Intelligent Customer Feedback Analysis System Using NLP Techniques

Omkar Jayendra Rane[a] and Deepali Naik[b]
Pimpri Chinchwad College of Engineering, Department of Computer Engineering, Pune, Maharashtra, India

Keywords: Sentiment Analysis, LDA, CYK, TF- IDF, Customer Feedback Analysis, Vader Sentiment Analysis.

Abstract: In the digital era, businesses receive vast unstructured client feedback containing valuable insights into customer satisfaction, product performance, and service quality. Thus, to extract actionable insights requires advanced analytical techniques. This study presents an Intelligent Customer Feedback Analysis System utilizing Natural Language Processing (NLP) techniques like Vader Sentiment Analysis, LDA topic modelling, and TF-IDF for sentiment classification, trend analysis, topic detection, and keyword extraction. This system utilized a Streamlit interactive application, visualization tools such as word clouds, sentiment distribution, rating trends, and filters for sentiment analysis. The implemented system is very much real-time and assists data-driven sentiments understanding in brand decision-making, which is the power of customer perspectives and proactive engagement.

1 INTRODUCTION

Some modern markets have witnessed an emerging trend where the user comes first, and the service provider must not only provide but accept user feedback. The rise of social media, online rating and commentary, and other forms of digital customer feedback has made the need for robust methods for collecting, evaluating, and synthesizing insights from large amounts of unstructured consumer-related information. However, in this context, its alternative - classical feedback mechanisms - are almost always limited in their application because they rely on rigid, rule-based systems that cannot comprehend the subtleties and complexities of human emotions. As a consequence, however, it becomes hard for enterprises to fully utilize consumer feedback in award-winning, consumer-dominated industries such as e-commerce, food delivery, and auto service (Hemalatha, Velmurugan, et al. , 2020), (Ramaswamy, and, Declerck, 2018)

The past decade has witnessed considerable advances in Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP), making it possible to conduct consumer opinion mining with enhanced detail and accuracy. Early studies began with traditional methods, such as logistic regression, Naive Bayes, and SVM, which laid a foundation for more sophisticated models (Shaeeali, Mohamed, et al. , 2020).

However, as consumer opinion mining techniques involve working with large amounts of unstructured text data, it was only natural that interest shifted toward NLP.

Ordinary machine learning techniques are most applicable in the case of structured and numerical data, and such methods fail to manage the intricacies of textual information, in particular, different sentence patterns, ambiguous meaning of language, and dependencies related to the context. At the same time,NLP is devoted to processing and comprehending human language, which allows us to understand emotion, intention, or meaning much more profoundly (Schreiber, Ramsey, et al. , 2020). This capability makes it easier to use NLP when processing large amounts of unpaid content, including sources of information such as product reviews, social networks, and complaints to the company, which in turn were problematic for the traditional ML methods (Anonymous.,et al. , 2020).

Research focusing on specific areas, like opinions about airlines (Li, Huang, et al., 2023) or food

[a] https://orcid.org/0009-0004-2942-2693
[b] https://orcid.org/0000-0001-6022-4565

Rane, O. J. and Naik, D.
Intelligent Customer Feedback Analysis System Using NLP Techniques.
DOI: 10.5220/0013584100004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 1*, pages 707-714
ISBN: 978-989-758-763-4

delivery (Malik and Bilal, 2023) services, has shown that sentiment analysis has improved with the introduction of BERT and its transformer architecture.NLP models such as BERT (Li, Huang, et al., 2023), GPT (Olujimi, Ade-Ibijola, et al. , 2023), etc., are pretty effective in obtaining contextual sentiments necessary to make persuasive arguments in highly competitive environments.

