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A Study of Hybrid Sentiment Analysis of Patient Feedback using Lexicon-Based and Machine Learning Approaches

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Abstract
The keyword-based approach in sentiment analysis offers a structured and interpretable method to assess patient feedback, aiming to enhance patient satisfaction and healthcare quality. This research proposes a hybrid sentiment analysis framework for evaluating patient feedback in the healthcare sector. The study employs both keyword-based and machine-learning approaches to classify patient comments as positive, negative, or neutral. Data was collected from the "RateMDs" website, containing physician profiles and patient reviews. The preprocessing phase involved text normalization, removal of noise, punctuation, numbers, and stop words, followed by transformation into a structured dataset for analysis. The R-Tool was used for implementing sentiment analysis, supported by positive and negative lexicons derived from publicly available repositories. Machine learning techniques, including Bayesian classifiers and the Weka data mining tool, were applied for accurate classification. The system architecture integrates preprocessing, sentiment scoring, and result visualization. Results indicate that the proposed model effectively identifies patient sentiments, helping hospitals and physicians assess service quality, patient satisfaction, and areas for improvement.
Keywords: *Sentiment Analysis, Patient Satisfaction, Healthcare Quality, Machine Learning, Patient Feedback.*

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I. Introduction

In the evolving landscape of healthcare, understanding patient emotions, opinions, and experiences has become a vital component in improving service quality and patient-centered care. Traditional feedback mechanisms, such as surveys and satisfaction questionnaires, provide valuable insights but often fail to capture the depth of patients' emotions and sentiments embedded within their narratives. With the rise of digital transformation and the widespread use of online healthcare platforms, patients today share their experiences openly on hospital websites, review portals, and social media. This vast pool of textual data presents both an opportunity and a challenge for healthcare providers—to meaningfully interpret these sentiments and translate them into actionable insights. Here, sentiment analysis, a subfield of Natural Language Processing (NLP) and artificial intelligence (AI), emerges as a powerful analytical tool for understanding patient satisfaction and enhancing healthcare quality. Sentiment analysis refers to the computational study of opinions, emotions, and attitudes expressed in text. By employing machine learning and deep learning algorithms, sentiment analysis models classify text as positive, negative, or neutral, thereby revealing the underlying emotional tone of patient feedback. In the context of healthcare, this technology enables hospitals and policymakers to analyze patient reviews, detect dissatisfaction trends, and respond proactively. Unlike conventional survey data, sentiment analysis captures spontaneous and unfiltered expressions of patient experiences, offering a more authentic representation of satisfaction levels. This technology also bridges the communication gap between patients and healthcare providers, allowing for continuous monitoring of patient perceptions in real time.

The importance of patient satisfaction in healthcare cannot be overstated. It is widely recognized as a key indicator of healthcare quality, patient safety, and institutional performance. Satisfied patients are more likely to adhere to medical advice, maintain follow-up appointments, and recommend healthcare providers to others. Conversely, dissatisfaction can lead to mistrust, treatment noncompliance, and negative public perception. Therefore, understanding patient satisfaction is not merely a public relations exercise—it is a cornerstone of effective healthcare delivery and organizational success. Sentiment analysis enables institutions to systematically evaluate these satisfaction levels and uncover specific areas for improvement, such as waiting time, staff behavior, communication clarity, or treatment efficacy. Recent advancements in AI and machine learning have significantly improved the accuracy and applicability of sentiment analysis in healthcare. Algorithms such as Support Vector Machines (SVM), Naïve Bayes, Recurrent Neural Networks (RNN), and Transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers) are capable of processing complex linguistic patterns and contextual meanings. These models can identify subtle emotional cues in patient feedback, such as anxiety, gratitude, or frustration, which traditional analysis methods might overlook. Moreover, integrating sentiment analysis with big data analytics allows healthcare organizations to evaluate thousands of patient reviews across multiple platforms efficiently. This leads to evidence-based decision-making and data-driven strategies for quality enhancement.

