NEW GENERATION COMPUTING

Aspect-Based Sentiment Analysis Using Attribute Extraction of Hospital Reviews

Ankita Bansal[1] · Niranjan Kumar[1]

Abstract
The Covid pandemic has become a serious public health challenge for people across India and other nations. Nowadays, people rely on the online reviews being shared on different review sites to gather information about hospitals like the availability of beds, availability of ventilators, etc. However, since these reviews are large in number and are unstructured, patients struggle to get accurate and reliable information about the hospitals, due to which they end up taking admission into a hospital which might not be appropriate for the specific treatment they require. This paper employs the use of sentiment analysis to understand various online reviews of hospitals and provide valuable information to the patients. Approximately 30,000 + reviews were collected from more than 500 hospitals. The broad objective of the study is to give the patients a comprehensive and descriptive rating of the hospitals based on the online reviews given by different patients. In addition to providing a comprehensive summary, the study has conducted aspect-based analysis where it compares the hospitals based on four different aspects of the hospital viz. "Doctors' services", "Staff's services", "Hospital facilities", and "Affordability". The database containing aspect-based ratings of the hospitals will be of great value to the patients by allowing them to compare and select the best hospital based on the optimum fit of the aspects of their preference.

Keywords Aspect-based sentiment analysis · Sentiment analysis · Natural language processing · Web scrapping · SentiWordNet

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Introduction

Due to Covid-19 pandemic, the healthcare sector is under great stress and is working beyond its capacity because of the sudden spike in the number of patients [1]. Lack of reliable sources of information regarding available healthcare infrastructure and services may result in adverse consequences for serious patients (both Covid and non-Covid) for whom getting right treatment in time is critical. Due to lack of information about the available facilities and services, it may be possible that the patients end up getting their treatment in the hospital which do not have adequate resources to cure their disease in particular. This becomes one of the major risks for the patients. For example, patients suffering from Covid should get their treatment from the hospital having adequate amount of oxygen availability. However, if the patients do not have information regarding oxygen availability for the hospitals at the time of admission, they may take admission in a hospital which is not appropriate for the disease.

Thus, to address such an information asymmetry, we need to build a dynamic database that could provide most of the vital information/details of various hospitals. Based on these details, people can make decisions judiciously and the available infrastructure of hospitals can be utilized optimally.

To build such a system, we propose to use online reviews in this work. In today's technology-savvy world, an increasing number of people are relying on reviews to make their decisions. The recent trends show that the importance of online reviews and ratings will increase further with the continued growth of Internet. Global Internet traffic is predicted to be 7.7 Exa-bytes per day in the year 2021, up from 2.4 Exa-bytes per day in 2016. This is more than a twofold increase. Global Internet traffic in 2021 will be equivalent to 707 billion DVDs per year, 59 billion DVDs per month, or 81 million DVDs per hour [2]. Recent technological advancements in the field of artificial intelligence and machine learning have now made it possible to synthesize this large amount of data and derive commercially valuable information from it [3].

There are multiple types of platforms that allow users to share their reviews, opinions or suggestions. There are many product-based e-commerce sites or digital marketplaces such as amazon.com or flipkart.com, then there are some service-oriented sites like trivago.com and makemytrip.com. Apart from all these sites social media sites like facebook.com and Instagram.com where many people share their opinions and suggestions related to various products or services. However, there are multiple challenges with basing decisions on online reviews. Primary problem is that they are mostly unstructured and colloquially written, which makes them difficult for extracting information from them. The large volume of reviews from multiple sources also makes the task of reading the reviews and making choices a very complex and tedious task. Usage of sarcasm and language slangs further makes the reviews difficult to be deciphered. Sentiment analysis provides us a tool for proper understanding of reviews and deriving meaningful information from them. Considering the healthcare sector, a proper mechanism to assimilate and decipher the online reviews of hospitals can help us develop a

database that contains comprehensive information set about hospitals including the quality of their services and condition of their facilities.

Sentiment analysis is a domain that classifies reviews, comments, or opinions into two intrinsic sentimental indicators, i.e., positive and negative [4]. Sentiment analysis means the understanding of the emotional essence of any text and the evaluation of the nature of emotion of the text [5]. Nature can be either on the spectrum of good and bad or simply neutral [6]. Sentiment analysis is generally applied to various materials such as reviews and survey responses from online sources. It extracts subjective information and facilitates businesses with a tool to understand the social sentiment of their brand, product, or service with the help of online reviews.

