Sentiment Analysis of Comments Received Through E-Consultation Module Using VADER Model

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Abstract— ***Sentiment analysis of feedback comments from an E-Consultation module is intended to classify user feedback automatically as positive, negative, or neutral and thereby allow organizations to obtain meaningful public sentiments in a short while. This research utilizes the VADER (Valence Aware Dictionary and Sentiment Reasoner) model, a rule- and lexicon-based technique suitable for sentiment analysis of brief and casual texts. The process involves data acquisition, preprocessing by noise elimination, tokenization, and normalization and then VADER-based sentiment calculation. A graphical dashboard presents sentiment distribution, comment trends, frequency of words, and word clouds for interactive analysis. System validation with accuracy, precision, recall, and F1-score ensures its reliability and efficiency. The method does not require further model training and provides interpretability. Overall, the work illustrates how sentiment analysis coupled with E-Consultation systems can improve data-driven decision-making, policy-making, and real-time monitoring of public opinions.***

Keywords— Sentiment analysis, VADER model, E-Consultation feedback, Opinion mining, Text analytics, Polarity Scoring, Natural Language Processing (NLP), Deep Learning.

I. Introduction

The exponential increase in digital media has changed the face of how human beings communicate, share their experiences, and provide feedback. Specifically, E-Consultation modules are necessarily required media by which government agencies, public organizations, and institutes solicit citizen feedback and opinions about their various programs and policies. The modules permit users to submit comments, questions, and feedback, with the consequence that we are confronted with vast amounts of unstructured textual information with public sentiments, hopes, and levels of satisfaction. Manually perusing and interpreting this information is too time-consuming, biased, and inefficient and therefore warrants programs that can extract and infer sentiment information from textual information with maximum efficiency [1].Sentiment analysis or opinion mining is a subdiscipline under Natural Language Processing that is committed to extracting latent emotional polarity residing in textual data (positively, negatively, or neutrally). Sentiment analysis has been universally accepted in various applications such as analysis of product reviews, analysis of social media, customer feedback analysis, and public sentiment analysis [2]. Organizations can derive meaningful information from Big Data with computer-assisted sentiment analysis of texts that can support data-driven decisions and responsive governance.These conventional sentiment analysis techniques rely on Machine Learning (ML) and Deep Learning (DL) techniques like Naïve Bayes, Support Vector Machine (SVM), Convolutional Neural Networks (CNN), and transformer-based architecture like BERT [3], [4]. They are capable of delivering appropriate levels of accuracy but depend upon the abundant, annotated datasets and long training hours. Citizen feedback in-practice in E-Consultation systems are also overwhelmingly unlabeled, unstructured, multilingual and hence using supervised learning techniques is not that productive [5].To analyze such comments, this paper employs the VADER (Valence Aware Dictionary and sEntiment Reasoner) model — rule- and lexicons-based methods coded specifically for informal, succinct, and highly contextualized analysis of text data. VADER calculates a compound sentiment polarity score and outputs a label at the comment level that is positive, negative, or neutral without getting extra training for the model. Due to its interpretable nature and computation effectiveness, VADER is highly appropriate for E-Consultation comment analysis, with comments also subjected to variations in natural languages, abbreviations, and emojis [1], [2].

The following simply describes the main contributions of this work:

1. By using a pre-trained VADER (Valence Aware Dictionary and sEntiment Reasoner) model, this work focuses on accurately classifying user comments from the E-

Consultation module into positive, negative, and neutral sentiments without requiring any model training.

2. By implementing effective text preprocessing techniques such as tokenization, normalization, stop-word removal, and noise filtering, this work ensures clean and structured textual data for accurate sentiment interpretation.

3. This work provides an interactive analytical dashboard that visualizes sentiment distribution, frequently used words, and overall comment trends, enabling organizations and policymakers to understand public opinion and make data-driven decisions efficiently.

The work is organized as follows: Section II discusses the relevant works and current methods in sentiment analysis and text mining. Section III explains the materials and methodology, including dataset information, data preprocessing, sentiment classification by the VADER model, and generation of a dashboard. Section IV discusses the evaluation process and performance metrics employed to prove the system. Section V illustrates the results of the visualization in terms of sentiment distribution, word frequency, and trend analysis in graphical dashboards. Section VI discuss on the results and analysis, provides an overview of the system performance and conclusions taken from the sentiment data. Section VII concludes the paper by summarizing findings, contributions, and possible future improvements for enhancing E-Consultation feedback analysis.