In addition to improving service quality, sentiment analysis plays a crucial role in public health monitoring and policy formulation. By aggregating sentiment data from various sources, policymakers can gauge community-level perceptions of healthcare services, identify regions with lower satisfaction levels, and allocate resources accordingly. During crises, such as pandemics or health emergencies, sentiment analysis can also serve as an early-warning mechanism by tracking public fear, misinformation, and trust in healthcare institutions. Furthermore, hospitals can use sentiment analysis to evaluate the success of new healthcare programs, measure the impact of interventions, and assess patient trust in technology-driven care models such as telemedicine or AI-assisted diagnosis. The integration of sentiment analysis into healthcare systems aligns with the broader shift toward value-based healthcare, where outcomes and patient experiences hold greater significance than mere procedural volumes. By leveraging sentiment analysis, healthcare institutions can move beyond numerical ratings to understand the emotional context behind patient opinions. This emotional intelligence empowers healthcare administrators and clinicians to adopt more empathetic communication styles, develop patient-friendly environments, and tailor medical services to individual needs. Additionally, predictive sentiment analytics can anticipate potential dissatisfaction and trigger timely interventions, thereby preventing negative experiences from escalating.

However, the implementation of sentiment analysis in healthcare is not without challenges. Issues such as data privacy, linguistic ambiguity, algorithmic bias, and the need for domain-specific training data must be addressed to ensure ethical and accurate outcomes. Despite these challenges, the benefits far outweigh the limitations. As healthcare becomes increasingly digitalized, sentiment analysis will continue to evolve, offering more sophisticated insights through multimodal analysis—combining text, voice, and facial expressions—to capture the full spectrum of patient sentiment. Sentiment analysis represents a paradigm shift in how healthcare organizations measure and enhance patient satisfaction. By combining AI-driven text analytics with human empathy and clinical insight, healthcare providers can transform patient feedback into actionable intelligence. This not only fosters patient trust and engagement but also contributes to the overall improvement of healthcare quality, efficiency, and transparency.

II. Review of Related Studies

He, Mu. (2024) with the rise of e-health systems, the problems with conventional healthcare systems, such as inaccessibility, high operating costs, and inefficiency, have been greatly alleviated. Improving patient care and system efficiency are two of the primary goals of this paper's examination of Natural Language Processing (NLP) and its pivotal position in electronic health record (EHR) systems. Utilizing sentiment analysis to glean emotional information from patient experiences, the research applies natural language processing methods to sift through and make sense of massive amounts of healthcare data. Patient satisfaction and the quality of care provided may be improved by using this data to gauge how patients feel about various treatments and services. By detecting possible problems based on patients' emotional reactions, sentiment analysis also plays an important role in mental health monitoring. The findings point to the fact that public health initiatives, mental health monitoring, and patient happiness may all be greatly improved with the use of NLP-driven sentiment analysis. Healthcare professionals may improve healthcare outcomes by using sentiment analysis to better identify and react to community needs. When it comes to improving decision support, managing unstructured data more effectively, and increasing the accuracy of data analysis, this study offers crucial insights for the future development of e-health systems.

Rizwan Rashid et al., (2023) Traditional healthcare systems were plagued by inefficiency, high operating costs, and restricted accessibility; however, these issues have been greatly alleviated with the rise of e-health systems. Natural Language Processing (NLP) plays an essential role in e-health systems, and this article delves into that function, specifically looking at sentiment analysis and how it may revolutionize patient care and system efficiency. The research uses natural language processing methods to sift through mountains of healthcare data in search of patterns, and it makes use of sentiment analysis to glean insights about patients' subjective experiences with treatment. Improving care quality and patient happiness is possible with the use of this data, which reveals how patients feel about various treatments and services. Sentiment analysis is also vital in mental health monitoring since it may spot problems depending on how individuals are expressing themselves emotionally. Patient happiness, mental health monitoring, and public health strategy effectiveness may all be greatly improved using NLP-driven sentiment analysis, according to the findings. Better healthcare outcomes may be achieved when healthcare practitioners use sentiment analysis to get a better understanding of community needs and react accordingly. Particularly in the areas of unstructured data handling, data analysis accuracy, and decision support, this study offers significant insights for the future development of e-health systems.

