

RESEARCH ARTICLE



Received: 31-12-2022

Accepted: 18-05-2023

Published: 03-06-2023

Citation: Panchal DS, Shelke MB, Kawathekar SS, Deshmukh SN (2023) Prediction of Healthcare Quality Using Sentiment Analysis. Indian Journal of Science and Technology 16(21): 1603-1613. <https://doi.org/10.17485/IJST/v16i21.2506>

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Funding: None

Competing Interests: None

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Published By Indian Society for Education and Environment ([iSee](#))

ISSN

Print: 0974-6846

Electronic: 0974-5645

Prediction of Healthcare Quality Using Sentiment Analysis

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Abstract

Objectives: To examine the quality of healthcare services and the features (aspects) of those services, as well as the variation in those services' quality over a time. **Methods:** The study presents a method which includes firstly by collecting patient feedback data from the internet, and then follows preprocessing, extracting aspects of healthcare, and finally performing aspect-based sentiment analysis of healthcare. This aspect-based sentiment analysis is created to determine the pattern of aspect in a sentence using the BERT model. Healthcare services and their aspect-quality service analysis are performed here date-wise, i.e., timestamp-wide. A total of 69 physician are selected to collect the feedback and analyzed the feedback using an aspect-based sentiment analysis technique. **Findings:** The quality of healthcare services is frequently changing. In healthcare, for example, sometimes there is good quality service and sometimes there is worst quality service. All 69 physicians' total of 300 sentences with aspect-based sentiment scores are extracted separately after preprocessing and normalization. The aspect-wise results are shown in percentages. After that, the extracted aspect-wise percentages are shown as per date. Out of a total of 69 physicians, sample of D9, i.e., Doctor 9, patient feedback results, are shown in this paper. **Novelty:** This study made the aspect-based sentiment analysis score, which demonstrates the date-wise, i.e., timestamp-wide variation in healthcare services. Previous research has made healthcare predictions using feedback ratings; no study has yet performed a date-wise analysis. The features, such as diagnosis, treatment, cleanliness, appointment, advice, medicine, staff service, etc., are included for analysis.

Keywords: Patient; Hospital; Patient feedback; Aspect based sentiment analysis; Healthcare Service; Healthcare Quality

1 Introduction

This research study predicts the quality of healthcare (hospital) services and their features. The features are, for example, diagnosis quality, treatment quality, staff service, medicine quality, etc. These are all features of healthcare services that need to be

maintained so that overall healthcare services can maintain their quality of service. Because healthcare is directly connected to human health, if the healthcare services are not of good quality, they are harmful to human health.

This research work collected patient comments from the www.ratemds.com website. This website contains information from lots of physicians all over the world. In this work, Indian physicians are selected to collect the patient's feedback. Patient feedback plays a key role in this work⁽¹⁾.

The aspect-based sentiment analysis (ABSA) technique is used to analyze textual data from healthcare patient feedback. Sentiment analysis is able to extract people's opinions about related sectors. In this work, patients' opinions about the quality of healthcare (hospital) services are gathered. Patients are giving positive, negative, or neutral opinions about the healthcare system. Healthcare quality, or the polarity of healthcare services, is predicted on the basis of the patient's opinion. The quality of healthcare services is expressed in percentages.

As data collection is completed, i.e., patient comments, the next task is to perform the sequential operations required on the dataset, i.e., preprocessing, tokenization, POS (part of speech) tagging, aspect extraction, ABSA, etc. As all tasks have been completed and shown in the section on results and discussion⁽²⁾, to complete these text analyses, an R tool and Python programming are both used. The R tool is used for preprocessing, and Python programming is used for aspect-based sentiment analysis. ABSA is created on the basis of the BERT model.

The polarity result determines healthcare quality, i.e., whether the health care service and feature quality are poor or good. The quality prediction depends on the predicted result of the patients' opinions using the sentiment analysis technique. The additional advantages of this research are the time-wise analysis of healthcare services and their features for service quality analysis. Because of Date Wise's patient feedback analysis, we can predict that the service quality of healthcare is constantly improving or declining⁽³⁾.

The advantage of this research for human society is to create or develop a quality healthcare information system for every human. Because of this research, we can analyze the drawbacks of health care services so that healthcare service providers can easily improve their service quality. Patients can get relief as per their healthcare needs.

