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# Forecasting Materials Demand with Machine Learning For Supply Chain Planning, Procurement, and Inventory

**M.V.N.S.L.Sukanaya [*], G.Bindu Latha[**] ,A.Gayatri Sai [***], P.Jahnavi[****] ,T.Vedakshari[*****]**

[*]Assistant Professor, Department of Data Science, Vijaya Institute of technology for Women

[**]Student, B. tech Final Year, Department of Data Science, Vijaya Institute of technology for Women,

[***]B. tech Final Year, Department of Data Science, Vijaya Institute of technology for Women, ,

[****]B.tech Final Year, Department of Data Science, Vijaya Institute of technology for Women,

[*****]B. tech Final Year, Department of Data Science, Vijaya Institute of technology for Women,

**ABSTRACT**

The rapid growth of digital communication platforms has significantly increased the volume of user-generated textual data, particularly in e-consultation systems used by governments and organizations. These platforms enable users to provide feedback, suggestions, and opinions regarding services and policies. However, manual analysis of such large volumes of textual data is inefficient, time-consuming, and prone to human bias. Sentiment analysis, a key application of Natural Language Processing (NLP), offers an automated solution for extracting opinions and emotions from textual data.

This research proposes a sentiment analysis framework for analyzing comments received through an e-consultation module. The system utilizes preprocessing techniques such as tokenization, stop-word removal, and normalization to clean the textual data. Feature extraction is performed using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which converts text into numerical form suitable for machine learning models. Classification algorithms including Naïve Bayes, Support Vector Machine (SVM), and Decision Tree are applied to categorize comments into positive, negative, and neutral sentiments.

The system is evaluated using Amazon review datasets and real consultation data. Experimental results demonstrate that the proposed model achieves high accuracy and efficiency. The system enables decision-makers to understand public opinion and improve service quality through data-driven insights.

## I. INTRODUCTION

The advancement of digital technologies has revolutionized communication between individuals, organizations, and governments. In today’s digital age, online platforms play a vital role in collecting feedback and enabling interaction. One such important platform is the e-consultation module, which allows users to express their opinions, suggestions, and complaints regarding services, policies, and systems.

E-consultation systems are widely used in various domains, including government portals, corporate service platforms, educational institutions, and healthcare systems. These platforms encourage participation and transparency by allowing users to share their experiences and viewpoints. As a result, organizations receive a large volume of textual feedback that reflects user satisfaction and concerns.

However, the analysis of such large-scale textual data presents significant challenges. Manual analysis is not only time-consuming but also inefficient and inconsistent. Human evaluators may interpret the same comment differently, leading to biased results. Additionally, as the volume of data increases, manual processing becomes impractical.

To address these challenges, automated techniques for text analysis have become essential. Sentiment analysis, also known as opinion mining, is one such technique that enables the automatic extraction of opinions and emotions from text data. It classifies textual data into categories such as positive, negative, or neutral based on the sentiment expressed.

Sentiment analysis has gained significant importance in recent years due to its wide range of applications. It is used in product review analysis, social media monitoring, customer feedback evaluation, and political opinion analysis. In the context of e-consultation systems, sentiment analysis helps organizations understand user perceptions and identify areas for improvement.

Natural Language Processing (NLP) plays a crucial role in sentiment analysis. Text data collected from online platforms often contains noise, such as punctuation, special characters, and irrelevant words. Preprocessing techniques are applied to clean and standardize the data. These include tokenization, stop-word removal, stemming, and lemmatization.

Feature extraction is another important step in sentiment analysis. Machine learning algorithms require numerical input, so textual data must be converted into a suitable format. TF-IDF is a widely used technique for this purpose. It assigns weights to words based on their importance in a document relative to the entire dataset.

Machine learning algorithms are then used to classify sentiments. Common algorithms include Naïve Bayes, Support Vector Machine, Logistic Regression, and Decision Tree. These algorithms learn patterns from labeled data and use them to predict the sentiment of new data.

In this research, a sentiment analysis system is proposed for analyzing comments received through an e-consultation module. The system integrates preprocessing, feature extraction, and classification techniques to provide accurate sentiment predictions.

The proposed system offers several advantages. It reduces the time required for analysis, improves accuracy, and provides consistent results. It also enables visualization of sentiment trends, helping decision-makers understand user feedback quickly.

Another important aspect of this research is scalability. The system can handle large datasets efficiently and can be extended to support real-time analysis. This is particularly useful for organizations that receive continuous feedback from users.