Ramyasri, V et al., (2019) The exponential growth of online communication platforms has given individuals all over the globe a platform to voice their thoughts and feelings on any given subject, service, or product. Patients are the ultimate arbiters of a healthcare service's success or failure. If most people who use the service are satisfied, then it's a success; otherwise, it requires some tweaks. It is necessary to examine consumer feedback in order to enhance the service. Extracting and evaluating online material by hand is a time-consuming and laborious process. As a result, the field of Sentiment Analysis was born. This practice is sometimes called opinion mining. Many health organizations are use it to make informed judgments about their service. In this work, we provide sentiment analysis as a tool for better healthcare by analyzing people' perceptions about hospitals. The implementation of this involves analyzing the sentiment using an approach based on a vocabulary.

Hopper, Anthony & Uriyo, Maria. (2015) This research aims to quantify text-based information found on the internet using sentiment analysis and time-to-next-complaint approaches. Equally important, the authors show how managers may arrange sentiment analysis data into meaningful information using time-to-next-complaint approaches; this information can then be shared with physicians and other personnel. The writers analyzed patient comments for a subset of Virginia gynecologists using sentiment analysis. In order to make sense of this data, the writers used time-to-next-complaint procedures among other ways. If healthcare administrators are interested in turning web-based material into meaningful, measurable information, the authors showed that sentiment analysis and time-to-next-complaint approaches could be helpful tools. The research isn't without its flaws. One problem is that gender, wealth, culture, and other socio-demographic biases in selection won't be taken into consideration by either the data collection or the methods used to evaluate it. The writers also failed to provide crucial information on the number of patients seen by the specified doctors. Lastly, healthcare administrators may be hesitant to use online data due to the difficulty in persuading clinicians to accept online remarks as actual. Using sentiment analysis and time-to-next-complaint approaches, the research shows how hospital managers may mine online patient comments for useful information. Clinic and doctor's office administrators may use sentiment analysis and time-to-next-complaint approaches to sift through online patient comments; this research is among the first to do so.

Khan, Taimoor & Khalid, Shehzad. (2015). In health care sentiment analysis, patients' self-reported issues with their treatment are the focus of the diagnostic process. By considering patient feedback, policies and changes may be developed to tackle patients' issues head-on. Sentiment analysis has matured and found new uses outside its original commercial product domain. In addition to making treatment and service recommendations, aspect based analysis of health care highlights the benefits of each option. An efficient and accurate judgment is reached by analyzing millions of review papers using machine learning algorithms. While supervised methods are quite accurate, they cannot be applied to domains that are unknown, while unsupervised methods are inaccurate. Since unsupervised methods are more applicable in this era of information deluge, there is a greater emphasis on improving their accuracy.

Greaves, Felix et al., (2013) Blogs, social networks, and physician rating websites all include vast volumes of unstructured, free-text material on healthcare quality that is not systematically collected. Sentiment analysis and other new forms of data analysis could help us make better use of this data to enhance healthcare quality. We looked at using machine learning to decipher patients' unstructured feedback on their treatment. We classified patients' online free-text remarks on their healthcare as good or unfavorable using sentiment analysis methods. After comparing the patient's free-text description with their quantitative evaluation of care, we attempted to automatically predict whether the hospital was clean, if they were treated with dignity, and if they would suggest the facility. In 2010, we used the data-mining tool Weka to analyze 6412 comments posted on the English National Health Service website on hospitals. We then used machine learning methods to these remarks. In addition, we used Spearman rank correlation to compare the sentiment analysis findings with the hospital-level results of the 161 acute adult hospital trusts in England's paper-based national inpatient survey. Comparing quantitative care ratings with those obtained from free-text comments using sentiment analysis, we find that 81% of patients felt the hospital was clean, 84% felt they were treated with dignity, and 89% would recommend the facility to others.

III. Proposed Methodology

Research Approach

One potential approach to this study is to collect patient feedback by hand. Users' comments, whether pleasant or bad. Following that, it will use two methods: a keyword-based approach and a machine-based technique.