1.1 Statement of the Problem

Many complaints about private and government hospital services are made by patients. Some health centers are providing quality services, while others have a negative record regarding their healthcare services, so it is necessary to analyze both types of services. Experienced patient feedback is needed to find a genuine hospital or to know the hospitals past history. With prior knowledge of the hospital, the patient can choose the hospital as per his requirements. The standard of hospital care must improve for the benefit of patients' satisfaction with their physical and mental well-being.

Healthcare services have a number of drawbacks that need to be recognized. Patients have complaints about a variety of aspects (features) of hospitals, such as the cleanliness of the facility, the friendliness of the staff, the cost of the medications, and other factors. As a result, it's important for all of these aspects to remain excellent. The hospital needs to be the primary focus of improvement in healthcare services. The healthcare service is also changing as time passes, i.e., sometimes it is good and sometimes it is very bad. As a result, timestamp-based healthcare service analysis is critical.

The contribution of this research work is that the issues found in healthcare services and analysis are studied and analyzed. Initially, features are extracted using POS tagging, and on the basis of the extracted features, their polarity is calculated. It is a challenging task to analyze the aspect-based sentiment analysis of text about healthcare feedback. Additionally, aspect-based sentiment analysis is used to predict timestamp-wide variation in healthcare services. On the basis of the polarity result, it is decided that the maximum percentage of polarity is towards quality services.

1.2 Literature Review

The literature explains the previous research work done by various researchers along with their research gaps in healthcare and aspects-based sentiment analysis⁽⁴⁾.

1.2.1 Sentiment Analysis

Sentiment analysis, or opinion mining, is the analysis of patients' opinions, reviews, assessments, sentiments, attitudes, evaluations, and feelings about various topics and characteristics. Figure 1 shows the sentiment analysis diagram, types of sentiment analysis, and the subtype of aspect-level analysis⁽⁵⁾. Aspect-level sentiment analysis delves into textual data analysis and predicts opinion summarization⁽⁶⁾.

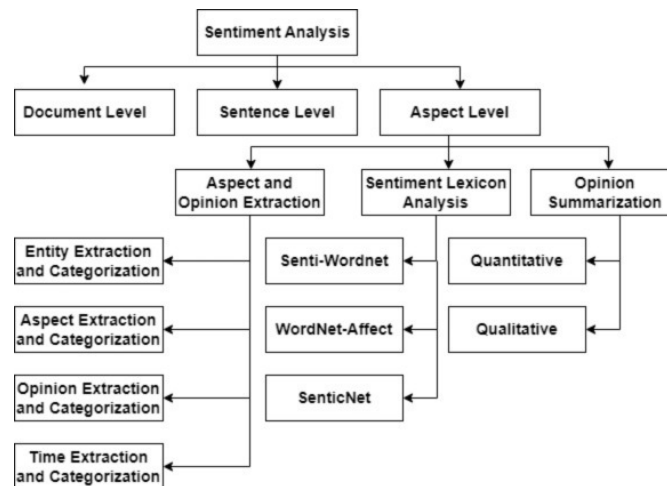


Fig 1. Sentiment Analysis

1.2.2 Healthcare Sector and Sentiment Analysis

P. Kamakshi used Twitter's data about patient feedback. Tweepsters have word limitations, i.e., a single tweet has a 140-word limit, so in this work, the entire patient feedback cannot be analyzed, which means the actual patients' entire opinion about the healthcare is not predicted. Also, here the entire sentence is analyzed instead of aspect-wise analysis. It means deep analysis is not performed.

In this paper, aspect-wise sentiment analysis is used to do an in-depth analysis of the complete patient input without applying any word limits. As a result, the full patient opinion on healthcare and its attributes is extracted with accuracy. Patient reviews from the healthcare website ratemds.com are processed and analyzed. There are many comments in the huge lines of patient feedback on this page⁽⁷⁾.

Siew Theng Lai and Raheem Mafas focus on the entire information about sentiment analysis, i.e., the applications, challenges, and limitations of sentiment analysis. The facts or techniques they use and how they help healthcare-related employees improve the healthcare service or how can sentiment analysis be much better for healthcare patient feedback analysis?

In this paper, the specific task is focused on analyzing the patient feedback, i.e., aspect-based sentiment analysis. Where the patient feedback is analyzed feature-by-feature, this concept is not explained in Siew Theng Lai and Raheem Mafa's entire research paper⁽⁸⁾.