The use of hybrid models such as SVM and CNN integrated with optimization algorithms such as Particle Swarm Optimization (Khaled, 2014) can also help improve the quality of the analysis and its precision. The study explores machine learning (ML) and natural language processing (NLP) to automate request classification in software companies' customer service areas. By applying ML algorithms such as Support Vector Machine (SVM), Extra Trees, and Random Forests to process and balance datasets, the research achieved a classification accuracy of 98.97% with SVM. This approach significantly enhances customer service efficiency by reducing response times and providing accurate categorizations. The findings underscore the effectiveness of data balancing and hyper-parameter optimization techniques, particularly with unbalanced datasets containing multiple categories (Barahona, Díaz, et al. , 2023).

Despite these improvements, the classification of the sentiments is insufficient, and there is a greater need for intelligent feedback mechanisms. According to the study, usability and interpretability are key to effective customer feedback systems. Existing research shows that visual feedback data displays help stakeholders grasp and respond to complex findings (Olujimi, Ade-Ibijola, et al. , 2023). The visuals generated on rigorous analysis can support better decision-making by showing trends, revealing patterns, and pointing out areas for improvement. According to R. Schreiber et al. (Schreiber, Ramsey, et al. , 2020), the addition of user-friendly visual analytics makes feedback systems even more helpful, and lets companies set priorities based on real-time results

Adding This study puts forward a new approach to building an Intelligent Customer Feedback System that combines various NLP techniques and adapts to specific fields. The proposed system handles large amounts of unstructured feedback data and provides dynamic, practical insights that meet the customer's needs. By using recent advances in NLP and ML, the system aims to address the shortcomings of traditional feedback analysis systems and offer a more customer-focused and responsive solution.

The rest of the paper is arranged as follows: section 2 focuses on the study of existing literature, and a detailed discussion of the proposed system's methodology is conducted in section 3. Meanwhile, the performance analysis of the implemented techniques is presented in the form of graphs and tables in section 4. The paper concludes with significant observations.

2 RELATED WORK

In recent times, technology in customer feedback analysis has developed with ML (Hemalatha, Velmurugan, et al. , 2020), NLP (Malik and Bilal, 2023) and DL (Ramaswamy, and, Declerck, 2018) techniques. This section will discuss state-of-the-art customer feedback analysis techniques. For the study, more focus is given to the methodology and tools adapted by the previous researchers and estimated future developments.

Researchers started with simple computer programs to figure out how customers feel about their reviews. Hemalatha and Velmurugan (2020) (Hemalatha, Velmurugan, et al. , 2020) showed that people used logistic regression, Naïve Bayes, SVM, and neural networks. These tools work well with organized information, which helps lay the groundwork for understanding feelings. But they often miss the little hints about emotions in people's words (Alibasic and Popovic, 2021). Take, for example. SVM and logistic regression algorithms are suitable for basic sorting tasks but need much tweaking to work accurately.

Moreover, they struggle with the tricky, context-dependent attitudes you often see in customer feedback (Olujimi and Ade-Ibijola, 2023) (Zheng, Zhou, et al. , 2024). These old-school computer methods set a bar for how well things should work. But they're not great at changing or adapting when you're dealing with tons of information.

NLP and DL introduced newer and more efficient data analysis methods to physicians. Ramaswamy and Declerck (2018) (Ramaswamy and Declerck, 2018) proved that tokenization and segmentation significantly improve real-time customer sentiment analysis. A study by XPath revealed that it also uses word vectorization and neural network models to enable the contextual understanding of sentiments, which is a direct step to getting actionable insights. In a parallel study, Shaeeali et al. (2020) (Shaeeali, Mohamed, et al. , 2020) applied NLP methods that the food delivery company is dealing with, like text tokenization and sentiment classification, to determine the customer's emotions and also the key components that make them satisfied (Shaeeali, Mohamed, et al. , 2020).