In this paper, the overall aim is to summarize the reviews of hospitals using sentiment analysis and also to develop a methodology that can be generalized for any product or service. We aim to develop a demonstration model based on the healthcare sector. The task of sentiment analysis of hospital reviews mainly includes the following steps in sequence: pre-processing [7], attribute extraction which is followed by the selection of the relevant attribute [8], emotional analysis [9], and at last quantifying the extracted attributes. A typical approach is to compute an average quantitative rating based on individual user ratings. However, this method does not describe the true nature of the hospital and the overall rating is not comprehensive as a single quantified parameter fails to convey any meaningful information about the hospital in detail. Thus, such average ratings are generally not a true indicator of the nature of the hospital. To solve the above-mentioned problem, the methodology discussed in this paper aims at providing an aspect-based summary of hospitals based on the online reviews. The aspects considered in this study are "Doctors' services", "Staff's services", "Hospital facilities" and "Affordability". These aspects are made of the set of attributes which are of similar meaning. For example, the attributes such as ["cost", "costly", "loot", "payment", "pricey", "cash", "affordable", "bill", "fees"] are related to the aspect of "Affordability". Similarly, each aspect is formed from a defined set of attributes. The aspect-based ratings will be more suitable for the patients as these ratings will enable them to compare hospitals based on more specific parameters. There might be a case where a hospital is expensive but the staff is very poor or a hospital is having good doctors but lacks other facilities for a specific disease. These types of details can only be measured using aspect-based rating and would probably be missed in a single-value average quantitative rating.

Significant work has been done with respect to analyses of reviews to provide a single qualitative rating of a product or service [5–9]. But there have been limited studies which quantify a product or service along multiple key attributes/aspects. Therefore, more research and experimentation is needed in this field to derive useful conclusions.

The contributions of this study are as follows:

- Develop a generalized model for aspect-based sentiment analysis applicable to any product or service.
- Specifically, identify the attributes of hospitals and group them into aspects.
- Measure aspect-based ratings of hospitals.

For the purpose of empirical validation, we have collected approximately 30,000 reviews from mouthshut.com for more than 500 hospitals.

The paper is organized as: Next section briefly discusses the studies in the related field. Data Collection explains the process of data collection and cleaning of the raw data file. Proposed Approach focuses on the methodology, where the overall approach of the implementation is discussed. Result Evaluation presents the evaluation of the results of the study and Future Work presents future work. Finally, the work is concluded in Conclusion.

Related Works

In the domain of sentiment analysis, sufficient work has been done at various levels of granularity. Some works have been done at the document level [10–12] in which the entire review is classified based on the opinion of the reviewer. There are some works at sentence level [13, 14] where the task is concentrated on recognizing the polarity of a sentence (e.g., positive, neutral, negative) according to semantic information learned from the textual content of sentences. Moreover, some of the recent works involves sentiment analysis at phrase level too [15–17], where the main focus is on phrases which is a group of words, often carrying a special idiomatic meaning. However, sentiment analysis at the aspect level is relatively a new field which requires more research.

Sentiment analysis have been applied in various sectors like entertainment industry and travel industry [18–21]. The work done in [19] used a combination of machine learning features with the lexicon features, while another paper [20] uses perceptron neural networks. In addition to this, work has been done on the data generated from social media like Twitter [22–28]. Neri et al. [27] did the mapping of sentiments on social media with observations and measurable data. The study argued that monitoring online sentiments of customer can act as a dynamic feedback for any business. The study [28] used a tree kernel-based model to categorize the sentiments of Twitter tweets into three classifications: positive, negative, and neutral. This can also be used for monitoring public sentiments related to any particular event, news, etc.

The studies in Table 1 summarize the works that have been done at aspect-level sentiments analysis. Aspect sentiment analysis determines the polarity of each attribute being considered, which is not the case for document-level or sentence-level sentiment analysis. Some works in literature have integrated the user sentiments related to the different aspects of a product or service [8, 21, 29–31]. The work [30] tries to extract features by taking advantage of the observation that a lot of product features are phrases, which introduces a concept of phrase dependency parsing and further extends traditional dependency parsing to phrase level. The authors of [31] try to formulate an approach to deal with single sentence with multiple emotions and features related to any product or service. The paper [32] is a literary survey that compares and contrasts various deep learning algorithms used for aspect-level sentiment classification. However, works in Table 1 did not propose any methodology regarding how to integrate attribute-specific emotions to obtain the overall

