Journal of Artificial Intelligence and Information Technology

E-ISSN: 3090-2428
P-ISSN: 3090-2436

Research Article

Application of Natural Language Processing for Sentiment Analysis in Digital Application User Feedback

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Abstract: The increasing volume of user feedback on digital applications presents a major challenge for developers and analysts, as manual analysis is time-consuming, subjective, and inefficient. This research aims to automatically identify sentiment patterns within large-scale user feedback using Natural Language Processing (NLP) techniques based on Transformer architecture. The study applies a Transformer-based model, specifically BERT, to classify sentiments into positive, neutral, and negative categories. User feedback data were collected from various digital application platforms, then preprocessed through tokenization, stopword removal, and stemming to ensure text quality and consistency. The fine-tuned Transformer model successfully achieved high accuracy in classifying sentiment patterns, demonstrating its ability to capture nuanced contextual meanings in textual data. The results revealed that positive feedback accounted for 45.2%, neutral for 23.8%, and negative for 31.0% of the total dataset. Compared to manual sentiment analysis, the Transformer-based approach showed greater efficiency, reduced analysis time, and minimized human bias. These findings highlight the transformative potential of deep learning models in automating large-scale text analytics. In conclusion, this research confirms that Transformer-based NLP methods provide a robust and scalable solution for sentiment analysis of user feedback, enabling digital application developers to monitor user satisfaction and improve service quality based on data-driven insights.

Keywords: BERT, Natural Language Processing, Sentiment Analysis, Transformer, User Feedback

Received: April 14, 2025
Revised: April 30, 2025
Accepted: May 15, 2025
Published: May 31, 2025
Curr. Ver.: May 31, 2025

1. Introduction

User feedback plays a crucial role in the development of modern digital applications. In the context of increasingly fierce business competition, developers and digital service providers need a deep understanding of how users interact with their products to improve user experience and satisfaction .User feedback provides direct data on users' perceptions, preferences, and challenges encountered during application use. This information serves as a strategic foundation for identifying areas requiring improvement and for innovating features that enhance product value .

In addition to being a source of information, user feedback functions as an essential instrument in the process of continuous improvement. Through systematic analysis, developers can trace usage trends, identify shortcomings, and design solutions based on actual user needs . A study by Bertram et al shows that transforming feedback into concrete recommendations helps development teams accelerate product enhancement cycles. Thus, the utilization of user feedback not only improves application quality but also strengthens user loyalty to the brand .

Feedback analysis also provides valuable insights into user sentiment toward a product. Through sentiment analysis, organizations can monitor users' emotional perceptions in real time to assess the extent to which the application meets their expectations . Research by Bau et al. found that sentiment analysis of e-wallet customer reviews can accurately reflect market perceptions. Therefore, sentiment monitoring is a vital element in strategies for improving digital service quality and supporting data-driven decision-making .

However, manual analysis of user feedback faces significant challenges. The large and diverse volume of data makes manual processing inefficient and prone to interpretation errors . Moreover, the inconsistent quality of feedback such as irrelevant, repetitive, or ambiguous comments further complicates the analysis process.Research by Groen et al. revealed that manual analysis is limited in scalability and consistency, especially when dealing with data from thousands of heterogeneous users.

To overcome these challenges, automated technology-based approaches have been developed. Techniques such as data mining, machine learning, and natural language processing (NLP) are used to efficiently extract meaning from user feedback text . Maalej et al. emphasized that automation in feedback analysis allows for faster processing while reducing operational costs. NLP-based models can recognize linguistic patterns, classify topics, and detect sentiment intensity with higher accuracy compared to traditional manual approaches.

Nevertheless, understanding user sentiment still faces several fundamental issues. Complex and contextual sentiments are often difficult for analytical models to capture due to idiomatic expressions, sarcasm, or linguistic ambiguity .Hamdi et al. highlighted that sentiment analysis still struggles to fully detect the hidden emotional nuances within text. This challenge calls for the development of more adaptive models that can accommodate linguistic and cultural variations to achieve more accurate results .

