



Sentiment Analysis of Comments Received Through E- Consultation Module Software

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Abstract: E-consultation platforms collect a large amount of feedback from users, but going through all these comments manually is difficult and time-consuming. This project focuses on building a sentiment analysis system that can automatically understand and classify user opinions as positive, negative, or neutral. It uses natural language processing (NLP) techniques such as text cleaning, tokenization, and removal of unnecessary words to prepare the data. Machine learning methods like Naïve Bayes and Support Vector Machine are applied to identify the sentiment, and advanced models can be added to improve accuracy when needed. The system also presents the results using simple charts and graphs, making it easier to understand overall user opinion and identify common issues. This helps organizations quickly take better decisions and improve their services. The project also highlights that many existing systems do not fully support real-time analysis, multiple languages, or easy interpretation of results, and aims to provide a more practical and efficient solution.

Keywords: Sentiment Analysis; Natural Language Processing (NLP); Machine Learning; Text Classification; Naïve Bayes; Support Vector Machine (SVM); Logistic Regression; Deep Learning; User Feedback Analysis; E-Consultation Systems; Opinion Mining; Data Visualization; Public Opinion Analysis; Predictive Analytics.

I. INTRODUCTION

E-consultation platforms have become an important channel for collecting user opinions, feedback, and suggestions across various domains. However, the large volume of unstructured textual data generated makes manual analysis difficult, time-consuming, and inefficient. This creates a need for automated systems that can quickly process and understand user feedback to extract meaningful insights.

Machine learning and Natural Language Processing (NLP) techniques have emerged as effective solutions for sentiment analysis. Earlier approaches used simple lexicon-based methods, while modern systems apply machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression for better accuracy. Advanced deep learning models like LSTM and BERT further improve the system's ability to understand context and handle complex language patterns.

This project aims to develop an automated sentiment analysis system that classifies user comments into positive, negative, and neutral categories. It involves data preprocessing, model implementation, and visualization of results using charts and graphs. The system helps organizations understand public opinion, identify key issues, and support effective data-driven decision-making while improving overall service quality.

II. THEORETICAL BACKGROUND

Before implementing sentiment analysis systems, it is important to understand the fundamental concepts and models that support text classification. Most sentiment analysis approaches rely on machine learning and Natural Language Processing (NLP) techniques to convert unstructured text into meaningful insights. The following subsections describe the key theoretical components used in this project.

A. Machine Learning Model

At a general level, sentiment analysis can be viewed as a supervised learning problem where a function maps input text data to a sentiment label:

$$Y = f(X, \theta) \quad (1)$$

$$\hat{Y} = \arg \max P(Y | X) \quad (2)$$



Here, X represents the input features (text data), Y represents the sentiment class (positive, negative, neutral), and θ denotes model parameters learned during training. Algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression are commonly used to perform this mapping.

B. Sentiment Classification Models

Sentiment analysis primarily uses classification techniques to assign polarity to text. Common models include Naïve Bayes (probability-based), SVM (margin-based classification), and Logistic Regression. The probability of a class can be represented using:

$$P(Y = c | X) = \frac{1}{Z} \exp(w_c \cdot X) \quad (3)$$

where w_c represents the weight vector for class c , and Z is a normalization constant. These models learn patterns from training data to predict sentiment effectively.

C. Natural Language Processing (NLP)

Text data must be converted into a structured format before applying machine learning models. NLP techniques such as tokenization, stop-word removal, and vectorization (e.g., TF-IDF or word embeddings) are used. The feature vector can be represented as:

$$X = (x_1, x_2, x_3, \dots, x_n) \quad (4)$$

Each x_i corresponds to a word or feature extracted from the text. The quality of preprocessing directly impacts the accuracy of sentiment classification.

D. Performance Metrics

The performance of sentiment analysis models is evaluated using standard classification metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN} \quad (6)$$

Where TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are derived from the confusion matrix. These metrics help assess model effectiveness.

E. Sentiment Scoring Model

In addition to classification, sentiment can also be represented as a score:

$$Sentiment = P(Positive | X) - P(Negative | X) \quad (7)$$

This allows fine-grained analysis, where comments can be ranked based on their sentiment intensity.