1.2.3 Healthcare and Aspect Based Sentiment Analysis

YUE HAN et al. developed a pretraining and multi-task learning model (PM-DBiGRU) to assist with the classification of drug reviews. This model uses several BiGRU networks to create the destination representation of the destination and medication review, which is then acquired via a convolutional neural network. Additionally, a short text-level drug review corpus's useful domain knowledge is transferred using multitask learning. SentiDrugs, which are used to categorize drug reviews and sentiment classification, have been found to outperform existing cutting-edge architectures.

In this paper, ABSA is used to extract the polarity of features in patient feedback. Simply put, an aspect-based sentiment analysis model is created to accurately extract the percentage of polarity in the form of a percentage. There is no word limit for patient feedback, whereas Yue Han et al. have a word limit of 200 words or less. This study will extract date-wise aspect-based patient feedback polarity instead of drug reviews⁽⁹⁾.

Tian Shi et al. developed a multi-task learning framework for multi-aspect sentiment classification at ratemds.com, where ratings for four separate categories and an overall rating are evaluated. The suggested model takes into account both doctor qualities and aspect-keywords, and various tests have been run on two subsets of the dataset to show the efficiency of the model.

In this paper, aspect-based sentiment analysis is done using unsupervised learning. The database is also used on the same website as Tian Shi et al., i.e., ratemds.com. Sentence-wise aspect analysis is performed instead of the whole document. Aspect-wise polarity percentage is extracted precisely instead of using complex methods and analysis⁽¹⁰⁾.

The challenge of aspect-based sentiment analysis is to locate relevant sentiment elements for a given text piece. Common natural language processing modelling paradigms for ABSA include sequence-level, token-level classification, machine reading

comprehension, sequence-to-sequence modelling, convolutional networks, recurrent networks or transformers, and CRF, RNN, and CNN-based sequence labelling techniques. Data augmentation is an efficient way to create pseudo-labelled data for training ATE models. Token-level classification labels each token individually and uses an encoder to turn input text into context-specific characteristics. Sequence-to-sequence is a traditional NLP application.

In our research paper, we concentrated on aspect extraction and aspect sentiment prediction using aspect recognition technique. To recognize aspect polarity, a model is developed to analyze the pattern of aspects in a sentence. This model is developed on the basis of the BERT (Bidirectional Encoder Representations from Transformers) model. The BERT model is a classifier in ABSA, i.e., it can classify the polarity of ABSA. First, extract the aspect using POS tagging, then encode the phrase and aspects, post-process the encoded phrase and aspect, and then predict the sentiment of the aspect⁽¹¹⁾.

1.2.4 Comparative Analysis

Bansal and Kumar performed the aspect-based sentiment analysis of hospital reviews using aspect-wise ratings of patient feedback. They extracted the aspects, analyzed the aspect ratings, and calculated the average aspect ratings for aspect-based sentiment analysis. The aspect rating is calculated based on the overall characteristics of hospitalized patient feedback. The authors compare their aspect ratings with net ratings. The authors analyzed patient feedback using 30,000 reviews of various text data from 500 hospitals. The authors are looking into different aspects of hospitals, such as doctor service, staff service, hospital facilities, and so on. The authors analyzed the overall collection of aspects of every doctor separately and found the overall polarity of each doctor separately. This research work is not helpful for regular healthcare service analysis.

In this paper, we have calculated the aspect-based sentiment score of each patient's feedback separately. The sentiment score for each aspect of patient feedback is expressed in percentages. Every aspect of the sentiment score is extracted polarity-wise, i.e., positive, negative, and neutral; for more details, see Table 3 and Figure 3. We used about 300 sentences of patient feedback, and out of them, Table 3 shows a sample of the results (Dr. D9) in this research paper. Here we have studied and analyzed the fact that the previous research paper had not yet performed the date-wise patient feedback analysis, i.e., the timestamp-wide patient review analysis. The benefit of this date-wise patient feedback analysis is that it shows whether or not the quality of healthcare services is consistently good. It is helpful to the healthcare provider as well as the patients. As compared with other healthcare aspects based on sentiment analysis, this is better for regular quality service analysis⁽¹²⁾.