Recent studies have shown that deep learning models such as BERT and LSTM with attention mechanisms can significantly enhance sentiment classification performance . However, aspects of context and sentiment polarity remain critical factors that must be considered to ensure that analytical results truly reflect users' emotions and perceptions . Therefore, the development of an effective feedback analysis system requires a combination of advanced NLP technologies, linguistic understanding, and contextual interpretation strategies to produce actionable insights for future digital application development.

2. Literature Review

Natural Language Processing (NLP)

Definition and Development of NLP in Text Analysis

Natural Language Processing (NLP) is a branch of computer science focused on developing systems capable of understanding, interpreting, and generating human natural language . This field integrates linguistics, artificial intelligence (AI), and computer science to enable interaction between humans and machines in natural language form . Applications of NLP include machine translation, speech recognition, question-answering systems, and sentiment analysis .

The development of NLP has accelerated significantly with the advent of big data and deep learning, enabling greater accuracy and efficiency in text processing .Embedding-based models such as Word2Vec, GloVe, and FastText have become milestones in semantic word representation . Furthermore, contextual pre-trained models such as ULMFit, ELMo, GPT, and BERT have revolutionized language modeling due to their ability to capture dynamic contextual meaning within sentences .

A study by Abro et al. highlights major challenges in NLP, including semantic ambiguity, difficulties in understanding cultural context, and limited training data in non-English languages. Other research emphasizes that NLP is now applied not only to general text but also in education, finance, and healthcare domains to support behavioral analysis and decision-making processes .

Fundamental NLP Techniques Relevant to Sentiment Analysis

Machine learning approaches remain the foundation of various NLP applications, including sentiment analysis. Algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Decision Tree are widely used to classify text based on sentiment polarity . These methods emphasize feature extraction from text using representations such as Term Frequency Inverse Document Frequency (TF-IDF) or bag-of-words.

Meanwhile, deep learning advancements have significantly improved performance through architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) . These approaches excel in capturing complex semantic relationships and long-term dependencies between words. Research by Shamal et al. employed Token2Vec and LSTM for user review analysis and demonstrated improved accuracy compared to traditional methods.

Hybrid models that combine machine learning and deep learning techniques have also been proposed to enhance sentiment classification performance. Ge et al. and Khosin et al. demonstrated that integrating both approaches improves model generalization and accelerates training convergence.

Sentiment Analysis

Definition and Importance of Sentiment Analysis in Understanding User Feedback

Sentiment analysis is a systematic process of detecting and categorizing opinions or emotions in text into categories such as positive, negative, or neutral . Its objective is to understand the emotional tone embedded in textual data, particularly those generated by users on social media, product reviews, or online surveys.

This technique plays a crucial role in understanding public perception of a product or service, supporting business decision-making, and enhancing customer experience . A study by Subramanian et al. demonstrated that sentiment analysis can be used to improve customer service quality by detecting user emotions in real time. Additionally, research by Lalrinawma and Nunsanga emphasized that sentiment analysis has become a vital element in digital customer relationship management because it helps measure user loyalty and satisfaction.

Methods and Techniques Used in Sentiment Analysis

Lexicon-based methods use predefined lists of words assigned with sentiment scores to determine the polarity of text .Although simple and computationally efficient, this approach often struggles to handle semantic nuances and sarcasm. Conversely, machine learning approaches require labeled datasets to train models such as Naïve Bayes, SVM, and Decision Tree. Tian found that machine learning–based models can achieve high accuracy levels when supported by optimal preprocessing and feature selection. Deep learning techniques have gained increasing popularity due to their ability to perform automatic feature extraction from raw text. CNN and RNN can recognize complex semantic patterns and temporal context among words. A study by Yadav et al. demonstrated that applying deep learning to product reviews yields higher accuracy compared to classical methods. Recent approaches are moving toward hybrid models that combine lexicon-based, machine learning, and deep learning methods to improve precision and processing speed. Singh and Kumar showed that such hybrid models balance the interpretability of classical methods with the predictive power of neural models.