Recent research shed light on the emergence of transformer-based models in capturing the intricacies of context-dependent sentiment expressions. As an example, Zehong Li et al. (2023) (Li, Huang, et al. , 2023) brought BERT into practice, one of the strong transformer models that were used in the sentiment analysis of airline customer feedback, and the model was able to attain high accuracy due to BERT's contextual ability to interpret word meaning and subtleties (Li, Huang, et al. , 2023). Specifically, these transformers can be seen as a detonator for information technology to the next stage of development, and this is mainly caused by the fact that we can attribute it according to the unstructured set of target data. Alongside the model, they also suffer from a massive demand for computations, and they need domain-specific fine-tuning for stable AI functioning (Schreiber, Ramsey, et al. , 2020). As a result, Transformers can be said to be the right tool for uncovering the customer's voice in a way that the existing neural network models could not.

Malik and Bilal (2023) (Malik and Bilal, 2023) proposed a technique that merges models like Structural Vector Models and Convolution Neural Networks (CNN) with optimization algorithms like Adaptive Particle Swarm Optimization to improve feedback analysis on e-commerce platforms (Malik and Bilal, 2023). By adaptive learning, these hybrid approaches gain efficiency in dealing with real-time updates; thus, the feedback systems remain relevant and adaptive to new data patterns.

Table 1: Summarizes the literature studied based on various aspects, implementation techniques, and relevant insights.

Aspect	Implementation	Insights from Literature Review
Objective	Analyze customer reviews for sentiment, key topics, and syntactic patterns.	Enhance customer feedback understanding using advanced NLP for sentiment analysis, topic modeling, and predictive analytics.
NLP Tools Used	VADER for sentiment analysis, TF-IDF for keyword extraction, LDA for topic modeling, and CFG for parsing.	Word2Vec, GloVe, BERT, RoBERTa for embeddings; SVM, Naive Bayes, Logistic Regression for sentiment analysis; advanced parsing tools like Spacy and CoreNLP.
Pre-processing	Tokenization, stopword removal, cleaning for LDA, CFG grammar definition for parsing.	Includes advanced cleaning, lemmatization, POS tagging, and contextual pre-processing specific to domains (e.g., healthcare, finance).
Sentiment Analysis	VADER scoring is used to classify reviews as positive, negative, or neutral.	Comparison of lexicon-based (e.g., VADER) with deep learning-based sentiment analysis (e.g., BERT) for higher accuracy and contextual understanding.
Topic Modeling	LDA model to identify 5 topics with dominant keywords from reviews.	Emphasis on coherence measures for validating topics and use of transformers (e.g., BERTopic) for dynamic topic modeling.
Visualization	Sentiment distribution (bar chart), trend analysis (line chart), and word clouds for sentiment groups.	Heatmaps, t-SNE, and clustering plots are utilized to interpret high-dimensional data and semantic relationships better.
Syntactic Analysis	Context-free grammar (CFG) parsing using the CKY algorithm.	More advanced dependency parsing (e.g., Stanford Parser) and syntactic tree generation for domain-specific grammar validation.
Sentiment Analysis	VADER scoring is used to classify reviews as positive, negative, or neutral.	Comparison of lexicon-based (e.g., VADER) with deep learning-based sentiment analysis (e.g., BERT) for higher accuracy and contextual understanding.

3 PROPOSED METHODOLOGY

This research uses an automated framework to Analyse customer feedback. Using a combination of pre-packaged libraries and original algorithms, it implements the methodology in Python to extract results from customer reviews. The pipeline begins with data pre-processing, which collates the reviews by fixing missing values, adjusting the text to lowercase, splitting the sentences into tokens, and filtering stop words. Descriptive statistics (mean ratings, review lengths, rating change over time) are generated through statistical and exploratory data analysis (EDA) techniques. The detailed architecture of the proposed system is demonstrated in the figure 1.

3.1 Dataset Description

The Consumer Reviews of Amazon Products dataset on Kaggle (Datafiniti, 2018) contains over 34,000 reviews of various Amazon products, such as the Kindle and Fire TV. It provides valuable information, including product names, ratings, reviews, and feedback dates. This dataset is ideal for text analysis, sentiment analysis, and machine learning applications focused on consumer behavior and product evaluation. Its structured format allows easy integration into analytical workflows to derive insights into customer satisfaction and preferences.