2 Methodology

This research proposes an ABSA model for healthcare improvement. To complete the patient feedback analysis, an R tool and Python programming are used. The steps in the proposed system are detailed as follows:

2.1 Data Collection

Patient feedback is collected from about 69 different physicians. We manually gathered this patient feedback data from the ratemds.com website by selecting doctors' specialties and locations. While collecting data, precautions are taken, i.e., the privacy of the doctor's identity is maintained and personal information about the doctor is removed. All physicians are drawn from various cities across India, with the majority hailing from the state of Maharashtra. This dataset contains over 300 English sentences from 69 different doctors, with some doctors' feedback being very few, some doctors' feedback being more than fifteen to forty comments, some feedback being large sentences, and some being 1 or 2 sentences. Patients can make comments on various aspects (or features) of healthcare; these aspects are extracted from the comments passed on by patients using POS tagging. The most commonly used nouns are selected from a sentence as aspects, i.e., from patient feedback. Also fixed several problems in the original dataset collected from ratemds.com.

The site permits patients to rank their physician's staff, trustworthiness, support, and information on a scale of more than zero; one star means "actually small in worth," while a score of five stars determines that the specialist is "greatly worth full service." Similarly, the survey includes a section for patients to provide feedback on specific aspects of their issue-related healthcare service that they liked or disliked. Here, patient satisfaction is preferred for better healthcare. Patients are giving preference to treatments that are effective for their health.

The full process for choosing aspect-wise polarity is depicted in Figure 2. First, reviews are collected, followed by preprocessing, normalization, and aspect identification. After preprocessing, aspects of patient comments need to be extracted using tokenization and POS tagging.

2.2 Preprocessing

Preprocessing is essential for processing the data. During preprocessing, some cleaning operations are performed to analyze the data, i.e., removing HTML tags, stop words, punctuation, white spaces, and URLs (Unified Resource Locators) and making the text lowercase.

2.3 Normalization

Normalization is used to extract meaningful information from preprocessed data. The R tool has various libraries that are able to perform various statistical operations on text. The following are the processes for performing normalization:

2.3.1 Lemmatization

Stemming and lemmatization are similar, but lemmatization is far more effective. Lemmatization never generates an invalid word since the word that results from removing the suffix is always meaningful and belongs in the dictionary. A lemma is the term used to describe the word produced after lemmatization.

2.3.2 Tokenization

Tokenization is the process of converting text into tokens before transformation into vectors. It is also easier to filter out unwanted tokens. Such as a document in paragraphs or phrases into words. In this case, we transform opinions into words.

2.3.3 POS-Tagging

Speech tagging is used to enforce grammatical rules by assigning specific meanings to words or sentences in a sentence. Noun, adjective, personal pronoun, determiner, adverb, verb, etc. tags such as NN, JJ, PRP, DT, RB, VBZ, etc. are the tags used to tag the noun, pronoun, determiner, etc. from the patient feedback.

2.3.4 Term Frequency (TF)

This is a quantity based on the number of times a particular term appears in the data source. The terms are like doctor, healthcare, hospital, patient, treatment, medical, etc.

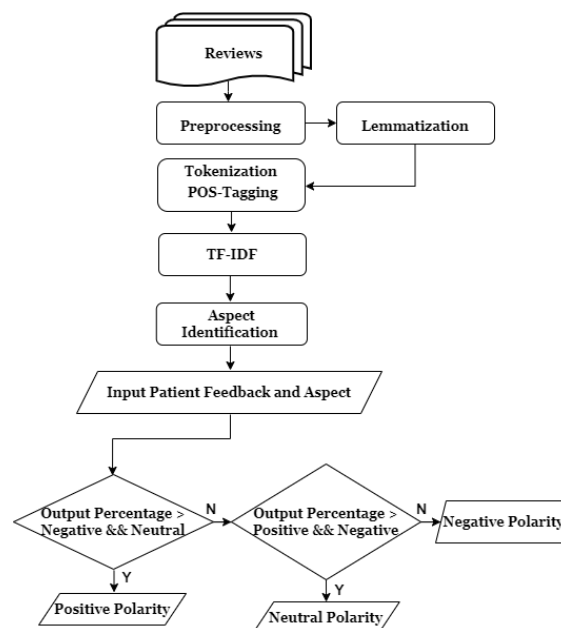


Fig 2. The diagram to find the aspect sentiment score and polarity of aspects

2.3.5 Inverse Document Frequency (IDF)

IDF is a metric for determining how frequently a word appears in a document.

2.4 Aspect Based Sentiment Analysis

An aspect-by-aspect analysis is critical. While analyzing grammatically for synonyms, antonyms, and so on, extracting aspects from sentences is programmatically confusing. If the healthcare infrastructure is good but the physicians aren't, the entire infrastructure will be unusual.