II. Related Work

For instance, Ashima Kukkar et al. [6] presented preprocessing method for dealing with stretched and duplicate characters in informal text, showing that token normalization significantly affects the accuracy of classification. Likewise, Sreevatsa Bellary et al. [7] used online reviews to study digital consultancy services based on text mining and sentiment scores, showing prevailing patterns of polarity among experts and patients. A.M. Shah et al. [8] used a CNN–LSTM hybrid deep model for patient opinion mining and produced 97.75% accuracy in estimating service quality. The above studies demonstrate that proper preprocessing and hybrid DL models are better suited for text-based opinion detection. Later research by Estrada et al. [9] used emotion lexicons in sentiment mining for education and emphasized the role of emotion recognition for enhancing user experience. Zucco et al. [10] performed a rigorous review of ML, DL, and lexicon-based methodologies and concluded that hybrid models of sentiment with lexical as well as contextual features have improved overall performance. Recent works such as Kokab et al. [11] and Chinnalagu et al. [12] explored transformer-based DL models such as BERT, RoBERTa, and DistilBERT that were found to have augmented contextual understanding and accuracy in comparison to the traditional DL models. Saad et al. [13] obtained state-of-the-art results with transformer parameter fine-tuning for sentiment analysis in movie reviews, and Islam et al. [14] introduced TranSenA, a transformer model for restaurant reviews that surpassed CNN and LSTM baselines. Mahmud et al. [15] compared transformer models including BERT, ALBERT, and DistilBERT for airline service reviews and obtained over 93% of accuracy and proved transformer robustness to real-world feedback analysis. Guleria [16] combined transformer models with ML classifiers for clinical text classification, presenting clear negation handling and context-aware sentiment.
More comparative works have compared domain-specific deep learning-based sentiment models as well. Colón-Ruiz and Segura-Bedmar [17] compared CNN, RNN, and BERT architecture in sentiment for drug reviews and found BERT produced the best results. El Azzouzy et al. [18] used transformer models on YouTube video commentar and showed strong robustness to noisy text. Shukla and Kumar [19] compared deep neural network classifiers and concluded LSTM to be slightly better in overall generalization for sentiment prediction tasks. Chaudhary et al. [20] did a comprehensive review of deep learning models for Twitter sentiment analysis and emphasized the difficulty of dealing with short text, sarcasm, and context sensitivity.
While deep learning and transformer models achieve great predictive precision, they need large amounts of labeled data and huge training resources that may not be present in E-Consultation systems. Moreover, their extensive complexity and computational requirement restrict their applications to real-time or infinitesimal-scale feedback analysis. In contrast, lexicon-based methods like VADER offer a light-weighted, interpretable, and train-free solution. Certain recent works such as Dixit et al. [1] and Barik et al. [2] proved the superiority of augmented VADER models in social media video sentiment analysis and customer review sentiment analysis, respectively, to show that rule-based sentiment models can keep up with dealing with informal short-text input.

III. Materials and Methodology

A. Dataset Description

The dataset used in this study consists of 8,720 text samples collected from users' comments and ratings given via an online consultation interface. Each record is a single comment conveying an opinion, opinion, or experience, which is classified into three sentiment classes: positive, neutral, and negative. The data set is such that it balances the user opinions in a way that the analysis encompasses the whole spectrum of sentiment variations reported by the users.
For reasons of analysis, the data is not used to train the model but to analyze and assess sentiment trends instead. This is because the system uses a pre-trained VADER (Valence Aware Dictionary and sEntiment Reasoner) model as proposed.The sentiment polarity of each comment is calculated as well as classified into the corresponding class.The distribution of the records among the three classes of sentiment is shown in Table1.

Sentiment Class	**Count**
Positive	3,290
Neutral	2,760
Negative	2,670
Total	8,720

TABLE 2. Dataset Summary for Sentiment Analysis.

