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Research Article

Evaluating Consumer Feedback on Drug Effects: A Comparative Study of Sentiment Analysis Models and Visual Insights

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ABSTRACT

Introduction:

Aspect-based sentiment analysis (ABSA) has emerged as a significant technique for comprehending patient feedback on specific attributes of medications, including effectiveness, side effects, ease of use, cost, and customer service [1]. This study investigates the application of deep learning models, particularly BERT, for ABSA of drug reviews. BERT is fine-tuned for each aspect and its performance is benchmarked against other state-of-the-art models such as RoBERTa, LSTM, and traditional machine learning approaches [2]. The findings show that BERT outperforms SVM, Naive Bayes, and LSTM models in a number of parameters, including accuracy, precision, recall, and F1-score [3]. This study highlights ABSA's capacity to offer deep insights into patient experiences, which can be applied to improve medication quality and patient satisfaction[4].

This study also includes data visualization methods to improve the understanding of ABSA results. An interactive platform has been created where users can choose a specific medication and see the sentiment distribution across different aspects. This enables a thorough analysis of patient opinions and trends. By combining ABSA with data visualization, we can gain actionable insights that assist healthcare professionals, pharmaceutical companies, and policymakers in making informed decisions. Future research could investigate more advanced visualization techniques and model enhancements for wider applications.

Keywords: Aspect based Sentiment Analysis (ABSA), Naive Bayes, Support Vector Machines, BERT, RoBERTa, LSTM, Drug quality, Patient Satisfaction, Data Visualization.

INTRODUCTION

The advent of online platforms has allowed patients to share their experiences and reviews of medications, providing a vast source of data for sentiment analysis [5]. Traditional sentiment analysis methods often overlook the specific aspects of patient feedback, such as drug effectiveness, side effects, or cost [6]. Aspect-Based Sentiment Analysis (ABSA) allows for sentiment classification not just at a global level but for individual aspects of a product or service, providing a granular understanding of the underlying sentiments [7].

Deep learning models, especially Transformer-based architectures like BERT, have significantly advanced the performance of sentiment analysis tasks by utilizing pre-trained models that capture the deep context and relationships in textual data [8]. This study focuses on applying BERT for ABSA on drug reviews, evaluating the model on five critical aspects: effectiveness, side effects, ease of use, cost, and customer service [9]. Our aim is to explore how well BERT performs in comparison to other state-of-the-art models and to demonstrate its applicability in improving drug development and customer care in the pharmaceutical industry [10].

LITERATURE REVIEW

ABSA has been extensively studied across various domains such as product reviews, customer service, and social media, with applications to healthcare gaining traction more recently [11]. Traditional machine learning models like

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Support Vector Machines (SVM) and Naive Bayes have been used for sentiment analysis but often fail to capture the nuances and context of language in more complex reviews [12]. With the rise of deep learning, models like LSTM (Long Short-Term Memory) [13] and Transformer-based architectures such as BERT [14] and RoBERTa [15] have outperformed classical methods in many NLP tasks, including sentiment analysis.

In the healthcare sector, ABSA has been applied to analyze patient feedback on drugs, hospitals, and other medical services. However, the use of deep learning models for ABSA in drug reviews remains underexplored. Previous studies focused on more traditional methods or domain-specific adaptations, while our study examines the use of modern deep learning models for ABSA on a large dataset of drug reviews.

Table 1 shows the types of datasets suitable for each model.