2.5 Extraction of Aspects

Extract all of the various aspect terms contained in a group of phrases with well-known entities (e.g., hospital) and produce a list. The word "aspect term" refers to a feature of the objective unit. E.g., "a brilliant doctor with great knowledge and diagnosis."

In the above example, the aspects are "doctor" and "diagnosis," two aspects that are extracted by using tokenization along with part of speech tagging (POS). Aspect terms with several words (e.g., "homoeopath doctor") should be treated as single terms (e.g., the single aspect term in "excellent homoeopath doctor for infectious conditions" is "homoeopathic doctor," which is a single term with multiple words).

Unsupervised approaches are preferred for extracting an aspect since they search the entire domain for aspects rather than guiding them to a certain sort of aspect. The known components of the supervised technique will be identified with great accuracy, but any unknown aspects will be ignored. Aspect extraction is divided into two stages, as follows:

2.5.1 Aspect Identification

Aspect identification is the process through which nouns and noun phrases are identified as portions. The relevant features are those that are most likely to produce results. The procedure for identifying aspects is based on their frequency of occurrence or the corresponding patterns in which they may occur. Diagnosis aspects include phrases like,

".....of the diagnose" or "diagnosis by....."

In the above sentence, diagnose and diagnosis are referred to as aspects, and the technique used to discover aspects is called a frequency-relation-based method. As the name implies, it generates a large list of relevant characteristics based on frequency and then filters out those that aren't found in the precise relationship pattern. The presence of a sentimental word together with a low-frequency aspect is added to the list as an indication of being an aspect. The probabilistic subject prototypes extract features based on the co-occurrence of words.

Multi-term aspects are created by grouping relevant aspects that appear together in a sentence from the list of relevant aspects. Only the order in which the words appear in the sentence determines the formation of sets. The multi-term aspects that were created are also included in the list. Therefore, create a dynamic database that might give most of the required information about different hospitals in order to overcome this information asymmetry. Using this information, people will make good judgments and make the best use of the hospital's infrastructure that is already in place.

2.5.2 Polarity of Aspect Term

Evaluate whether the polarity of every aspect term in a sentence is positive, negative, or neutral for the inclusion of specific aspect terms. The examples of patient feedback (patient comments) and their polarity are given in Table 1 as follows:

The first comment in Table 1 has two aspects, namely, doctor and treatment, and their polarity is indicated in the polarity column next to the aspects. Aspect doctors and their polarity are positive; aspect treatments and their polarity are also positive. These aspects are extracted from the sentence. Sentences 2 and 3 both have single aspects, i.e., management and doctor; their polarity is negative and neutral sequentially⁽¹³⁾. For more details, see Table 1. After encoding, post-processing is performed. Post-processing is recognizing the pattern of aspects. Polarity is determined through an aspect-based sentiment analysis: positive means greater than 0, negative means less than 0, and other than this, neutral. Aspect sentiment is shown in percentage; this percentage of polarity is calculated using the sentiment words and the opinions included in the feedback text. Also, the model classifies the relationship between text and aspect.

Table 1. A Sample of Patient Feedback and the Polarity of Its Aspects

Sr. No.	Patient Feedback	Aspect	Polarity
1	'Excellent doctor awesome treatment'	doctor treatment	Positive Positive
2	'saddened management care information moving patients freshman doctors arriving min patient overview clear treat- ment upset'	management	Negative
3	'doctor available'	doctor	Neutral

2.6 Unsupervised Learning

For the aspect-based sentiment analysis of healthcare in English, we used an unsupervised method based on lexicons and grammatical correlations. Algorithms for unsupervised learning extract information and relevant aspects from unlabeled data.

2.7 Aspect based sentiment analysis model

The model followed here is the BERT model. Which consist of pattern recognition of an aspect of a sentence. The model consists of the language model BERT and the linear classifier, which formulates the goal as a sequence-pair classification using BERT's next-sentence prediction. Using this BERT model, we create an aspect pattern recognizer that is able to predict the aspect sentiment. Here, aspects are considered nouns, which are extracted using POS tagging. Here, this model needs input in the form of a sentence along with its aspect, and then it has the mechanism to analyze the sentence, encode it, post-process the encoded sentence, and finally identify the aspect sentiment. For this, the aspect values are considered zero and one. Here, the model has positive polarity, which means a one, while zero means negative polarity, and no polarity is considered neutral.