F. System Performance and Scalability

In practical applications, system performance depends on processing and prediction time:

$$T_{response} = T_{processing} + T_{prediction} \quad (8)$$

Where $T_{processing}$ includes text preprocessing and feature extraction, and $T_{prediction}$ represents model inference time. Efficient design ensures fast response and scalability for large datasets.

III. FOUR-TIER TAXONOMY

Analyzing sentiment analysis systems without a structured framework makes comparison difficult. To address this, we classify sentiment analysis approaches into four tiers based on their level of complexity and functionality. This taxonomy is derived from existing research and practical implementations in the field of NLP and machine learning.

Tier 1: Basic Sentiment Classification Systems

These systems perform simple classification of text into predefined categories such as positive, negative, or neutral. They typically use lexicon-based approaches or basic machine learning algorithms like Naïve Bayes and Logistic Regression. Tier 1 systems are easy to implement, require less computational power, and work well for simple datasets. However, they often fail to capture context, sarcasm, and complex sentence structures.



Tier 2: Context-Aware Sentiment Analysis Systems

Tier 2 systems improve upon basic classification by incorporating contextual understanding of text. They use advanced machine learning models such as Support Vector Machine (SVM) and deep learning techniques like LSTM. These systems can better understand sentence structure and word relationships, leading to improved accuracy. However, they still have limitations in handling domain-specific language and multilingual data.

Tier 3: Aspect-Based Sentiment Analysis Systems

These systems go beyond overall sentiment classification by identifying specific aspects or features within the text (e.g., service quality, response time). They analyze sentiment at a more detailed level, providing fine-grained insights. Aspect-based models are highly useful for identifying key issues but require more complex data processing and annotation.

Tier 4: Intelligent Sentiment Analysis Systems (Proposed)

Tier 4 systems aim to integrate all previous capabilities into a unified and advanced framework. These systems combine real-time sentiment analysis, multilingual support, explainable AI, and interactive dashboards for visualization. They may also include features like trend analysis, automated reporting, and integration with decision-making systems. Such systems are designed to handle large-scale data efficiently and provide actionable insights. However, achieving this level requires addressing challenges related to scalability, computational cost, and model interpretability.

IV. LITERATURE REVIEW

The literature reviewed for this project was collected from sources such as IEEE Xplore, Springer, ScienceDirect, and other reputed journals. The selection focused on research papers that provided measurable performance metrics like accuracy, precision, recall, or real-world application results in sentiment analysis. Studies that only provided theoretical explanations without practical validation were excluded. The reviewed works cover various approaches including lexicon-based methods, machine learning algorithms, and deep learning techniques used for sentiment classification. Table I presents a summary of the selected papers.

TABLE I: LITERATURE REVIEW SUMMARY

Sl. No	Author(s)	Title	Method/Technique	Key Findings	Year, Venue & Index
1	S. Gupta et al	Sentiment Analysis Using ML	Naïve Bayes, SVM	Achieved good accuracy in text classification	2024, IEEE Conference
2	M. Singh & P. Jain	NLP in E-Governance	NLP, ML models	Effective in analyzing public feedback data	2023, IEEE Conference
3	A. Verma et al.	ML Algorithms Comparison	SVM, Logistic Regression	Performance depends on dataset quality	2023, IEEE Access
4	H. Patel & D. Shah	Deep Learning for Sentiment Analysis	LSTM, BERT	Improved context understanding and accuracy	2024, IEEE Conference
5	R. Kumar & S. Bansal	Opinion Mining Survey	Survey methods	Identified various techniques	2024, IEEE Access
6	T. Nguyen & L. Pham	Multilingual Sentiment Analysis	ML, NLP	Supports multiple languages but accuracy varies	2025, IEEE Conference
7	J. Brown & M. Wilson	Real-Time Sentiment Analysis	Streaming ML models	Enables real-time opinion tracking	2023, IEEE Transactions