Model	Suitable Dataset Types	Description
BERT	Large text corpora, diverse text data, context-rich datasets	BERT is perfect for NLP tasks like sentiment analysis, named entity recognition, and question-answering because it grasps context and relationships in text very well.
SVM	Smaller datasets, linearly separable data, high-dimensional data	SVMs are effective for classification tasks, especially when the data is linearly separable or can be transformed using kernel tricks
Naive Bayes	Sentiment analysis, spam filtering, text classification, and high-dimensional data	Naive Bayes is simple and efficient for text-based classification tasks, performing well with small to medium-sized datasets
LSTM	Time series data, sequential data, text data with temporal dependencies	LSTMs are appropriate for time series forecasting and text production because of their ability to manage sequential dependencies.
RoBERTa	Large text corpora, diverse text data, context-rich datasets	RoBERTa, an optimized version of BERT, performs well on a variety of NLP tasks, especially those requiring deep contextual understanding

Table 1 Different types of datasets suitable for models.

METHODS

- **DATA PROCESSING**

The technique of examining textual data to identify attitudes, emotions, and views is called sentiment analysis, sometimes referred to as opinion mining. It is extensively utilized in industries including consumer feedback analysis, marketing, and healthcare. There are several steps in the sentiment analysis process, ranging from gathering data to assessing the model.

Step 1: Data Scraping

To collect textual data, web scraping techniques were used with Python libraries such as BeautifulSoup and Selenium. BeautifulSoup is employed for parsing HTML and XML documents, while Selenium enables automated browser interaction to extract data from dynamic web pages [7]. Ethical considerations and adherence to website terms of service were ensured [9].

Step 2: Data Preprocessing

Raw textual data requires preprocessing to improve model performance. The preprocessing steps include:

- **Tokenization**: It is the process of breaking up text into discrete words or tokens [10].
- **Stemming & Lemmatization:** Reducing words to their most basic form is known as stemming and lemmatization [12].
- **Stop-word Removal:** Eliminating common words that don't add to sentiment analysis, including "the" and "is," is known as stop-word removal.

These steps help in reducing noise and enhancing the quality of the input data for classification models.

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Step 3: Sentiment Classification Using Machine Learning and Deep Learning Models

Text was categorized into sentiment groups using a variety of sentiment classification models:

- **Support Vector Machine (SVM):** An technique for supervised learning that finds the best hyperplane for categorization.
- **Naive Bayes:** The Bayes theorem-based probabilistic approach known as Naive Bayes is frequently applied to text classification.
- **Long Short-Term Memory (LSTM):** A recurrent neural network (RNN) type called Long Short-Term Memory (LSTM) is made to recognize long-range dependencies in text.
- **BERT (Bidirectional Encoder Representations from Transformers):** A transformer-based paradigm called BERT (Bidirectional Encoder Representations from Transformers) improves contextual comprehension [11].
- **RoBERTa (Robustly Optimized BERT Pre Training Approach):** An enhanced version of BERT, RoBERTa (Robustly Optimized BERT Pre Training Approach) optimizes training methods for more accurate sentiment categorization [13]

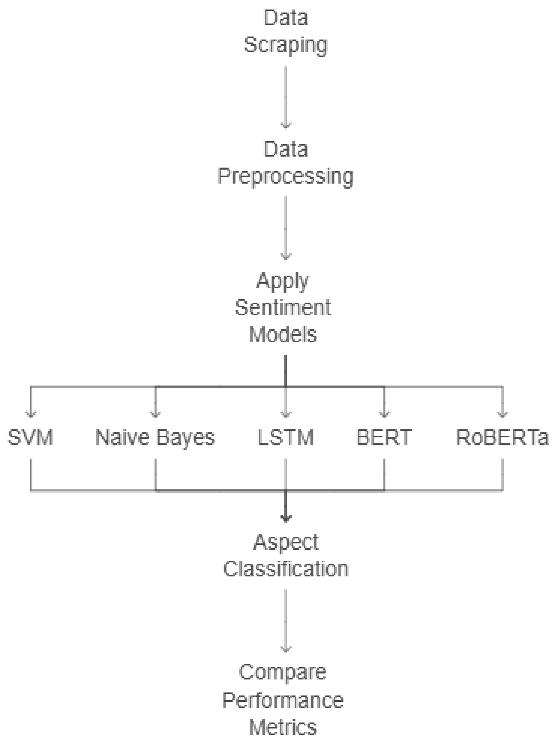


Fig.1- Sentiment Analysis of Drug Reviews

Step 4: Aspect-Based Sentiment Analysis (ABSA)