3 Results and Discussion

The results and discussion sections show the outcomes of the preprocessed data. The next procedure is applying sentiment analysis techniques to preprocessed patient feedback and aspects. Healthcare data analysis has some limitations. Due to the inadequacy of available data, it is challenging to determine the truth of patient comments.

3.1 Aspect Extraction

Following is algorithm 1 to extract aspects from the text. To extract aspects from a text, a corpus of stopwords is used to remove the unwanted stop words, and for POS tagging, lemmatization, and stemming, a sentiwordnet dictionary is used⁽¹⁴⁾.

Step1: Start

Step2: Preprocessing of text (remove stop words) using stopword corpus

Step3: POS Tagging, lemmatization, Stemming ((Using Sentiwordnet dictionary)

Step 4: if tag == noun

```
{  
  It is an aspect  
}
```

Else if tag == Adjective

```
{  
  It is a Sentiment polarity  
}
```

Step 5: encode to code and Doc2Vec

Step 6: Feature extraction using TF IDF Vectorizer

Algorithm 1. Algorithm for Aspect Extraction

3.2 Aspect: Sentiment Polarity

Focusing on aspects that are included in the patient's feedback. Every aspect is essential for an overall healthcare service analysis. While doing this task, patient feedback and the aspects (features) of patient feedback are required to be processed.

Depending on the aspects contained within the feedback information, the sentence is broken down into smaller parts. The sentence's parts are all related to various aspects. An aspect score pair that contains the overall scores or polarity of an aspect inside a particular sentence is formed after the scores for each part are calculated using a sentiment dictionary or lexicon.

3.2.1 Aspect based sentiment polarity computation

Words used in perspective are typically regarded as aspects. For each type of domain independently, a sentiment dictionary of words is created in order to extract opinions from the content in Sentiwordnet. Resources are broken down into verbs and adjectives, such as "No + (adj+vb)". By computing matching scores, the connections between all sentiment units are mapped. Pointwise occurrence (PTOCCR) is used to determine how comparable different units are. Positive and negative PTOCCR are

calculated using Equation 1 for positive polarity and Equation 2 for negative polarity.

$$P + ve(WRa, +ve) = \log 2 \frac{\sum_a^y(WRa, +ve) \cdot N}{\sum_a^y(WRa) \cdot \sum_a^y(+ve)} \quad (1)$$

$$P - ve(WRa, -ve) = \log 2 \frac{\sum_a^y(WRa, -ve) \cdot N}{\sum_a^y(WRa) \cdot \sum_a^y(-ve)} \quad (2)$$

$\sum_a^y(WRa, +ve)$ - Number of WRa aspect terms in a sentence which are positive.

$\sum_a^y(WRa, -ve)$ - Number of WRa aspect terms in a sentence which are negative.

N_y - All tokens used in the sentence

$\sum_a^y(WRa)$ - Total number of WRa aspect terms in a sentence

$\sum_a^y(+ve)$ - Number of terms in a positive sentence

$\sum_a^y(-ve)$ - Number of terms in negative sentence

The above single formulas are used in equations 1 and 2. Equation 3 is used to determine the pointwise occurrence (PTOCCR) scores for each text in the full feedback, and the sentiment score is then determined by taking the text with the highest similarity score. Examples of results for various phrases are included in Table 3.

$$ABSAscore(WRa) = P_{+ve}(WRa, +ve) - P_{-ve}(WRa, -ve) \quad (3)$$

3.2.2 The sentence as input

Table 2 shows the input values that are given to the program. The program is created to analyze patient feedback and aspects of patient feedback. The patient feedback of Physician D9 is shown in Table 2's second column in the form of a sentence.

3.2.3 Aspect as input

Table 2 shows aspects mentioned in a sentence. Aspects are given as input to the Python program along with a sentence (a "feedback comment"). All aspects are assigned to a variable. The aspects of the first sentence are "diagnosis, treatment, and appointment."

Table 2. D9's Sentence and Aspect as Input

Input			
Dr. No.	Sentence	Aspect	Date
D9	humble soft spoken point diagnosis happy line treatment lost weight thyroid control sir pre appointment preferred	diagnosis, treatment, appointment	6/3/2019
	honest suggestion appropriate diagnosis uncle spent time questions relating diagnosis undue tests doctor options medication depending suit	diagnosis, doctor, medication	6/3/2019
	doctor following advice results experienced treatments highly recommend	doctor, advice, treatment	8/17/2018

Table 2 shows around three sentences, and the third column shows the aspects mentioned in the sentence, i.e., the aspects column. The fourth column of Table 2 is labelled "date, which is the time when the patient posted the comment. Here, date-wise patient reactions are assessed. The three possible states of the polar field are "positive," "negative," and "neutral." Table 2 shows the aspects known as "diagnosis" and "treatment," both of which are repeated on various dates.

