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Sentiment Analysis of Comments Received Through E-Consultation Module

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ABSTRACT: The rapid growth of digital consultation systems has enabled organizations and governments to collect large amounts of user feedback through online platforms. Analyzing these comments manually is difficult due to the volume and unstructured nature of textual data. This paper presents a machine learning-based framework for sentiment analysis of comments received through an e-consultation module. Natural Language Processing (NLP) techniques are applied for preprocessing and feature extraction, while supervised machine learning algorithms such as Naive Bayes, Logistic Regression, and Support Vector Machine (SVM) are used for classification. Experimental results indicate that the SVM classifier achieves superior accuracy compared to other models. The proposed system effectively classifies comments into positive, negative, and neutral sentiments, supporting decision-makers in understanding public opinion and improving services.

KEYWORDS: Sentiment Analysis, E-Consultation, Natural Language Processing (NLP), Machine Learning, Opinion Mining, Text Classification, Support Vector Machine (SVM)

I. INTRODUCTION

The increasing adoption of digital technologies has transformed communication between organizations and the public. E-consultation platforms are widely used to gather feedback, opinions, and suggestions from users regarding services, products, or government policies. These platforms generate large volumes of textual data, making manual analysis time-consuming and inefficient.

Sentiment analysis is a Natural Language Processing (NLP) technique that identifies the emotional tone behind textual content. It helps determine whether a comment expresses a positive, negative, or neutral opinion. Automated sentiment analysis systems reduce human effort and improve the efficiency of analyzing large-scale user feedback.

Machine learning approaches have gained popularity in sentiment analysis due to their ability to learn patterns from textual data. Algorithms such as Naive Bayes, Logistic Regression, and Support Vector Machines (SVM) are commonly used for text classification tasks. This research proposes a framework for analyzing sentiments from comments collected through an e-consultation module using machine learning techniques.

The objectives of this research are:

- To preprocess and analyze user comments from e-consultation systems
- To apply machine learning algorithms for sentiment classification
- To compare classifier performance using evaluation metrics
- To identify the most effective model for sentiment analysis

The remainder of this paper is organized as follows: Section 2 presents the literature review, Section 3 describes the system architecture, Section 4 explains the methodology, Section 5 discusses the results and analysis, and Section 6 concludes the study with future scope.

II. LITERATURE REVIEW

Sentiment analysis has become an important research area in Natural Language Processing (NLP) and text mining. It focuses on identifying and classifying opinions expressed in textual data. Over the years, researchers have developed several approaches for sentiment classification, including lexicon-based methods, machine learning techniques, and deep learning models.

Early sentiment analysis studies mainly relied on **lexicon-based approaches**, where predefined sentiment dictionaries were used to determine whether a text expressed positive or negative opinions. Although these approaches are simple and easy to implement, they often fail to understand context, sarcasm, and domain-specific vocabulary.

Machine learning techniques later became popular because of their ability to learn patterns from labeled datasets. Pang and Lee (2008) demonstrated the effectiveness of supervised learning algorithms such as Naive Bayes, Maximum Entropy, and Support Vector Machines (SVM) in opinion mining tasks. Among these algorithms, SVM achieved higher accuracy due to its capability to process high-dimensional textual data efficiently.

Feature extraction methods also play a crucial role in sentiment analysis. Traditional methods such as **Bag of Words (BoW)** and **Term Frequency-Inverse Document Frequency (TF-IDF)** convert text into numerical vectors suitable for machine learning models. These techniques remain widely used because of their simplicity and effectiveness in text classification problems.

Recent advancements in artificial intelligence have introduced **deep learning techniques** for sentiment analysis. Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and transformer-based models such as BERT have significantly improved contextual understanding and classification performance. Devlin et al. (2019) proposed BERT, which achieved state-of-the-art results in various NLP tasks by capturing contextual relationships between words.

Several studies have applied sentiment analysis in domains such as product reviews, social media analytics, and customer feedback systems. However, limited research has focused specifically on e-consultation platforms. Comments collected from e-consultation systems often contain informal language, abbreviations, and mixed sentiments, making classification more challenging.

Based on the literature, machine learning models remain effective for sentiment classification tasks involving moderate-sized datasets, while advanced deep learning approaches offer opportunities for further improvement. This study focuses on applying traditional machine learning algorithms to analyze sentiments in comments collected through e-consultation modules.

