th Int. Carpathian Control Conf. (ICCC),* Starý Smokovec, Slovakia, 2025.
4. Y. S. Liang, C. Y. Chen, C. T. Li, and S. M. Chang., "Personalized Product Description Generation with Gated Pointer-Generator Transformer," *IEEE Transactions on Computational Social Systems*, vol. 12, no. 1, pp. 52–63, 2025.
5. P. Triawan, I. Tahyudin, and P. Purwadi, "Impact of NLP algorithms on sentiment analysis efficiency and accuracy," *Journal of Information Systems and Informatics*, vol. 7, no. 3, pp. 2684–2709, 2025.
6. V. Tripathy, S. Samanta, and J. Briskilal, "Leveraging customer sentiment analysis with deep learning for business growth forecasting and product flaw identification*," in Proc. International Conference on Current Trends in Advanced Computing (ICCTAC),* Bengaluru, India, 2024.
7. P. Paul, S. Acharya, B. Misra, S. Majumder, N. Dey, and P. Pise, "Sentiment analysis for e-commerce product reviews using CNN-LSTM," *in Proc. 1st Int. Conf. Women in Computing (InCoWoCo),* Pune, India, 2024.
8. E. H. Aydoğan and F. Y. Okay, "Sentiment analysis of reviews for e-commerce applications," *in Proc. 9th Int. Conf. Computer Science and Engineering (UBMK),* Antalya, Türkiye, 2024.
9. F. Khanum, P. S. Lakshmi, and H. V. R. K., "Sentiment analysis using natural language processing, machine learning and deep learning*," in Proc. 5th Int. Conf. Circuits, Control, Communication and Computing (I4C),* Bengaluru, India, 2024.
10. V. Vanshika, N. Rani, and R. Walia, "A comprehensive review of sentiment analysis: Techniques, datasets, limitations, and future scope*," in Proc. 6th Int. Conf. Computational Intelligence and Communication Technologies (CCICT)*, Sonepat, India, 2024.
11. A. Godia and L. K. Tiwari, "Sentiment analysis and classification of product reviews: A comprehensive study using NLP and machine learning techniques*," in Proc. 10th Int. Conf. Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, 2024.
12. S. Y. Sheemu, M. A. A. Symum, A. Zaman, A. S. M. Asif, A. Shakil, and R. Zannah, "Sentimental analysis of customer product reviews to understand customer needs using machine learning*," in Proc. 27th Int. Conf. Computer and Information Technology (ICCIT),* Cox's Bazar, Bangladesh, 2024.
13. D. R. Wulandari, M. A. Murti, and T. S. P. Hilman Fauzi, "Sentiment analysis based on text about president candidate 2024 in Indonesia using artificial intelligence with parameter optimization algorithm," *in Proc. IEEE Int. Conf. Internet of Things and Intelligence Systems (IoTaIS),* Bali, Indonesia, 2023.
14. W. Kumara, P. P. N. V. Kumara, and F. S. Sourjah, "Value customer reviews in e-commerce platforms using sentiment analysis tactics: A review," *in Proc. 3rd Int. Conf. Emerging Technology (INCET),* Belgaum, Karnataka, India, 2022.
15. R. Y. Kim, "Using online reviews for customer sentiment analysis," *IEEE Engineering Management Review,* vol. 49, no. 4, pp. 162–168, 2021.