Sl. No	Authors(s)	Title	Method/Technique	Key Findings	Year, Venue & Index
8	P. Sharma & N. Gupta	Text Classification Models	Naïve Bayes, SVM	Simple models perform well for basic tasks	2023, IEEE Conference
9	K. Reddy & V. Rao	E-Governance Sentiment Analysis	NLP, ML	Useful for analyzing citizen feedback	2024, IEEE Conference
10	D. Lee & J. Kim	Explainable Sentiment Analysis	XAI, ML models	Improves transparency in predictions	2025, IEEE Access
11	L. Chen et al.	Transformer-Based Sentiment Analysis	BERT, Transformers	High accuracy with contextual understanding	2023, IEEE Conference
12	S. K. Das & R. Mishra	Hybrid Sentiment Model	ML + Lexicon-based	Improved performance using hybrid approach	2024, Springer
13	Y. Zhang et al.	Aspect-Based Sentiment Analysis	Deep Learning, Attention Models	Provides fine-grained insights	2023, ScienceDirect
14	A. Kumar & N. Verma	Deep Learning for Sentiment Analysis	CNN, LSTM	Better performance for large datasets	2025, IEEE Access
15	P. Roy et al.	Social Media Sentiment Analysis	NLP, ML models	Effective for real-time analysis	2024, IEEE Conference

V. COMPARATIVE ANALYSIS

A comparative evaluation of the reviewed sentiment analysis studies reveals several consistent patterns across methodologies, performance, and practical deployment considerations. Rather than examining each study individually, the observations are organized into key thematic insights.

Baseline models demonstrate strong performance. Traditional machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression are widely adopted across the literature and consistently achieve competitive accuracy levels, typically ranging between 75% and 90% on structured text datasets. These models are computationally efficient and effective for standard classification tasks. While deep learning approaches such as Long Short-Term Memory (LSTM) networks and Transformer-based models (e.g., BERT) offer improved contextual understanding, they do not always significantly outperform traditional models, particularly in domain-specific or limited-data scenarios.

Feature engineering and preprocessing remain critical. A recurring observation across multiple studies is the significant impact of preprocessing techniques on model performance. Text normalization, tokenization, stop-word removal, and feature extraction methods such as Term Frequency–Inverse Document Frequency (TF-IDF) or word embeddings play a vital role in improving classification accuracy. Effective feature selection reduces noise and enhances model generalization, often yielding greater performance improvements than increasing model complexity.

Real-world deployment introduces additional challenges. Systems evaluated on real-world datasets often report lower performance compared to those tested on curated benchmark datasets. This discrepancy arises due to factors such as informal language, spelling variations, multilingual content, and the presence of sarcasm or ambiguity in user-generated text. Additionally, handling large-scale data and ensuring real-time processing capabilities remain significant challenges in practical implementations.



TABLE II: COMPARATIVE ANALYSIS OF REVIEWED PAPERS

Sl. No	Paper	Protocol / Technique	Performance	Advantages	Limitations	AI/ML
1	Gupta et al. [1]	Naïve Bayes, SVM	High	Efficient and simple classification	Limited contextual understanding	Yes
2	Singh & Jain [2]	NLP, ML models	Moderate–High	Effective for public feedback analysis	Limited multilingual capability	Yes
3	Verma et al. [3]	SVM, Logistic Regression	High	Good accuracy on structured data	Dataset dependency	Yes
4	Patel & Shah [4]	LSTM, BERT	High	Strong contextual understanding	High computational cost	Yes
5	Kumar & Bansal [5]	Survey-based study	Conceptual	Comprehensive overview of techniques	No empirical validation	Yes
6	Nguyen & Pham [6]	ML, NLP	Moderate–High	Supports multilingual analysis	Reduced accuracy for regional languages	Yes
7	Brown & Wilson [7]	Streaming ML models	High	Enables real-time sentiment tracking	High processing requirements	Yes
8	Sharma & Gupta [8]	Naïve Bayes, SVM	Moderate–High	Easy to implement	Limited handling of complex text	Yes
9	Reddy & Rao [9]	NLP, ML	High	Useful for e-governance applications	Limited scalability	Yes
10	Lee & Kim [10]	Explainable AI (XAI)	High	Improves model transparency	Increased system complexity	Yes
11	Chen et al. [11]	BERT, Transformers	High	Superior contextual accuracy	Resource-intensive	Yes
12	Das & Mishra [12]	Hybrid (ML + Lexicon)	High	Enhanced accuracy through hybridization	Complex implementation	Yes
13	Zhang et al. [13]	Attention-based DL models	High	Fine-grained sentiment analysis	Requires labeled data	Yes
14	Kumar & Verma [14]	CNN, LSTM	High	Effective for large datasets	High training time	Yes
15	Roy et al. [15]	NLP, ML models	High	Real-time sentiment insights	Limited domain adaptability	Yes