3.2 Implemented Models

- Classify the sentiment:

The VADER (Valence Aware Dictionary and sEntiment Reasoner) model is deployed for sentiment analysis, which assigns a compound score (from −1 to +1) to the reviews to classify it to positive, negative, and neutral sentiments. We augment this by visualizing how sentiment is distributed with bar charts and word clouds to explore the most common terms associated with each sentiment type.

- Topics identification

The Latent Dirichlet Allocation (LDA) algorithm is one of the methods used to perform topic modeling, which detects the abstract themes of reviews. Reviews are tokenized and transformed into a corpus. Topics and most representative keywords are generated from the corpus. A TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer is used to calculate words' scores in reviews and find the most important terms.

- Syntactic examination

The syntactic analysis of selected reviews is conducted using context-free grammar (CFG), with the CKY algorithm employed to create a parse table for checking grammatical structure.

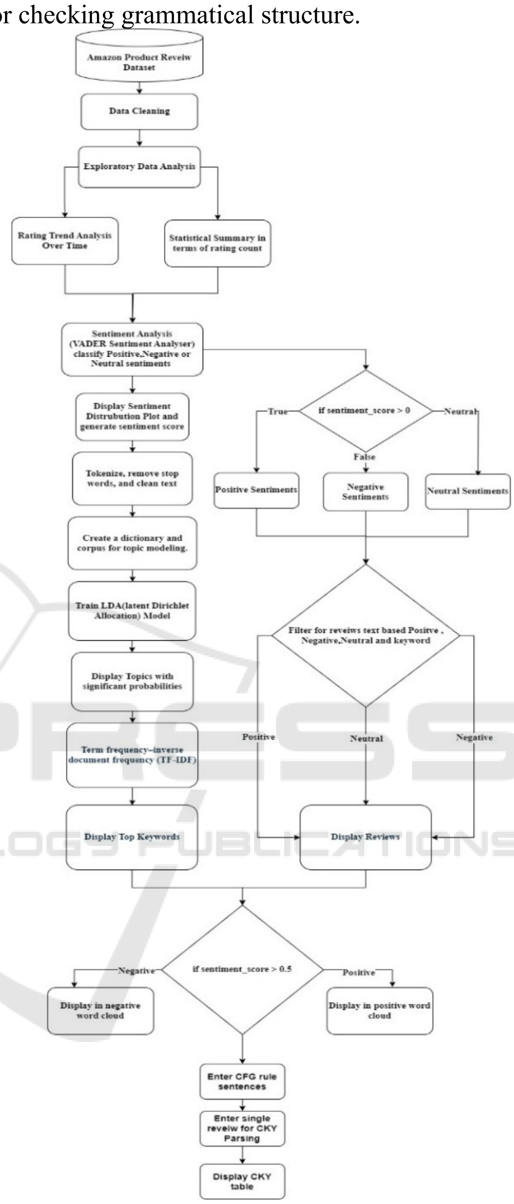

Figure 1: Architecture of NLP-based Customer Feedback System

4 RESULTS

The system is implemented to analyze Amazon customer reviews through various NLP techniques. These results can be grouped into three main types: sentiment analysis, topic analysis, and syntactic analysis. The results and associated visualizations assist companies in providing actionable insights into customer feedback.

The developed models are executed for the Amazon datasets, and the results are presented as analysis. The extracted results are shown in Figures 2 and 9.

The statistical summary of the review data indicates a highly positive trend in customer feedback. The average rating stands at 4.5968, demonstrating an overall favourable perception. The rating distribution reveals that most ratings are concentrated at the higher end of the scale, with over 3,500 reviewers assigning a 5-star rating. Ratings of 4 also appear frequently, while lower ratings, including 1, 2, and 3, are comparatively rare. Additionally, the average length of reviews is calculated at 161.35 characters, suggesting concise user feedback. This distribution highlights a strong positive sentiment among most reviewers.