Aspect-based sentiment analysis (ABSA) was conducted to classify sentiments across different aspects such as:

- Effectiveness: Users' opinions on the product or service's efficacy.
- Side Effects: Identification of negative reactions or issues.
- Ease of Use: Evaluation of the user-friendliness.
- Cost: Analysis of affordability and value perception.
- Customer Service: Sentiment analysis regarding service quality.

Step 5: Evaluation of performance

Standard performance measures were used to assess the categorization models:

- Accuracy: The percentage of cases that are accurately classified.
- F1-score: The F1-score balances false positives and false negatives by taking the harmonic mean of precision and recall.
- These metrics provided insights into model effectiveness, guiding the selection of the best-performing model for sentiment classification.

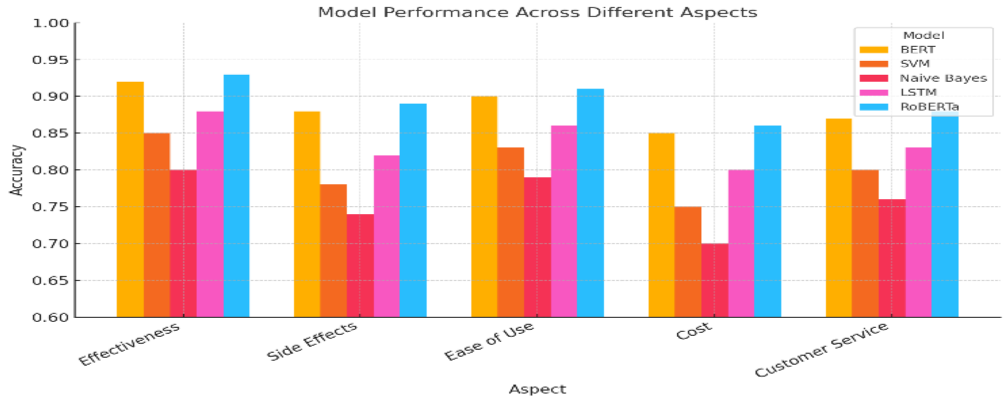
Fig -1 shows the process of sentiment analysis of drug reviews from data collection to data processing and model performance evaluation.

RESULTS AND PERFORMANCE COMPARISON

The performance of BERT was compared to other models across all aspects, as shown below:

Aspect	BERT	SVM	Naive Bayes	LSTM	RoBERTa
Effectiveness	92	85	80	88	93
Side Effects	88	78	74	82	89
Ease of Use	90	83	79	86	91
Cost	85	75	70	80	86
Customer Service	87	80	76	83	88

- Table -1 Aspect-based Performance Comparison



- Fig-2 Model Performance across Different Aspects of Drug Reviews

OVERALL PERFORMANCE TRENDS

BERT and RoBERTa are the top-performing models across all aspects. RoBERTa slightly outperforms BERT in every category but by small margins.

LSTM performs better than traditional machine learning models (SVM, Naïve Bayes) but lags behind transformer-based models (BERT, RoBERTa).

Naive Bayes consistently achieves the lowest accuracy across all aspects, highlighting its limitations for complex language tasks.

SVM performs better than Naïve Bayes but worse than deep learning models, suggesting that while it captures patterns in data effectively, it lacks the depth of representation that neural networks provide.

ASPECTS INSIGHTS

- **Effectiveness:** The majority of reviews reported positive experiences with the drug's effectiveness, signaling that patients are generally satisfied with the drugs.