Table 1 Comparison of existing work done

S. No	Studies in literature	Year	Objective	Source of data/domain of database	Algorithm/approach used	Data collection
1	[29]	2016	Development of deep memory networks that capture the importance of context words for aspect-level sentiment classification	Laptop and restaurant datasets from SemEval 2014	Deep Memory Network with Multiple Layers	Yes
2	[21]	2019	Analysis of reviews by travelers for aspect-based sentiment analysis	TripAdvisor user reviews	BiLSTM-CRF, ATE-PC Task, and LDA	Yes
3	[8]	2017	Usage a Gini-Index-based feature selection method with SVM classifier for sentiment classification for movie review data set	Database of most recent review messages from websites like Bollywood-hungama, Rediff, Times of India, Rottentomatoes, and Mouthshut	SVM	Yes
4	[32]	2019	Focuses on deep learning-based aspect-level sentiment classification (ASC) which aims to decide the sentiment polarity for an aspect mentioned within the document	Product Reviews	Discusses Deep Learning-based approaches	
5	[30]	2009	Presents a novel approach for mining opinions from product reviews, where it converts opinion mining task to identify product features, expressions of opinions and relations between them	Product reviews collected from Amazon. com and CNet.com	Tree kernels (SVM-Word Tree and SVM-Parser Tree)	Yes
6	[31]	2012	Presents a new approach to identify feature specific expressions of opinion in product reviews with different features and mixed emotions	Datasets of various product reviews	Rule-Based and Supervised Classification System	Yes

NB Naïve Bayes, *SVM* Support Vector Machines, *KNN* K-Nearest Neighbors, *RF* Random Forest, *DT* Decision Tree, *ME* Maximum Entropy, *NN* Neural Network, *CNN* Convolutional Neural Network, *DANN* Dynamic Architecture for Artificial Neural Networks, *LDA* Latent Dirichlet Allocation, *NBM* Naïve Bayes Multinomials

sentimental polarity of reviews. Moreover, all the works mentioned in Table 1 are primarily based on analysis of product review like mobiles, laptops, television etc. and not based on services like hospitality sector or healthcare sector. This work tries to present an approach to integrate attribute-specific emotions and obtain the overall sentimental polarity of reviews and is based on the healthcare industry.

Research related to the application of sentiment analysis in the healthcare sector has also been done but they are very few. The successful demonstration of the fact that sentiment analysis of patients' online comments, posts, tweets, etc. about their experiences in a hospital or any health-care-related institution is possible, opened a new dimension of possibilities in the healthcare industry [33]. This new approach might be a better alternative than the traditional methods such as surveys and feedback forms. The establishment of a strong relationship between the patient's reviews and the services which are lacking or the services which need improvement in the healthcare system emphasized the need for more work in this domain [34, 35]. But, to the best of the authors' knowledge, in healthcare sector, no work has been done at aspect-level sentiment analysis. So, this work tries to broaden the horizon for the healthcare industry and demonstrate an approach toward processing online reviews of patients at aspect level and extract useful information for both patients and hospital administration.

The objective of this paper is to develop a model to obtain the aspect-based ratings related to various attributes of the hospitals. From the calculated aspect-based ratings, we can further create a comprehensive summary of the hospitals, their facilities and the services. The result will be a reliable and comprehensive database that can be beneficial for both the patients and hospital administration.

Data Collection

This section provides a comprehensive perspective of the structure of the dataset used in this research and its collection procedure. We collected data using web scraping. Web scraping is a method to extract data such as given numbers, texts and tables from the web using appropriate tools that can efficiently store and manage all the data that have been downloaded from the web. The method of web scrapping has become very popular as it is simple, fast and cheap to extract information from the world wide web. In this study, we have done web scraping using Python where we have used the Beautifulsoup library and the Request library. The review data extracted from the site are stored as a JSON format file. The basic method of data collection can be compiled into four simple steps:

1. Issue a request with the requests module with the desired URL.
2. Extract the HTML documents' content as a plain text file.
3. Analyze the HTML documents' structure and select the required element from which we have to retrieve the data.
4. Use Beautifulsoup to search the required element from the response text and retrieve the same from the text.