Note:

ML = Machine Learning, NLP = Natural Language Processing, SVM = Support Vector Machine, LSTM = Long Short-Term Memory, XAI = Explainable Artificial Intelligence



VI. RESEARCH GAP

The survey of existing sentiment analysis systems for e-consultation platforms reveals several recurring limitations. These gaps highlight areas where current approaches fall short and where further research and development are required.

Gap 1 — Lack of Fully Integrated Sentiment Analysis Systems: Most existing systems focus on individual components such as sentiment classification or visualization, but few provide a complete solution. Systems that perform accurate classification often lack real-time dashboards, while those with visualization features may not include advanced NLP or machine learning models. A unified system combining data collection, real-time sentiment analysis, visualization, and decision support is still missing.

Gap 2 — Limited Real-Time Processing Capability: Many sentiment analysis models operate on static datasets and do not support real-time data processing. In e-consultation platforms, where feedback is continuously generated, the absence of real-time sentiment tracking limits the ability to respond quickly to user concerns and emerging issues.

Gap 3 — Challenges in Handling Informal and Multilingual Text: User-generated content often includes slang, abbreviations, spelling errors, and multiple languages. Existing models struggle to accurately interpret such variations, especially in multilingual environments. This reduces the overall reliability of sentiment classification in practical scenarios.

Gap 4 — Insufficient Context Understanding: Basic models fail to capture complex linguistic features such as sarcasm, irony, and contextual meaning. Even advanced models may struggle with domain-specific language used in e-consultation platforms, leading to misclassification of sentiments.

Gap 5 — Limited Explainability of Models: Many sentiment analysis systems function as black-box models, providing predictions without clear explanations. This lack of interpretability reduces trust among users and decision-makers, especially when the results are used for policy or service improvements.

Gap 6 — Data Privacy and Security Concerns: User comments may contain sensitive or personal information, yet many systems do not adequately address data privacy and security. Techniques such as anonymization and secure data handling are not consistently implemented in existing solutions.

Gap 7 — Scalability and Deployment Issues: Handling large volumes of data efficiently remains a challenge. Many research models perform well in controlled environments but face difficulties when deployed at scale due to computational requirements and system limitations.

VII. CONCLUSION

This study reviewed a range of research works on sentiment analysis, focusing on techniques used to analyze user feedback from e-consultation platforms. The findings indicate that machine learning algorithms such as Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression provide reliable performance for basic sentiment classification tasks. Recent advancements using deep learning models like LSTM and BERT further enhance the ability to capture contextual meaning and improve classification accuracy. These approaches demonstrate that sentiment analysis can effectively transform unstructured textual data into meaningful insights.

At the same time, the review highlights a significant gap in the integration of different system components. While individual studies successfully address specific aspects such as classification, visualization, or real-time processing, no single system combines all essential features into a unified platform. The proposed four-tier taxonomy makes this limitation clear, where basic and intermediate systems are well developed, but fully integrated intelligent sentiment analysis systems remain largely underexplored. The missing elements include real-time processing, multilingual support, explainable outputs, and seamless integration with decision-making systems.

Future research should focus on building comprehensive and scalable solutions rather than only improving model accuracy. Emphasis should be placed on integrating multiple functionalities into a single system that can handle large-scale data, provide real-time insights, and ensure transparency and data privacy. Additionally, incorporating advanced features such as multilingual processing and adaptive learning can further enhance system performance. Addressing these challenges will enable the development of practical, efficient, and user-friendly sentiment analysis systems that support better decision-making and improved service quality.



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