Figure 2: Statistical Summary of Product Ratings

The rating trend over time demonstrates a generally consistent and positive trajectory. From late 2014 through mid-2016, ratings broadly hovered around the 5-star mark, reflecting intense satisfaction among users. However, a noticeable drop occurred around mid-2016, when ratings dipped significantly, potentially indicating a specific issue or event during this period. Following this decline, ratings quickly rebounded and maintained a stable upward trend, returning to near-perfect levels by late 2018. This pattern suggests that while there was a brief disruption in user satisfaction, it was effectively addressed, resulting in sustained positive feedback over the long term.

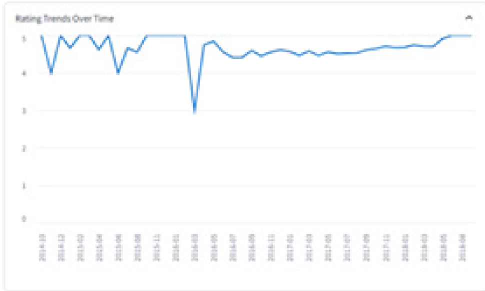

Figure 3: Review Rating Trend Analysis

The reviews were filtered based on sentiment and specific keywords to understand user feedback better. For example, using the keyword "Kindle" and focusing only on positive sentiments, we identified reviews that highlighted users' favourite features.

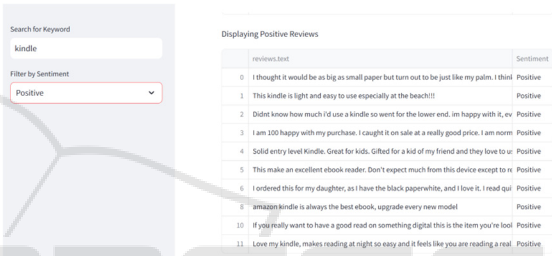

Figure 4: Reviews Filtering based on Keyword and Sentiments.

The sentiment analysis results reveal a predominantly positive tone in the dataset, with a significant majority of 4,532 entries classified as positive. In contrast, negative sentiments are much fewer, with only 289 instances, while neutral sentiments account for 179 entries. This distribution, illustrated in the accompanying bar chart

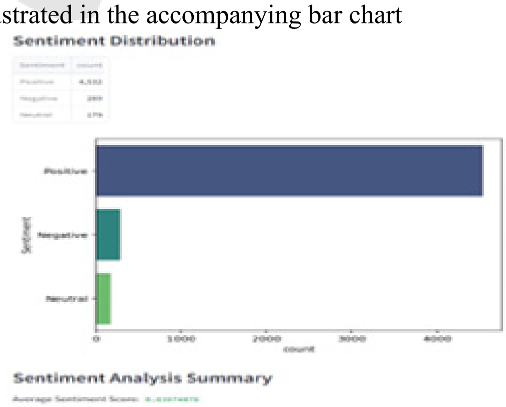

Figure 5: Sentiment Analysis Summary with LDA

The LDA analysis revealed five main topics in customer reviews. Topic 0 focuses on tablets, with keywords like "tablet," "fire," and "amazon." Topic 1 canters on voice-enabled devices such as "Alexa" and "music." Topic 2 is about e-readers, with terms like "Kindle" and "books." Topic 3 reflects product use and entertainment, while Topic 4 discusses ease of use and pricing. The numbers, like 0.050*tablet, represent the weight of each word in a topic, showing how relevant it is to that topic.