To find representative qualities and distinguishing features, this case makes advantage of the classifier's load. A class's "representative attributes" are its outward manifestations, while its "distinctive characteristics" are its internal details. With these categorization weights, the Bayesian algorithm can determine the likelihood and provide superior results. This two-stage mechanical sentiment analysis approach was developed by Barbosa et al. for the purpose of tweet classification. To reduce the labeling trial, they use a noisy build upset while creating classifiers. The first thing they do is sort tweets by method, whether subjective or objective. After that, we classify subjective tweets as either favorable or negative.

Based on normalized noisy tweet pronunciation, researchers have created a clustering approach. Words with the same utterance are grouped together using common tokens in an utterance-based word cluster. Tokens representing numbers, HTML links, user IDs, and the names of objective organizations are some of the text processing methods used for normalization. Following normalization, polarity lexicons were recognized using probabilistic models. The BoosTexter classifier achieved a lower error rate when trained with these polarity lexicons as features. A practical probability model for analyzing sentiment on Twitter was introduced by Wu et al. An action is valued and placed into helpful likelihood if they commence the usage of @tweetusername in the body of a tweet. Retweets that begin with @tweetusername generate motivated action and commit themselves to motivated likelihood. A robust relationship between these probabilities was discovered. Using the Twitter API and Emoticons, Pak et al. automated the process of collecting tweets and annotating them to create a Twitter corpus.

A method of machine learning that makes use of the data mining tool Weka to train an algorithm to categorize comments into distinct groups based on their similarities and differences. Weka, which has been employed in most prior studies, provides accurate categorization results and is also useful in healthcare.

Compare results to quantitative ratings obtained from similar individual patients on a Likert scale to validate accuracy. The next step is to analyze the patient's feedback using a three-question-and-answer format, such as "what I liked," "what could have been improved," and "any other comments." The patient will then be asked to rate the cleanliness of the hospital and the level of respect and dignity they received during their stay.

Sources of data

Data comes from a variety of places; for example, surveys, social media, healthcare websites, blogs, etc. We gathered our database from https://www.ratemds.com for this project. You may find extensive biographical information on doctors here, along with links to their areas of expertise and feedback from actual patients. The information on the doctor and hospital that is included in these remarks is feedback. There are a lot of doctors' profiles on our site, and they come from all around the globe.

The website "ratemds" also featured the specializations of Indian physicians from various cities in India. Select the specialization of the doctor, the city, and then either male or female to narrow your search for a doctor on the "ratemds" website. After that, we may see the profiles of doctors and read comments from their patients right here. More than sixty patient comments on physician feedback texts were culled from this website. The text data is compiled according to the medical specialties of the doctors. We will transfer this data from an Excel file to a "CSV" format so it may be processed later.

Pre-processing

Data pre-processing is a process in which processing is performed on raw data to organize it to remove noise or unwanted text for the purpose of data cleaning and for better classification. Pre-processing is like to removing unwanted text, punctuation, NA values, numbers, etc. Pre-processing begins with the Comments Review Database, which serves as the initial source of input data. The next stage is Preprocessing, where textual data undergoes several cleaning operations to prepare it for analysis. These preprocessing steps include converting all text to lowercase, removing stop words, eliminating punctuation marks, deleting numerical values, discarding missing (NA) entries, and removing hyperlinks. Once the data is cleaned, it moves to the Transformation phase, where the text is converted into a structured format suitable for computational analysis. After transformation, Feature Selection is performed to identify and extract the most relevant attributes or variables that significantly contribute to model accuracy and efficiency. Finally, the refined data is subjected to Classification, where machine learning or statistical algorithms categorize the processed comments into predefined classes or sentiment categories, completing the analytical workflow.

Pre-processing

In the pre-processing part, it was indicated that you should lowercase all content, remove punctuation marks, stop words, NA values, numerals, links, etc. This section discusses the infrastructure in detail that will be used to forecast healthcare outcomes based on patient input, namely online text comments.

System Architecture

In this paper, proposed architecture consists- R data analysis tool, sentiment analysis, and pre-processing workflow.

a) **R-Tool:** R-Programming makes use of this tool. It is possible to create a software that can predict the emotion score of text using this tool.
b) **Sentiment Analysis:** Here we show how to use the R programming language to determine the sentiment score of a patient's response.
c) **Positive text:** Here you may find a library of positive words together with their synonyms.
d) **Negative Text:** This text file contains both positive and negative words, as well as their synonyms.