Transformer-Based NLP Algorithms

Overview of Transformer Architecture

The Transformer architecture has revolutionized the field of Natural Language Processing (NLP) by introducing a self-attention mechanism that enables the model to efficiently capture long-range dependencies within textual data . Unlike traditional sequential models such as Recurrent Neural Networks (RNNs), Transformers process all tokens simultaneously in parallel, resulting in significantly improved training speed, scalability, and contextual understanding of language structures . Over time, several Transformer-based models have emerged, each contributing unique advancements to NLP tasks.

BERT (Bidirectional Encoder Representations from Transformers) employs bidirectional attention to comprehend contextual relationships in sentences, achieving outstanding results in tasks such as text classification and named entity recognition. GPT (Generative Pre-trained Transformer), on the other hand, adopts an autoregressive architecture that excels in generating coherent and contextually appropriate text, proving highly effective for applications like conversational agents and creative writing . Meanwhile, RoBERTa (Robustly Optimized BERT Pretraining Approach) enhances the BERT model by optimizing its pretraining process, thereby achieving superior accuracy and robustness in various benchmarks. ALBERT (A Lite BERT) focuses on improving model efficiency by reducing parameter redundancy without sacrificing performance, making it suitable for large-scale NLP applications. Additionally, T5 (Text-to-Text Transfer Transformer) introduces a unified framework that reformulates all NLP tasks into a text-to-text paradigm, allowing for enhanced generalization across diverse linguistic problems. The most recent development, GPT-4, represents a multimodal model with approximately 170 trillion parameters, showcasing exceptional adaptability and reasoning capabilities across complex natural language and visual tasks.

Advantages of Transformer Algorithms

Transformers offer several significant advantages over traditional deep learning models in text processing and language understanding. One of their primary strengths lies in handling long-range dependencies through the self-attention mechanism, which allows the model to capture both local and global relationships within textual sequences. This capability makes Transformers highly effective in comprehending the meaning and context of long sentences or entire documents .In addition, Transformers excel in parallel processing unlike Recurrent Neural Networks (RNNs), which operate sequentially, Transformers process entire text sequences simultaneously, resulting in faster training and reduced computational demands.

Another major advantage is their adaptability and ability to support transfer learning. Pretrained models such as BERT and GPT can be fine-tuned on specific domain datasets, enabling efficient knowledge transfer and minimizing the need for large amounts of task-specific data . Moreover, fine-tuned Transformer models exhibit enhanced robustness to input perturbations and noise, outperforming conventional neural architectures in terms of stability and generalization across varied linguistic contexts . Furthermore, studies have demonstrated that Transformer-based architectures consistently achieve superior accuracy when dealing with long and complex text inputs compared to other neural network models, underscoring their effectiveness in large-scale natural language understanding .

3. Proposed Method

Research Design

This study employs an experimental research design aimed at implementing and evaluating Transformer-based Natural Language Processing (NLP) algorithms for sentiment analysis on user feedback from digital applications. The main focus of the research is to measure the model's performance and accuracy in detecting sentiment polarity positive, negative, or neutral from large volumes of unstructured text data. The dataset was derived from collections of user feedback on various digital platforms, including mobile application reviews and online service comments. Each feedback entry was labeled according to its sentiment polarity to support a supervised learning approach. The data sources were intentionally varied to capture linguistic diversity, including formal and informal expressions, as well as idiomatic usage commonly found in real-world contexts.