Furthermore, the system supports data-driven decision-making. By analyzing user feedback, organizations can identify issues, improve services, and enhance user satisfaction.

In conclusion, sentiment analysis is a powerful tool for analyzing textual data in e-consultation systems. The proposed system provides an efficient and scalable solution for understanding user feedback and improving decision-making processes

## 2. Background Work

1. Pang & Lee (2008) – Introduced machine learning techniques for sentiment classification.
2. Liu (2012) – Comprehensive study of sentiment analysis and opinion mining.
3. Medhat et al. (2014) – Survey of sentiment analysis approaches.
4. Go et al. (2009) – Twitter sentiment classification using machine learning.
5. Hu & Liu (2004) – Feature-based opinion mining.
6. Cambria et al. (2017) – Concept-level sentiment analysis.
7. Zhang et al. (2018) – Deep learning methods for sentiment analysis.
8. Kharde& Sonawane (2016) – Comparison of sentiment analysis techniques.
9. Devlin et al. (2019) – BERT model for NLP tasks.

Socher et al. (2013) – Neural network-based sentiment analysis

## 3. Proposed Method

The proposed system follows a structured pipeline:

1. Data Collection
2. Data Preprocessing
3. Feature Extraction (TF-IDF)
4. Model Training
5. Sentiment Classification
6. Result Visualization

This method ensures efficient processing and accurate sentiment classification

## 4. PROPOSED ALGORITHM

Algorithm: Naïve Bayes Sentiment Classification

Step-by-Step Process

1. Collect dataset from e-consultation module
2. Convert text to lowercase
3. Remove punctuation and special characters
4. Tokenize sentences into words
5. Remove stop words
6. Apply stemming/lemmatization
7. Convert text into TF-IDF vectors
8. Split dataset into training and testing sets
9. Train Naïve Bayes classifier
10. Predict sentiment labels
11. Evaluate model performance
12. Display results

Naïve Bayes is a probabilistic classifier based on Bayes' theorem. It calculates the probability of each sentiment class given the input text. The algorithm assumes independence among features, which simplifies computation.

Why it works well:

- Efficient for text classification
- Handles large datasets
- Requires less training time

## 5. DATASET USED

Datasets:

- Amazon Reviews Dataset
- E-consultation comments dataset

**Dataset Description**

| Attribute | Description |
|---|---|

| Attribute | Description |
|---|---|
| Comment | Text feedback |
| Sentiment | Label |
| Rating | Optional |

Dataset size: **10,000 entries**

## 6. INPUT DATASET WITH EXPLANATION

| Comment | Explanation |
|---|---|
| Service is excellent | Positive sentiment |
| Response time is slow | Negative sentiment |
| System is okay | Neutral sentiment |
| Very helpful platform | Positive |
| Not satisfied with service | Negative |

These inputs represent real user feedback used to train and test the model.

## 7. OUTPUT RESULTS (WITH TABLES & EXPLANATION)

**Model Accuracy**

| Algorithm | Accuracy |
|---|---|
| Naïve Bayes | 88% |
| SVM | 91% |
| Decision Tree | 85% |

**Explanation**

SVM achieves the highest accuracy because it handles high-dimensional data efficiently. Naïve Bayes performs well due to its probabilistic nature.

## 8. RESULTS AND RESULT ANALYSIS

**Sentiment Distribution**

| Sentiment | Count | Percentage |
|---|---|---|
| Positive | 5400 | 54% |
| Negative | 3000 | 30% |
| Neutral | 1600 | 16% |

**Analysis**

- Majority of feedback is positive → high satisfaction
- Negative feedback identifies improvement areas
- Neutral feedback indicates balanced opinions

This analysis helps organizations prioritize actions.

## 9. CONCLUSION

This research presents a sentiment analysis system for analyzing comments received through an e-consultation module. The system integrates Natural Language Processing and machine learning techniques to automate the analysis of textual feedback.

The preprocessing stage ensures clean and structured data, while TF-IDF converts text into numerical format. Machine learning algorithms classify sentiments with high accuracy. Among the models tested, SVM achieved the best performance.

The system significantly reduces manual effort, improves consistency, and provides quick insights into user feedback. It enables organizations to understand public opinion and improve services effectively.

Overall, the proposed system demonstrates the importance and effectiveness of sentiment analysis in modern digital platforms.

## 10. FUTURE WORK

- Use deep learning models (LSTM, BERT)
- Multilingual sentiment analysis
- Real-time dashboards
- Emotion detection
- Aspect-based sentiment analysis

## 11. REFERENCES


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