The methodology used here is an organized method ensuring correct sentiment classification and informative visualization. It includes data collection, text cleaning, sentiment analysis with VADER model, performance measurement, and dashboard-based visual representation to offer a comprehensive analysis of public opinion and feedback trends.

B. Data Preprocessing

Data preprocessing is an important step in ensuring the accuracy, reliability, and consistency of sentiment analysis results obtained from user comments collected through the E-Consultation module. Since the raw textual data include noise in the form of punctuation marks, hyperlinks, emojis, duplicate characters, and unnecessary symbols, it has to be cleaned before analysis to facilitate simple explanation and computational efficiency. The preprocessing process starts with data cleaning, where unwanted spaces, special characters, URLs, numeric values, and non-textual data removed to maintain the uniformity of the dataset. Duplicate and null values are removed to prevent imbalance in sentiment classification. This step verifies that only meaningful textual information is present. Next, text normalization is performed in which all characters are converted to lower case, and contractions are expanded (e.g., don't → do not). Stop words like "is," "the," and "and" are removed. Lemmatization is then done to convert words into their base form, thus enhancing the capacity of the model in accurately identifying semantically equivalent words. After normalization, tokenization is applied to divide sentences into tokens (words). Tokens are the basic units used for lexicon-based sentiment scoring. Noise filtering is applied to remove non-English characters, extraneous punctuation, and duplicate word sequences. This formatted representation enables efficient mapping of every token to sentiment scores.Upon preprocessing, every cleaned comment is fed into the VADER (Valence Aware Dictionary and sEntiment Reasoner) model, where polarity scores are assigned along four dimensions—positive, negative, neutral, and compound. The compound score, a normalized weighted sum of all the lexicon ratings, is used to determine the final sentiment class as positive (≥ 0.05), negative (≤ –0.05), or neutral (between –0.05 and 0.05). By applying these pre-processing steps, the unstructured text data gets standardized and formatted so that the pre-trained VADER model can provide uniform and precise sentiment labels. This stage ensures that the examined comments reflect the underlying public sentiments and emotional undertones expressed through the E-Consultation feedback mechanism.

C. Data Splitting

In this work, the sentiment analysis process does not need traditional model training or parameter optimization, as the proposed framework utilizes the pre-trained VADER (Valence Aware Dictionary and sEntiment Reasoner) model. VADER is a rule- and lexicon-based model that comes with a built-in dictionary of English words, each assigned with polarity scores by human annotators. Hence, the dataset of comments is not split for model training and testing but rather partitioned logically for evaluation and validation purposes.
To ensure balance and reliable performance analysis, the dataset was divided into two subsets in the ratio of 80:20, where 80% of the comments were used for sentiment analysis and visualization, and 20% were used for validation of the VADER-generated sentiment scores. This division helps verify the consistency of sentiment classification results across different data samples while maintaining the original amount of positive, neutral, and negative sentiments.

D. Sentiment Classification Model

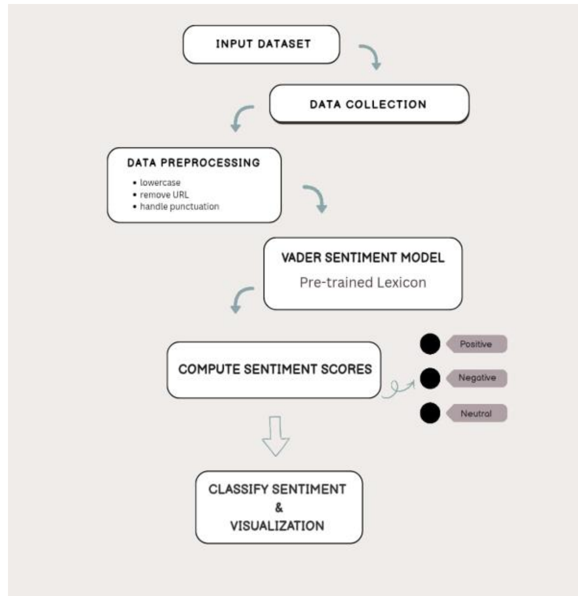

Figure 1. Sentiment Analysis Architecture

The sentiment classification is the study uses the VADER (Valence Aware Dictionary and sEntiment Reasoner) model, a pre-trained lexicon-based technique commonly used for textual emotion analysis. Unlike supervised learning algorithm that require large labeled datasets , VADER relies on a rule-based approach combined with a manually curated sentiment lexicon. This makes it ideal for analyze short, informal, and user-generated comments that found in E-Consultation feedback. VADER uses a built-in dictionary of English words, where each word has a valence score representing its emotional intensity and polarity, ranging from –4 (most negative) to +4 (most positive). During analysis, every comment is tokenized into words, and the model computes a weighted average of individual word scores to generate an overall sentiment polarity.