IV. Results and Discussion

Sentiment Score

The emotion score must be counted after pre-processing. The R-tool is used to tally sentiment scores. The next step is to write an R program that will compare each comment's sentiment score to two text files, one containing positive comments and the other containing negative ones. This text file contains both positive and negative sentiments extracted from the "Twitter sentiment analysis tutorial" repository on Github. The sentiment score is obtained by comparing the text files containing positive and negative comments made by patients with the physician's database. After tallying all of the good and negative words in a statement, this score will display the emotion score. The sentiment score of a comment sample predicted using R programming in R-Tool. See that a score of 0 indicates no opinion, a score of -1 indicates a bad remark, and a score of 3 indicates a good comment.

Table 1 shows the total comments and the extracted comments organized in a categorized way. Find the doctor's number, the total number of comments, the percentage of positive remarks, the percentage of negative comments, and the percentage of neutral comments in this table. These remarks provide the patient's perspective on their doctor, which may be categorized as good, negative, or neutral.

Table 1: Classified commented feedback of patients

Sr. No.	Number of Comments	Negative Comments Count	Positive Comments Count	Neutral Comments Count
D1	25	7	15	3
D2	22	3	17	2
D3	21	5	13	3
D4	19	2	15	2
D5	15	1	12	2
D6	13	0	12	1
D7	11	2	8	1
D8	10	1	7	2

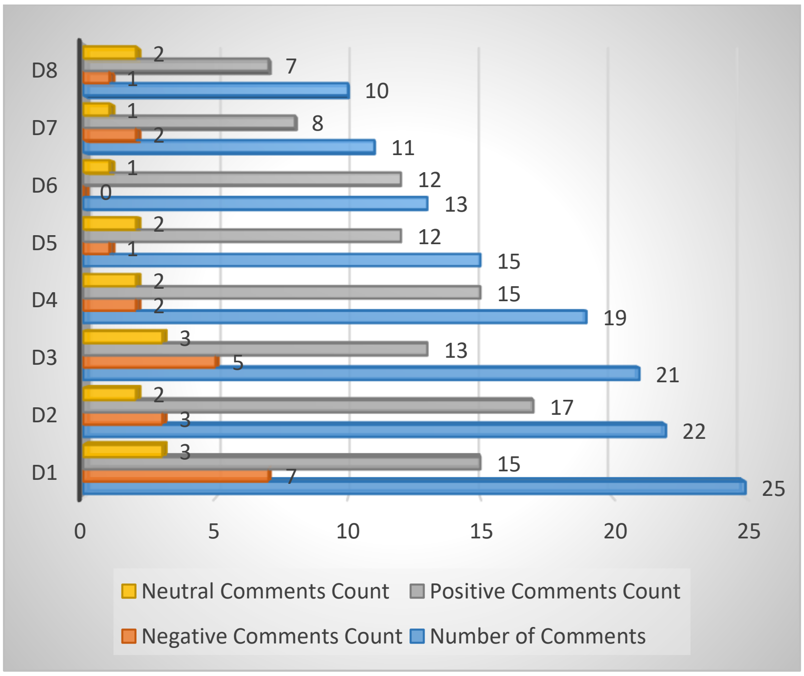

Figure 1: Distribution of Positive, Negative, and Neutral Comments Across Datasets (D1–D8) Showing Overall Comment Volume

Table 1 is shown graphically in Figure 1. The data shows that patients are more likely to have a good impression of their doctor when compared to those who are indifferent or have a bad impression.

Table 2: Percentage Distribution of Comment Sentiments Across Datasets

Dataset ID	% Negative Comments	% Positive Comments	% Neutral Comments
D1	28.0	64.0	8.0
D2	10.0	85.0	5.0
D3	22.0	65.0	13.0
D4	14.0	76.0	10.0
D5	5.0	80.0	15.0
D6	0.0	90.0	10.0
D7	20.0	78.0	2.0
D8	12.0	78.0	10.0

The table shows the fraction of patients' views based on the data. The percentage breakdown of comments on a doctor is shown in the table. The data in the table show that most patients have a good opinion of their doctor, with just a tiny minority holding a neutral or negative view. Unfortunately, some patients did not provide their good comments.