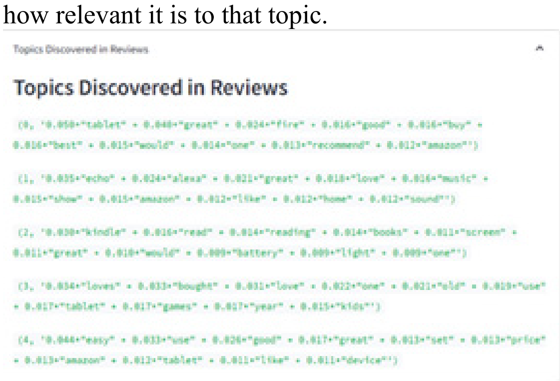

Figure 6: LDA Output Represents the Topics Discovered in the Reviews, Most Significant Words, and Corresponding Weights (Probabilities)

List of top keywords extracted from customer reviews using the TF-IDF (Term Frequency-Inverse Document Frequency) method. These keywords highlight the most relevant terms frequently mentioned across the reviews while discounting commonly used words that add less value. The identified keywords include terms such as "value," "amazon," "bought," "easy," "echo," "good," "great," "kindle," "love," "tablet," and "use." These words likely indicate recurring themes in customer feedback, reflecting user sentiment and frequently discussed aspects of the reviewed product or service.

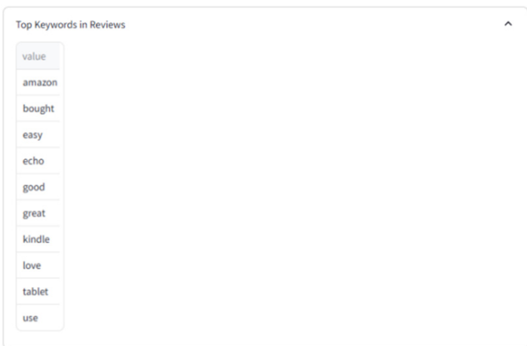

Figure 7: TOP Keywords Extracted by Applying TF-IDF Technique

The below word clouds represent frequently mentioned terms in positive and negative customer reviews. In positive reviews, words like "love," "tablet," "use," and "great" stand out, reflecting customer satisfaction with usability, quality, and overall experience. In contrast, the negative reviews highlight terms such as "problem," "work," "Kindle," and "battery," pointing to issues with performance, reliability, or specific features. These visualizations offer insight into customer sentiment, highlighting both praised aspects and areas of concern.

Figure 8: Word Cloud of Positive and Negative Words from the Analyzed Reviews

Context-free grammar (CFG) Parsing uses the CKY algorithm for the "read the book" sentence. The provided CFG includes rules for sentence structure, such as breaking a sentence into a noun phrase (NP) and a verb phrase (VP). The CKY parse table shows how the input sentence is parsed step-by-step according to these rules, with components like "read" identified as a verb (V), "the" as a determiner (Det), and "book" as a noun (N). The parsing was successful, illustrating the grammatical breakdown of the sentence.

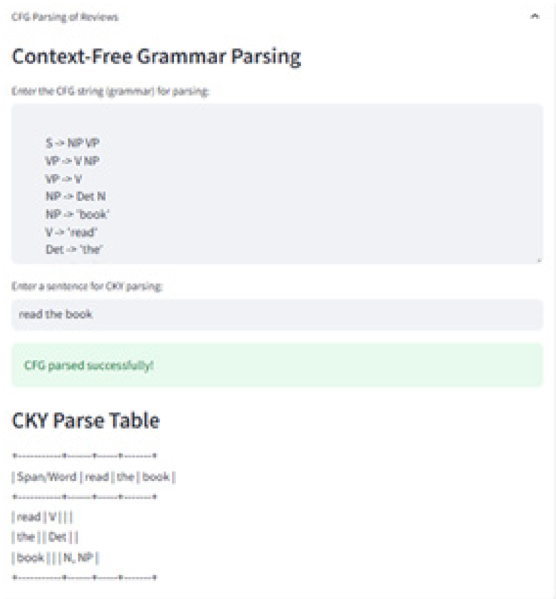

Figure 9: Result of CKY Algorithm Applied to Review Text.

5 CONCLUSIONS

This research provides an expansive framework for evaluating customer feedback by utilizing various natural language processing techniques, including sentiment analysis, topic modelling, and syntactic parsing. The execution uses VADER to classify the sentiment, LDA to identify topics, and CFG parsing using the CKY algorithm for syntactic examination. The results show that the implemented system can reveal critical insights regarding trends in the sentiment expressed, frequent themes, and grammatical patterns, thus providing practical intelligence for organizations aiming to improve customer satisfaction.