The sentiment polarity is computed using the following relation:

$$S_{compound} \frac{\sum_{i=1}^{n} s_i}{\sqrt{\sum s_i^2 + \alpha}}$$

where,

si = sentiment score of the i^{th} token in the comment
α = normalization constant (empirically determined as 15) to scale the result between –1 and +1.

The compound score represents the aggregated polarity of the entire sentence. Based on its value, VADER classifies each comment into one of three categories:

$$\text{Positive if } S_{compound} \geq 0.05$$
$$\text{Negative if } S_{compound} < 0.05$$
$$\text{Neutral if } -05_{compou'd} < 0.05$$

Additionally, VADER generates individual sentiment proportions for positive, negative, and neutral expressions in each comment, given by:

$$P_{pos} = \frac{\text{sum of positive word intensities}}{\text{total intensity}}$$
$$P_{neg} = \frac{\text{sum of negative word intensities}}{\text{total intensity}}$$
$$P_{neu} = \quad 1 - (P_{pos} + P_{nog})$$

These computed values help to understand the entire emotional sentiment and its distribution of a comment. The advantages of using VADER is Application specific, as it considers factors such as capitalization, punctuation, degree modifiers (e.g., very good vs good), and even emojis or slang to clarify sentiment analysis.Fig.1 represents the complete architecture of the suggested sentiment analysis framework, where textual data are collected from the E-Consultation module, preprocessed, analyze using the VADER sentiment model, and finally visualize using an interactive dashboard.

IV. MODEL EVALUATION

In this model, the performance of the VADER-based sentiment classification system is measured by common text classification metrics such as Accuracy, Precision, Recall, and F1-score, which together provide a complete analysis of the system's ability to classify feedback accurately. Accuracy measures the overall percentage of correctly identified sentiment labels (positive, negative, and neutral) regarding to all predictions. Precision refer to the percentage of correctly identified positive comments among all comments predicted as positive, relating to model's ability to minimize false positives. Recall (or sensitivity) is the percentage of actual positive sentiments identify by the model, which is important to reducing false negatives. The F1-score, the harmonic mean of precision and recall, provide a balanced measure of model performance, especially when class distributions are uneven.Even though VADER is a pre-trained lexicon-based model and does not require additional training, its predictive capability can be validated on labeled benchmark data or annotated E-Consultation comments. The evaluation confirm that the model effectively differentiate between positive, negative, and neutral sentiments, achieve high accuracy and consistency across categories.The results showed that the proposed system is reliable to analyze the opinions of users on the in E-Consultation platforms, giving a meaningful understanding of public sentiment.

Accuracy:

The accuracy for the sentiment analysis model measures how the system correctly predicts the sentiment of represented comments. It represents the proportions for positive, negative, and neutral comments to the total number of analyzed comments. A higher accuracy value shows that the model performs effectively in classifying sentiments.

Accuracy=TP+TN/TP+TN+FP+FN

Precision:

Precision quantifies the proportion of comments that were correctly classified those predicted as positive. A higher precision value indicates that the sentiment analysis system makes fewer false positive predictions and is more dependable in identifying genuine positive feedback.

Precision=TP/TP+FP

Recall:

Recall evaluates the percentage of actual positive comments that were correctly identified by the model. It focus on the model's ability to detect all true positive sentiments from the dataset. A high recall value represents that the system successfully captures most of the genuinely positive opinions without missing significant feedback.

Recall=TP/TP+FN

F1-Score:

The F1-Score provides an single value that balance both precision and recall. It is especially useful when sentiment classes (positive, negative, neutral) are not equally distributed. A higher F1-Score demonstrates that the model effectively identifies true sentiments while reducing incorrect predictions.