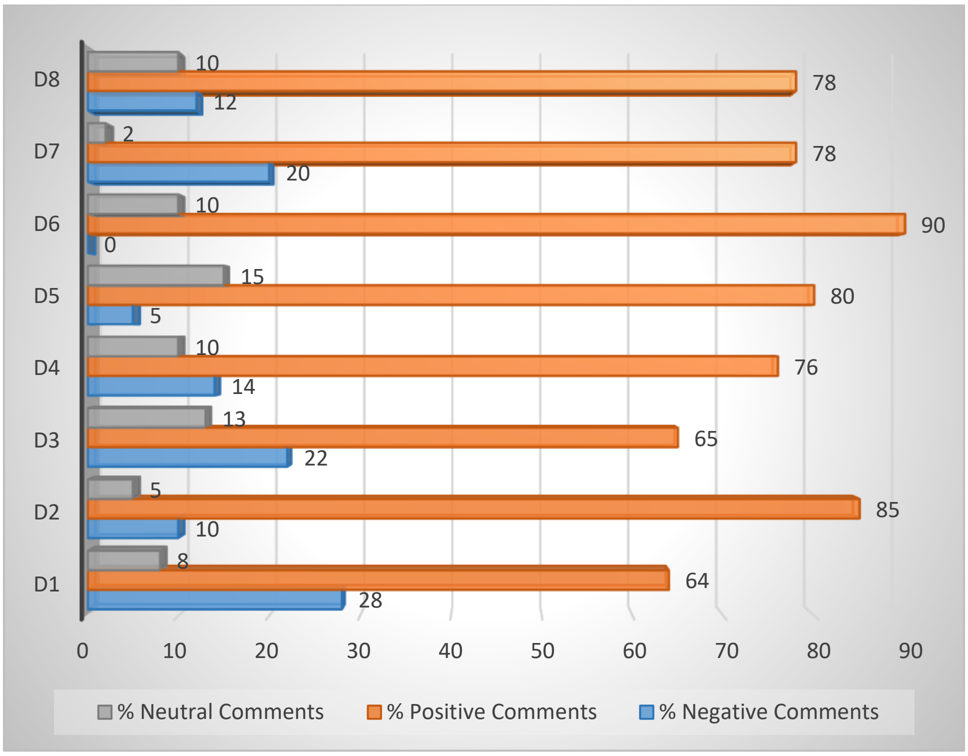

Figure 2: Distribution of Positive, Negative, and Neutral Comments Across Datasets (D1–D8) Showing Overall Comment Volume based on patients' opinions

Table 2's visual depiction is shown above Figure 2. Compared to negative and neutral graphs, positive graphs on patients' graphs had a greater rate of responses. Compared to the positive graph, the negative and neutral graphs make up a negligible amount.

V. Conclusion

In sentiment analysis serves as a transformative tool in the pursuit of patient-centered healthcare and continuous quality improvement. By analyzing patient feedback through advanced AI and machine learning algorithms, healthcare providers gain deeper insights into the emotional and experiential dimensions of care. This approach transcends traditional survey-based assessments, offering a more nuanced and authentic understanding of patient satisfaction. The ability to classify sentiments as positive, negative, or neutral enables healthcare institutions to identify service strengths, address areas of dissatisfaction, and implement targeted improvements. Furthermore, the integration of sentiment analysis into healthcare management promotes transparency, responsiveness, and data-driven decision-making. Although challenges related to data ethics, linguistic complexity, and algorithmic accuracy remain, ongoing advancements in NLP and AI continue to refine these technologies. Ultimately, sentiment analysis empowers healthcare organizations to not only monitor satisfaction but also cultivate a culture of empathy, trust, and excellence—thereby enhancing the overall quality of healthcare delivery and strengthening the relationship between patients and providers.

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