The interactive nature of the implementation, enabled through the Streamlit platform, allows users to visualize and interpret data effectively. However, the system's reliance on traditional NLP methods presents opportunities for improvement, particularly by integrating advanced techniques like transformer-based models (e.g., BERT, GPT) for enhanced accuracy and scalability. Future work will expand the system's capabilities to include multilingual analysis, domain-specific customizations, and real-time feedback processing, extending its applicability to diverse contexts and datasets.

While customer feedback analysis has come a long way, specific problems persist with existing systems, which may have future work as an area of research. Future research may gain traction by focusing on domain-specific models that adapt and the other traditional NLP pipeline into a rat's feedback loop. However, state-of-the-art models still leave room for improvement in real-time prompt adaptation (especially in domain-specific areas), fine-tuning, and computational efficiency. In continuation, our proposed intelligent customer feedback system seeks to alleviate the challenges mentioned above by combining advanced NLP techniques with adaptive learning models to provide customized real-time solutions at scale specific to the domain.

REFERENCES

1. Hemalatha, B. and Velmurugan, T. (2020). Impact of customer feedback system using machine learning algorithms for sentiment mining. *International Journal of Innovative Technology and Exploring Engineering*.
2. Ramaswamy, S. and Declerck, N. (2018). Customer perception analysis using deep learning and NLP. *Procedia Computer Science*.
3. Shaeeali, N. S., Mohamed, A., and Mutalib, S. (2020). Customer reviews analytics on food delivery services in social media: a review. *IAES International Journal of Artificial Intelligence (IJ-AI)*.
4. Li, Z., Huang, C., and Yang, C. (2023). A comparative sentiment analysis of airline customer reviews using bidirectional encoder representations from transformers (BERT) and its variants. *Mathematics*.
5. Malik, N. and Bilal, M. (2023). Natural language processing for analyzing online customer reviews: A survey; taxonomy; and open research challenges. Unpublished.
6. Khaled, K. A. (2014). Natural language processing and its use in education. *International Journal of Advanced Computer Science and Applications*.
7. Arias-Barahona, M. X., Valencia-Díaz, M. A., Tabares-Soto, R., Flórez-Ruíz, J. C., Arteaga-Arteaga, H. B., and Orozco-Arias, S. (2023). Requests classification in the customer service area for software companies using machine learning and natural language processing. *PeerJ Computer Science*.
8. Shaik, T., McDonald, J., Tao, X., Redmond, P., Galligan, L., Li, Y., and Dann, C. (2022). A review of the trends and challenges in adopting natural language processing methods for education feedback analysis. *IEEE Access*.
9. Alibasic, A. and Popovic, T. (2021). Applying natural language processing to analyze customer satisfaction. Unpublished.

10. Olujimi, P. A. and Ade-Ibijola, A. A. (2023). NLP techniques for automating responses to customer queries: A systematic review. *Discover Artificial Intelligence*.
11. Schreiber, R., Ramsey, G., and Nawab, K. (2020). Natural language processing to extract meaningful information from patient experience feedback. *Applied Clinical Informatics*.
12. Anonymous. (2020). AI-based natural language processing (NLP) systems. *Journal of Algebraic Statistics*.
13. Abro, A. A., Talpur, M. S. H., and Jumani, A. K. (2023). Natural language processing challenges and issues: A literature review. *Gazi University Journal of Science*.
14. Zheng, H., Zhou, H., Su, G., Xu, K., and Wang, Y. (2024). Medication recommendation system based on natural language processing for patient emotion analysis. *Academic Journal of Science and Technology*.
15. Datafiniti. (2018). Consumer reviews of Amazon products, version 1. Retrieved November 24, 2024, from https://www.kaggle.com/datasets/datafiniti/consumer-reviews-of-amazon-products.