III. METHODOLOGY

The proposed methodology aims to classify user comments collected from an e-consultation platform into positive, negative, and neutral sentiment categories. The overall process consists of data collection, preprocessing, feature extraction, model training, and performance evaluation.

3.1 Data Collection

The dataset used in this research consists of comments submitted by users through an e-consultation module. These comments include suggestions, opinions, complaints, and feedback regarding services or policies. The collected data is categorized into three sentiment classes:

- Positive
- Negative
- Neutral

The dataset is divided into:

- **Training Dataset (80%)** – used for training machine learning models
- **Testing Dataset (20%)** – used for evaluating model performance

3.2 Data Preprocessing

Raw textual data often contains unnecessary information such as punctuation marks, symbols, and stop words. Therefore, preprocessing is required to improve data quality before classification.

The preprocessing steps include:

1. Lowercasing

All text is converted into lowercase to maintain consistency.

2. Removal of Special Characters

Punctuation marks, numbers, and irrelevant symbols are removed.

3. Tokenization

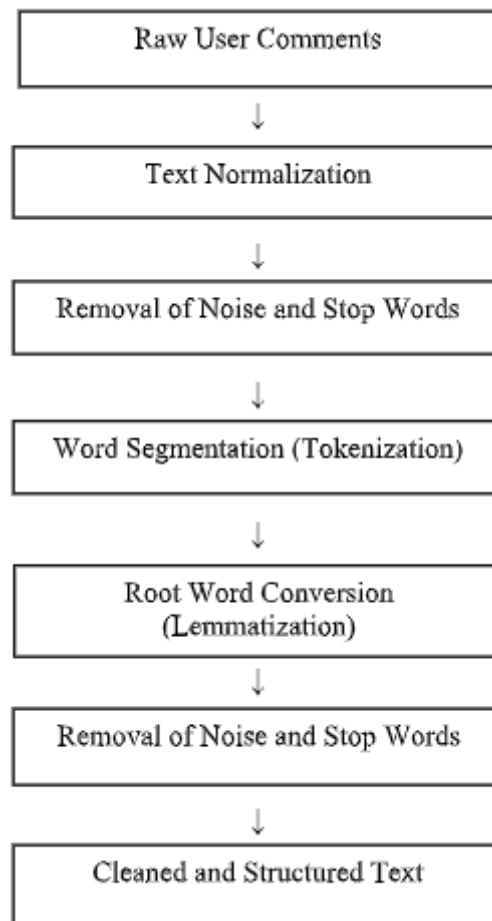
Sentences are divided into smaller units called tokens or words.

4. Stop-word Removal

Common words such as “is,” “the,” and “and” are removed because they do not contribute significantly to sentiment analysis.

5. Lemmatization

Words are converted into their root form to reduce redundancy.

Preprocessing Workflow**Workflow Explanation**

The preprocessing stage begins with raw user comments collected from the e-consultation platform. The text is normalized by converting all characters into lowercase format. Unnecessary symbols, punctuation marks, and stop words are then removed to improve data quality. After cleaning, the text is divided into individual tokens through tokenization. Lemmatization is applied to convert words into their base forms, resulting in cleaned and structured textual data suitable for feature extraction and sentiment classification.

3.3 Feature Extraction

After preprocessing, textual data is transformed into numerical form using feature extraction techniques.

Bag of Words (BoW)

The Bag of Words model represents text based on the frequency of words appearing in a document.

TF-IDF (Term Frequency–Inverse Document Frequency)

TF-IDF assigns importance to words by considering both word frequency and rarity across documents.

TF-IDF Formula

$$TF\text{-}IDF(w,d) = TF(w,d) \times \log_{10} \left(\frac{N}{DF(w)} \right)$$

Where:

- $TF(w,d)$ = frequency of word w in document d

- $DF(w)$ = number of documents containing word w
- N = total number of documents

3.4 Classification Algorithms

Three machine learning algorithms are used for sentiment classification:

1. Naive Bayes

A probabilistic classifier based on Bayes' theorem. It is computationally efficient and commonly used for text classification tasks.