3.3 Aspect-Based Sentiment Score Extraction

Here, firstly, the sentiment score of the aspects mentioned in patient feedback is extracted using an aspect-based sentiment analysis Python program, and for this, preprocessed patient feedback data is used. The extracted sample patient feedback, aspects, and aspect sentiment scores are shown in Table 3. Doctor D9's information is provided in Table 3 (here, D1, D2, D3, and D4 are the physician's serial numbers, which are given in the database). D9 is chosen as a physician serial number as a sample for obtaining an aspect-wise sentiment score out of a total of D69 physicians.

Doctor Number, City, Preprocessed Patient Feedback, Aspects of Preprocessed Patient Feedback, and Feedback Date are all included in Table 3. Three reviews of Dr. D9 were posted by patients on different dates. Dates are formatted as "MM/DD/YYYY."

The serial number of the physician is D9. Doctors' identities are hidden for the purpose of protecting their privacy. The aspect rating score extraction program is created in Python, and the result is shown as an aspect-wise rating percentage in Table 3.

The inputs are given as "preprocessed patient feedback," initially the first sentence as stated in Table 3, along with their aspects, i.e., the aspects of the first comment are "diagnosis," "treatment," and "appointment," which are "Aspects 1," "Aspect 2," and "Aspect 3." These inputs are given for calculating the aspect-wise sentiment score. The input must consist of a single sentence and its aspects (aspects can be one or more than one).

Table 3. Doctor D9 Feedback information

Dr. No.	City	Preprocessed Patient Feedback	Aspects of Preprocessed Patient Feedback			Feedback Date
			Aspect1(Neutral, Negative, Positive)	Aspect2(Neutral, Negative, Positive)	Aspect3(Neutral, Negative, Positive)	
D9	Pune	humble soft-spoken point diagnosis happy line treatment lost weight thyroid control sir pre-appointment preferred	Diagnosis [0.001 0.003 0.996]	Treatment [0.106 0.594 0.301]	appointment [0.94 0.013 0.047]	6/3/2019
		honest suggestion appropriate diagnosis uncle spent time questions relating diagnosis undue tests doctor options medication depending suit	diagnosis [0.015 0.002 0.982]	Doctor [0.958 0.008 0.034]	medication [0.993 0.003 0.004]	6/3/2019
		doctor following advice results experienced treatments highly recommend	doctor [0.002 0.001 0.997]	Advice [0.051 0.003 0.946]	treatment [0.001 0.999]	8/17/2018

The program will generate the desired outcomes after receiving input. The extracted aspect sentiment scores are displayed in Table 3's Aspects of Preprocessed Patient Feedback column under the labels Aspect 1, Aspect 2, and Aspect 3, respectively. The first comment focuses on diagnosis, treatments, and appointments. The aspects with the highest scores are diagnosis (0.996), treatment (0.594), and appointment (0.94).

The program of aspects extracts the three polarity values, i.e., positive, negative, and neutral; among these polarity values, the maximum percentage value means that the polarity is assigned to that particular aspect. The maximum polarity value among the extracted scores is shown in a variety of colors, with the first value being neutral (blue color), the second being negative (green color), and the third being positive (red color) (only the highest polar value is shown in color).

On the date 6/3/2019, the positive polarity percentage of 0.996 is greater than the neutral polarity percentage of 0.001 and the negative polarity percentage of 0.003 of the first aspect, i.e., "diagnosis," of the first sentence. The date format is given as "MMDDYY." Similarly, the first aspect of the second sentence, i.e., "diagnosis," is the same word, and on the same date (6/3/2019), it is also a positive aspect, i.e., 0.982.

The second aspect of the first sentence is that "treatment" on the date, 6/3/2019, has a negative polarity, i.e., 0.954. On the date 8/17/2018, the third aspect of the third sentence is the same as the first sentence's second aspect, i.e., treatment. The third aspect of the third sentence, "treatment," has a positive polarity, i.e., 0.999, as evaluated from Table 3 and shown in Figure 3.

An ABSA Python program is used to carry out this implementation. A Python program is used to create various models related to sentiment analysis. Sentiment analysis has a huge scope for analyzing text data. The percentage of polarity and aspect in patient feedback is calculated using the aspects and sentences that lean towards polarity.