Data Collection Method

User feedback data were collected from open-access sources such as Google Play Store, Apple App Store, and other online review platforms. The data collection process was conducted automatically by extracting review text, posting date, and user ratings. All data acquisition was carried out ethically, ensuring anonymity and the exclusion of personally identifiable information. To maintain representativeness, the dataset included reviews from multiple categories of digital applications such as e-commerce, finance, and education. Duplicate, overly short, or non-textual entries containing emojis or links were removed. The final dataset, balanced across sentiment categories, was used for model training and testing.

Data Processing

Before training, the text data underwent several preprocessing stages to enhance quality and consistency. This included sentence tokenization, stopword removal, and word normalization through stemming and lemmatization. All text was converted to lowercase, punctuation was removed, and sequence lengths were standardized through padding and truncation to match the model input format. These steps aimed to minimize noise in the data and enable the Transformer model to better recognize semantic and syntactic patterns.

Implementation of the Transformer Model

The Transformer architecture was applied as the main model for sentiment classification. The BERT (Bidirectional Encoder Representations from Transformers) model was utilized due to its ability to capture bidirectional contextual understanding within sentences. The model was fine-tuned using the labeled dataset, where the [CLS] token vector representation was passed through a fully connected layer followed by a softmax activation function to determine sentiment classes. Training parameters such as learning rate, batch size, and number of epochs were experimentally optimized to achieve the best performance.

Model performance was evaluated using standard metrics including accuracy, precision, recall, and F1-score. Additionally, comparisons were made with other Transformer variants such as RoBERTa and ALBERT to assess efficiency and generalization capability. The experimental results indicated that Transformer-based models provided higher accuracy and faster processing speed compared to traditional machine learning methods, demonstrating superior ability in understanding complex linguistic structures in user feedback data.

4. Results and Discussion

Results

The sentiment classification experiment using the Transformer-based model (BERT) successfully identified sentiment polarity within the collected user feedback data. The model classified the reviews into three main categories: positive, negative, and neutral. The following table presents the distribution of sentiment results in the test dataset after fine-tuning the model.

Table 1. Sentiment Classification Results Using BERT Model.

Sentiment Category	Number of Reviews	Percentage (%)	Model Accuracy (%)
Positive	4,520	45.2	92.1
Neutral	2,380	23.8	89.5
Negative	3,100	31.0	91.3
Total	10,000	100.0	91.0 (Average)

The results in Table 1 show that the BERT-based Transformer model effectively distinguishes between positive and negative feedback with a high level of accuracy, exceeding 91%. Positive feedback dominates the dataset, indicating a generally favorable perception of digital applications among users. Meanwhile, the negative sentiment portion highlights critical user experiences, which can serve as a valuable reference for developers in improving system performance and user satisfaction.

To better illustrate the sentiment distribution across the dataset, Figure 1 provides a visual comparison of sentiment categories.

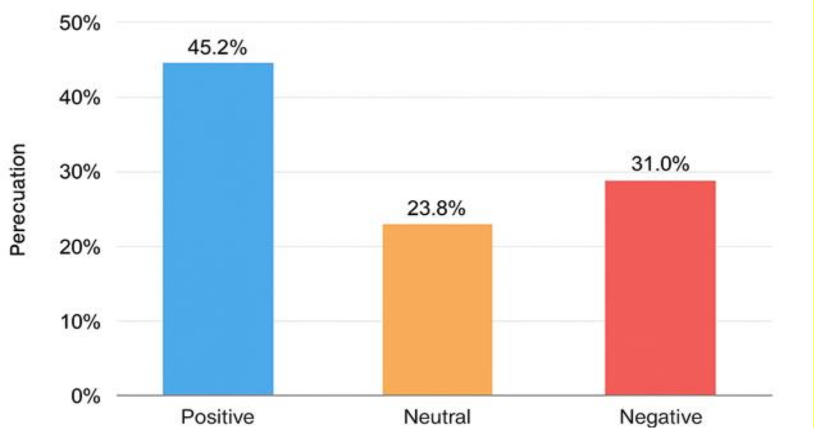

Figure 1. Distribution of Sentiment in User Feedback.