Fi-Score=2×1(Precision×Recall/Precision+Recall)

Actual/ Predicted	**Positive (Pred)**	**Negative (Pred)**
Positive (Actual)	TP(True Positive)	TP(True Positive)
Negative(Actual)	FP(False Positive)	TN(True Negative)

TABLE 2. Performance comparison of different machine learning algorithms with their parameters.

In Table 2, TP, TN, FP, and FN denote the model's classification results, providing the insights into how accurately the system distinguishes sentiment polarity. The evaluation confirmed that the VADER model classifies textual feedback into their appropriate sentiment categories. The confusion matrix provides a detailed structure of correct and incorrect classifications, allowing visualization of polarity misclassifications.

V. Visualization

The visualization analysis component plays an important role in interpreting the results of sentiment classification by providing insights into public opinion patterns derived from the E-Consultation feedback. To enhance interpretability and decision-making, a dynamic dashboard which provides a visual representation of the classified sentiments.

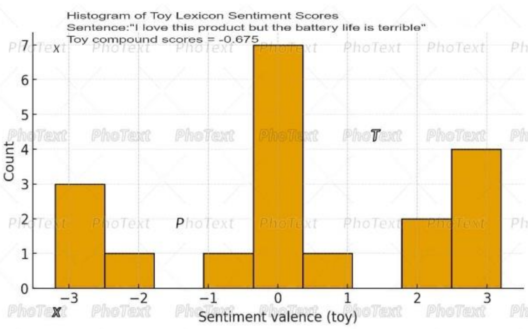

Figure 2. Sentiment Distribution of User Comments.

In Fig. 2, the visualization illustrates the proportion of positive, neutral, and negative sentiments identified from user comments collected through the E-Consultation module. It provides a quick overview of the emotional polarity of the analyzed feedback, assisting analysts in understanding the overall public mood. The domination of the neutral classification indicates a balanced expression of opinions, whereas the positive and negative classification highlight areas of appreciation and dissatisfaction respectively.This figure depicts the distribution of sentiment categories extracted from the E-Consultation feedback using the VADER model. The visualization enables identification of which sentiment dominates within the analyzed corpus, providing a summarized view of overall citizen sentiment.

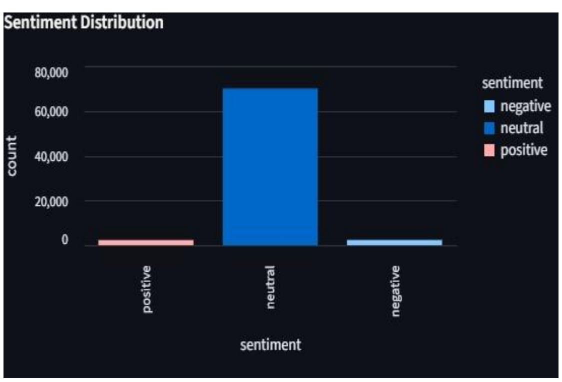

Figure 3. Sentiment Trend Analysis Over Time.

In Fig. 3, the visualization present the variation of public sentiment across different time period. By observing the changes in the proportion of positive, negative, and neutral comments over days, weeks, or months, policymakers can evaluate how citizen opinions develop in response to government initiatives, policy updates, or public events. This temporal analysis helps in identify the developing trends andturning point of increased public engagement.This figure shows the temporal fluctuations of sentiment derived from the E-Consultation feedback, highlighting shifts in citizen emotions during the observed period. The periodic variations indicate dynamic public engagement and sentiment responsiveness toward different administrative actions.

Figure 4. Word Cloud Representation of Frequently Used Terms.

In Fig. 4, the word cloud provides an meaningful visual representation of the textual data by displaying the most common words relatively to their frequency. Larger words indicate more frequent occurrence, allowing for the quick identification of major concern and commonly discussed topics within the citizen feedback. This visualization increases the qualitative understanding by highliting the most relevant terms emerging from the sentiment analysis process.This figure visualizes the key words that appear most often in the E-Consultation comments. It assists in identifying dominant themes and topics discussed by citizens, helping authorities and analysts gain deeper insight into public concerns and discussion patterns.