The aspects (features) and their percentage of the sentiment score are graphically represented in Figure 3. The aspects of patient feedback, i.e., diagnosis and treatment, are shown in the graph (Figure 3). According to the graph, the positive polarity is highest when compared to the neutral as well as the negative polarity for the doctor "D9." The graph clearly shows the variation in sentiment scores for the aspects across dates. See the same aspects at various dates.

"Treatment" is an aspect found on different dates between 6/3/2019 and 8/17/2018, and their sentiment score polarity varies; aspect "treatment" has negative polarity on 6/3/2019 and positive polarity on 8/17/2018 (see Figure 3 for more details). It is proof that healthcare services and their aspects are changing frequently as time passes. Or, as time passes, the quality of healthcare services changes. The quality of the healthcare service is said to be reducing if the polarity of healthcare aspects continues to decline, while the quality of the healthcare service is said to be improving if the polarity of healthcare aspects continues to increase.

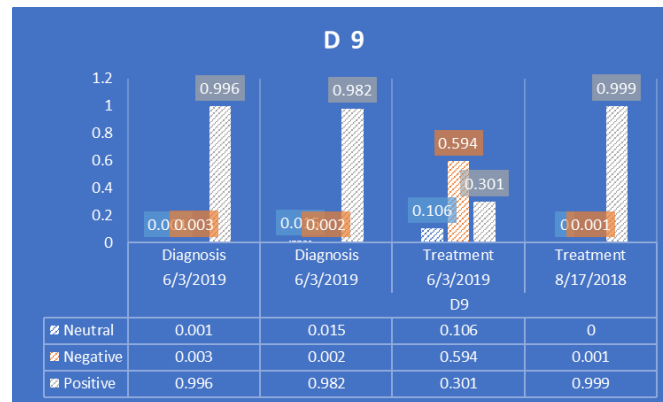


Fig 3. Graphical representation of aspects on various dates

3.4 Precision, Recall and F1 Score

Precision, recall, and the F1 score of Doctor D9 are calculated on the basis of Table 3 of aspect-based sentiment polarity, i.e., positive, negative, and neutral. The following Table 4 shows the precision, recall, and F1 score of D9 polarity. Here, we can say that this ABSA analysis is helpful to healthcare services in terms of their feature analysis⁽¹⁵⁾.

The calculation of precision, recall, and f1 score is calculated using equations 4, 5, and 6. The result is shown in Table 4. First, we give the program true values, followed by predicted values.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

Here TP means true positive and FP means false positive.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

FN means false negative.

$$\text{F1Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

truth = ["Positive","Negative","Neutral","Positive","Negative","Neutral","Positive","Negative","Neutral"]
 prediction = ["Positive","Negative","Neutral","Positive","Neutral","Neutral","Positive","Positive","Positive"]

Table 4. Precision, Recall and F1 Score of D9

Precision			Recall			F1 Score		
Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
0.6	1	0.67	1	0.33	0.67	0.75	0.5	0.67

4 Conclusion

This implementation has addressed several aspects of healthcare service quality. However, in the health care industry, service quality varies regularly, as we have examined with the use of comments provided by patients over a period of time. The aspects of a healthcare facility are evaluated using aspect-based sentiment analysis and consider various aspects such as diagnosis, treatment, doctor availability, medicine quality, medication, advice, cleanliness, appointments, prices, and so on.

The proportion of positive polarity for Dr. D9's aspect "treatment" changes over time, as shown in Figure 3. For example, on August 17th, 2018, the positive percentage was 0.99, and on June 3rd, 2019, it is 0.30; there was also a change in the negative polarity, which was 0.00 on August 17th, 2018, and 0.59 on June 3rd, 2019. As a result, it is clear that the quality of services varies with time.

This model result is helpful to healthcare owners, patients, and healthcare service providers. It can be beneficial to improve healthcare service quality and identify the drawbacks of healthcare and its service quality on the basis of healthcare service quality results. The study of healthcare patient feedback data has several limitations due to the inadequacy of the available data. Moreover, it is challenging to determine the truth of patient comments.

In future work, in order to help users find information more precisely and enhance services, research will continue to integrate additional aspects of healthcare facilities and perform classification operations.

Acknowledgement

The authors gratefully acknowledge the Departments of Computer Science and I. T., Dr. B. A. M. U. Aurangabad for providing a research lab, and the other authors whose work is used in this research.

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