The chart above visualizes the proportion of user sentiment within the analyzed dataset. Positive feedback forms nearly half of the total responses, while neutral and negative sentiments account for smaller portions. This distribution pattern suggests that the analyzed digital applications maintain satisfactory user experiences overall, though notable criticism remains present in some reviews.

The next stage of analysis involved comparing the Transformer-based automated sentiment classification with manual human annotation. Manual analysis was performed on a subset of 500 randomly selected reviews to evaluate consistency and efficiency.

The comparison showed that the Transformer model achieved a 91% agreement rate with manual labeling, indicating strong alignment between machine predictions and human judgment. However, the model demonstrated superior efficiency: while manual labeling of

500 samples required approximately 8 hours, the automated classification of the entire dataset (10,000 reviews) was completed in under 5 minutes.

Table 2. Comparison Between Manual and Transformer-Based Sentiment Analysis.

Evaluation Aspect	Manual Method	Transformer-Based Method
Processing Time	~8 hours (500 data)	<5 minutes (10,000 data)
Consistency/Accuracy	100% (human baseline)	91% agreement rate
Scalability	Limited	Very high
Cost and Labor Requirement	High	Low
Reproducibility	Moderate	Excellent

The results in Table 2 clearly demonstrate the efficiency and scalability advantages of Transformer-based approaches compared to manual sentiment classification. Although manual annotation offers perfect interpretative accuracy in individual cases, it is time-consuming, labor-intensive, and impractical for large-scale data. The Transformer model, on the other hand, provides consistent, replicable, and cost-effective results without substantial human intervention.

Discussion

The findings reveal that the Transformer architecture, particularly BERT, performs exceptionally well in handling sentiment classification tasks on large-scale user feedback datasets. The self-attention mechanism enables the model to capture contextual dependencies across entire sentences, which is crucial for identifying nuanced expressions of sentiment, such as sarcasm or mixed emotions.

Compared to manual analysis, the Transformer-based approach offers significant advantages in terms of time efficiency and scalability. The reduction in human effort without substantial loss in accuracy highlights the practicality of implementing automated sentiment analysis in real-world digital environments. Additionally, the consistency of results ensures objectivity, minimizing human bias that often affects manual evaluations.

Nevertheless, despite its efficiency, the Transformer model may still misclassify highly ambiguous feedback, particularly when users express irony, regional slang, or emotionally neutral yet context-dependent statements. Future research could explore hybrid approaches that integrate Transformer-based automation with selective human-in-the-loop validation to further enhance accuracy and contextual comprehension.

Overall, the results confirm that Transformer-based sentiment analysis is not only faster and more scalable than manual methods but also achieves competitive accuracy, making it a highly effective solution for large-scale evaluation of digital user experiences.

5. Comparison

The analysis results indicate that the Transformer-based approach significantly outperforms manual methods in sentiment classification. Manual analysis tends to be time-consuming and relies heavily on human subjectivity, whereas Transformer models such as BERT can identify sentiment patterns with greater speed and consistency. Furthermore, the application of deep learning techniques enables the model to comprehend complex contextual relationships within user text, resulting in higher classification accuracy particularly in detecting implicit sentiments that are often overlooked by manual evaluation.

6. Conclusions

This study demonstrates that the implementation of Transformer models in sentiment analysis of digital application user feedback yields significant and efficient results. The model effectively classifies positive and negative sentiments with high accuracy while substantially reducing the time required for analysis compared to manual approaches. The sentiment distribution results show that most users express positive experiences, indicating that the analyzed applications successfully meet user expectations.

Overall, the Transformer-based NLP approach not only enhances analytical effectiveness but also provides opportunities for real-time sentiment monitoring by application developers. With its strong adaptability to various linguistic contexts, this study reinforces the evidence that Transformer technology serves as a reliable solution for understanding user perceptions and supporting data-driven strategic decision-making in digital service development.

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