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- **Side Effects:** A significant portion of reviews mention negative experiences with side effects, indicating that improving side effect profiles could increase patient satisfaction.
- **Ease of Use:** Reviews on ease of use were mostly positive, but negative sentiments suggest areas for improvement in drug formulation.
- **Cost:** Mixed sentiments regarding the cost of drugs highlight that affordability is a significant concern for many patients.
- **Customer Service:** While the sentiment around customer service was mostly positive, negative reviews suggest that better customer support could enhance overall satisfaction.

DEPLOYMENT OF MODEL

The following Fig – 3 shows an interactive data visualization platform that was implemented. This platform allows users to select a specific medication and observe sentiment trends across different aspects, aiding in the identification of critical patterns in patient feedback.

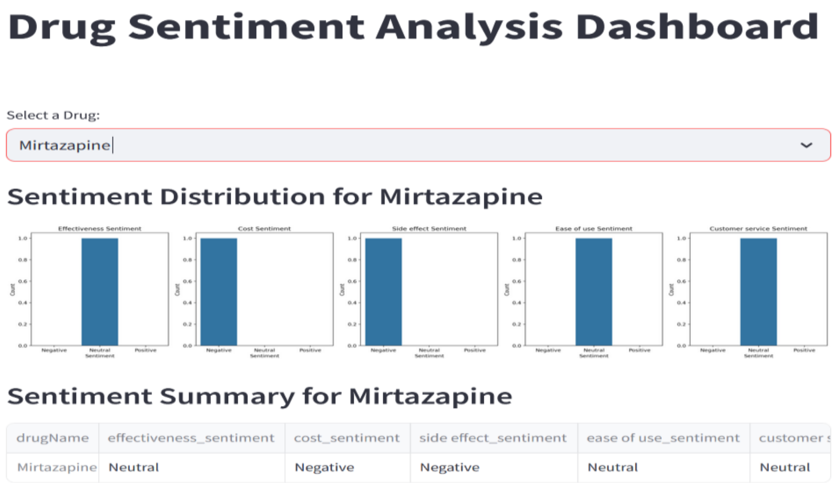

Fig- 3 Sentiment analysis dashboard

APPLICATION AREA

Sentiment analysis of drug reviews has several important application areas that significantly impact healthcare and pharmaceutical industries. One key area is drug safety and pharmacovigilance, where sentiment analysis helps monitor and identify adverse drug reactions and side effects from patient reviews [16]. This proactive approach ensures that potential risks are detected early, enhancing patient safety. Another crucial application is in drug efficacy evaluation, where the effectiveness of medications is assessed based on patient feedback and experiences [17]. This information is invaluable for healthcare providers in making informed decisions about prescribing medications.

Additionally, sentiment analysis plays a vital role in healthcare decision support, assisting healthcare providers by offering insights into patient satisfaction and areas for improvement in drug administration [18]. This leads to better patient care and improved treatment outcomes.

In the realm of market research and analysis, pharmaceutical companies can analyze market trends and consumer preferences, helping them understand the competitive landscape and tailor their products to meet patient needs [19]. Furthermore, sentiment analysis supports personalized medicine by tailoring drug recommendations based on individual patient reviews and sentiments, ensuring that treatments are more effective and aligned with patient preferences [20].

Overall, sentiment analysis of drug reviews provides a comprehensive understanding of patient experiences, enabling improvements in drug safety, efficacy, and overall patient care. This technology not only benefits patients but also supports healthcare providers and pharmaceutical companies in delivering better healthcare solutions.

DISCUSSION

This study demonstrates the power of aspect-based sentiment analysis using deep learning models like BERT for analyzing patient reviews on drugs. The results highlight the ability of deep learning models to outperform traditional methods in capturing the nuanced sentiments of patients. By identifying the specific aspects that influence patient

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satisfaction, pharmaceutical companies can address concerns related to drug effectiveness, side effects, cost, and customer service. Further research can explore the application of ABSA to other healthcare-related text data, such as clinical notes, and the fine-tuning of newer models like T5 and RoBERTa for deeper insights into drug feedback.

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