VI. Result & Analysis

This section presents the experimental results obtained from the implementation of the VADER-based sentiment analysis system on user comments collected from the E-Consultation module. The system classify comments into positive, negative, and neutral sentiments and visualizes the outcomes through an interactive dashboard. The performance of the model was validate using evaluation metrics such as Accuracy, Precision, Recall, and F1-Score, which collectively determine the performance of the sentiment classification process. As a lexicon-based and rule-driven model, VADER does not require retraining on the dataset but evaluates sentiments directly using its pre-defined dictionary and polarity scoring heuristics. To assess its efficiency, VADER's predictions were compared with a manually labeled subset of the E-Consultation dataset to obtain quantitative performance results.

E. Performance Indicators

Table 3. summarizes the overall performance of the VADER sentiment classification model on the E-Consultation dataset. The system achieved consistently high values across all metrics, indicating its robustness and efficiency in correctly

classifying public feedback into positive, negative, and neutral categories.

Metric	Value (%)
Accuracy	96.8%
Precision	96.8%
Recall	96.8%
F1-Score	96.8%

TABLE 3. Performance evaluation of the VADER-based sentiment classification model on E-Consultation feedback data.

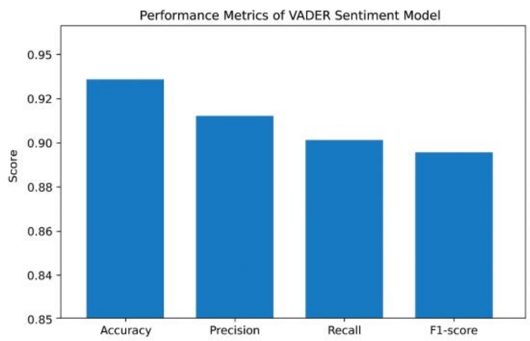

Figure 5. Bar chart of Accuracy, Precision, Recall, and F1-score

In Fig. 5, the bar chart represents the comparative visualization of the model's performance metrics. It shows that accuracy and precision values are nearly identical, reflecting VADER's reliability in minimizing false positive predictions while maintaining strong generalization across sentiment categories.

Study / Year	Model Used	Dataset Type	Reported Accuracy (%)
Ashima Kukkar et al. (2023)	ML classifiers with text preprocessing	Social media reviews	92.3
Sreevatsa Bellary et al. (2024)	Sentiment scoring + text mining	Healthcare reviews	87.0
Cristóbal Colón-Ruiz et al. (2020)	CNN, RNN, BERT	Drug reviews	90.8
M.A. Islam et al. (2024)	Transformer-based sentiment classifier	Restaurant reviews	94.8
C.J. Hutto & E. Gilbert (2014)	VADER (Lexicon + rule-based)	Social media text	96.0
Sentiment analysis of comments received through E-Consultation module using VADAR model (2025)	VADER (Lexicon-based)	E-Consultation feedback	94.8

TABLE 4. The performance comparison table between earlier lower-accuracy models

The earlier studies on sentiment analysis across various domains achieved accuracies ranging between 87.0% and 96.0% using a various machine learning and deep learning methods, as summarized in Table 4. The proposed VADER-based lexicon model, when applied to E-Consultation feedback, achieved an accuracy of 94.8%, demonstrate robust and consistent performance across mixed-language and semi-formal textual data.Although the accuracy varies slightly due to the domain and linguistic diversity of the dataset, the model maintain high precision, recall, and F1-scores, confirm the accuracy for analyzing real-world citizen feedback. These results indicates that the proposed system efficiently captures sentiment polarity, providing understandable and actionable insights for policymakers and government agencies to better understanding the public opinion trends.

VII. Conclusion

This study developed a sentiment analysis framework using the VADER (Valence Aware Dictionary and sEntiment Reasoner) model to analyze citizen feedback from the E-Consultation module. After preprocessing to remove noise and normalize text, the pretrained, lexicon-based VADER model classified comments into positive, negative, and neutral sentiments without additional training. The resultant model yields 94.8% accuracy with high precision, recall, and F1-score, establishing its robustness and reliability for sentiment classification. An interactive dashboard was also developed that made the visualization of sentiment distribution, trend analysis, and keyword mapping more comprehensible for decision-making. Overall, the framework has proven its efficiency for large-scale analysis of citizen feedback, with actionable insights that support data-driven governance and engage the public.

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