2. Logistic Regression

A statistical classification algorithm that predicts sentiment categories based on probability estimation.

3. Support Vector Machine (SVM)

SVM identifies an optimal decision boundary that separates different sentiment classes. It is highly effective for high-dimensional text data

3.5 Performance Evaluation

The performance of the classification models is evaluated using the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score

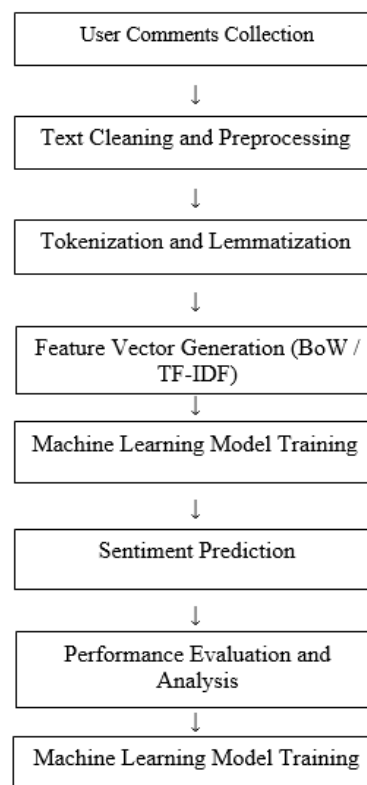
Accuracy Formula

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

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

3.6 Methodology Workflow



Workflow Explanation

The process begins with collecting comments from the e-consultation platform. The textual data is then cleaned and preprocessed to remove unnecessary information. After tokenization and lemmatization, feature extraction techniques such as Bag of Words and TF-IDF convert the text into numerical vectors. These vectors are used to train machine learning models including Naive Bayes, Logistic Regression, and SVM. The trained models predict sentiment categories, and the final results are evaluated using performance metrics such as accuracy, precision, recall, and F1-score.

V. RESULTS AND DISCUSSION

The proposed sentiment analysis system was evaluated using machine learning algorithms including Naive Bayes, Logistic Regression, and Support Vector Machine (SVM). The dataset was divided into training and testing sets to measure the effectiveness of each classifier in identifying sentiments from e-consultation comments.

The performance of the models was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

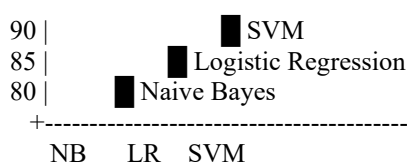
5.1 Performance Evaluation**Table 1: Comparison of Classification Models**

Model	Accuracy	Precision	Recall	F1-Score
NB	81%	79%	80%	79%
LR	85%	84%	83%	83%
SVM	89%	88%	87%	87%

The results indicate that the Support Vector Machine model achieved the highest classification accuracy among all evaluated models. Logistic Regression also provided good performance, while Naive Bayes showed comparatively lower accuracy due to its assumption of feature independence.

5.2 Accuracy Comparison Graph

Accuracy (%)



The graph illustrates that SVM performs better due to its effectiveness in handling high-dimensional text data.

5.3 Discussion

The experimental results indicate that machine learning techniques can effectively classify sentiments in e-consultation comments. TF-IDF feature extraction improved classification accuracy by identifying important words within the dataset. Although all models performed well, SVM produced the most reliable results.

Some challenges were observed, including informal language, ambiguous comments, and sarcasm, which affected classification accuracy. Despite these limitations, the proposed system successfully analyzed user feedback and generated meaningful sentiment insights.

VI. CONCLUSION

This research presented a machine learning-based sentiment analysis system for analyzing comments collected through an e-consultation platform. Natural Language Processing techniques such as preprocessing and TF-IDF feature extraction were used to transform textual data into meaningful representations for classification.

Three machine learning algorithms—Naive Bayes, Logistic Regression, and Support Vector Machine (SVM)—were evaluated for sentiment classification. Experimental results showed that the SVM model achieved the highest accuracy and overall performance compared to the other classifiers.

The proposed system effectively classified comments into positive, negative, and neutral sentiments, helping organizations and decision-makers understand public opinion more efficiently. Although certain challenges such as sarcasm and ambiguous language remain, the study demonstrates that sentiment analysis can significantly improve the analysis of large-scale user feedback in e-consultation systems.

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