For this work, we have collected approximately 30,000+ reviews from more than 500 hospitals. The dataset gathered after web scrapping was unstructured and heterogeneous which made it difficult to manage. To manage such unstructured and heterogeneous dataset, semantic web technologies provide efficient methodologies [36, 37]. We have cleaned and reorganized the data as it was unstructured and needed pre-processing so that it can be used for further analysis. The data are stored as a JSON file which structures data as key–value pair where the key indicates the hospital's name and the value represents the list-type data structure which stores all the reviews of the given hospital. The reviews are further divided into key–value pairs, where the key is the title and the value is the body of the review during the data clean-up process.

Clean-up of the raw data file is a necessary step for any further processing. Figure 1 represents a flowchart for the clean-up procedure. In this, we have used two python libraries Textblob and Beautifulsoup. The resultant JSON file obtained after clean-up is used for application of algorithm discussed in Result Evaluation. Following are the steps for this procedure along with a detailed explanation.

1. Removal of HTML tags and URLs or any other unnecessary text left from the original HTML document.
2. Spelling correction using Textblob python library.
3. Bifurcation of reviews into title and body.

Extracted reviews might contain bold/underlined/ italic texts for emphasizing the meaning of certain words or phrases. There are different formatting HTML tags that are used for such tasks such as $<b>$ for bold, $<u>$ for underline and $<i>$ for
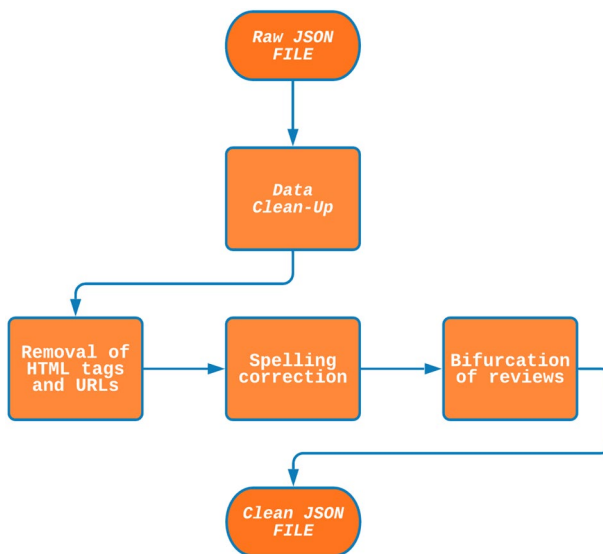

Fig. 1 The process of data clean-up

italics. The emphasis given to any word or a phrase through different tags is not required while analyzing the sentiments of the reviews. Thus, all the formatting tags such as < b > , < u > and < i > are removed. Similarly, the tokens such as punctuation marks, special characters, white spaces, stop-words, etc. are also removed as they do not contribute in providing any valuable information towards the emotion of the review. Another important step is the correction of erroneous spelling that might be present in the reviews because they can result in deviation from the correct analysis. Textblob is a Python library for processing textual data. We used the correct () function from the Textblob library for the correction of wrong spellings.

Proposed Approach

In this section, we discuss in detail the approach proposed in this paper. The proposed approach broadly consists of the following steps: attribute extraction, rating of attributes, aspect formation, and rating of aspects. Each of these is explained in detail and supported by suitable examples and algorithms, wherever necessary. Figure 2 represents a comprehensive flowchart of the proposed algorithm.

Attribute Extraction

An attribute is a feature or a characteristic of a product or service. To efficiently describe a product or service, we need to select a minimum number of attributes which can be used to represent the details of the product or service. Depending on the type of product or service, the number and types of attributes may vary. In this work, all the nouns from the reviews of hospitals are extracted which are considered as attributes. The algorithm for the extraction of attributes is given below. Figure 2 summarizes the steps of attribute extraction.

Algorithm for Attribute Extraction

Step 1: Word tokenize the sentences and make a word list

    Step 2: POS tagging of the words

    We have used 'averaged_perceptron_tagger' for tagging words with their parts of speech for all the sentences

    tagged _list = [] (tagged_list[] is list-type data structure that contains all the tokens with their POS tags)

    tagged_text_list.append(nltk.pos_tag(word_tokenize(text)))

    Step 3: Removal of stop-words

    We have used NLTK (Natural Language Toolkit) for the removal of such words from the reviews, which provides us with a list of stop-words from 16 different languages. We used the list for the English language: "stopwords.words('English')"

    Step 4: Extraction of nouns using POS tags and counting the frequency of each noun
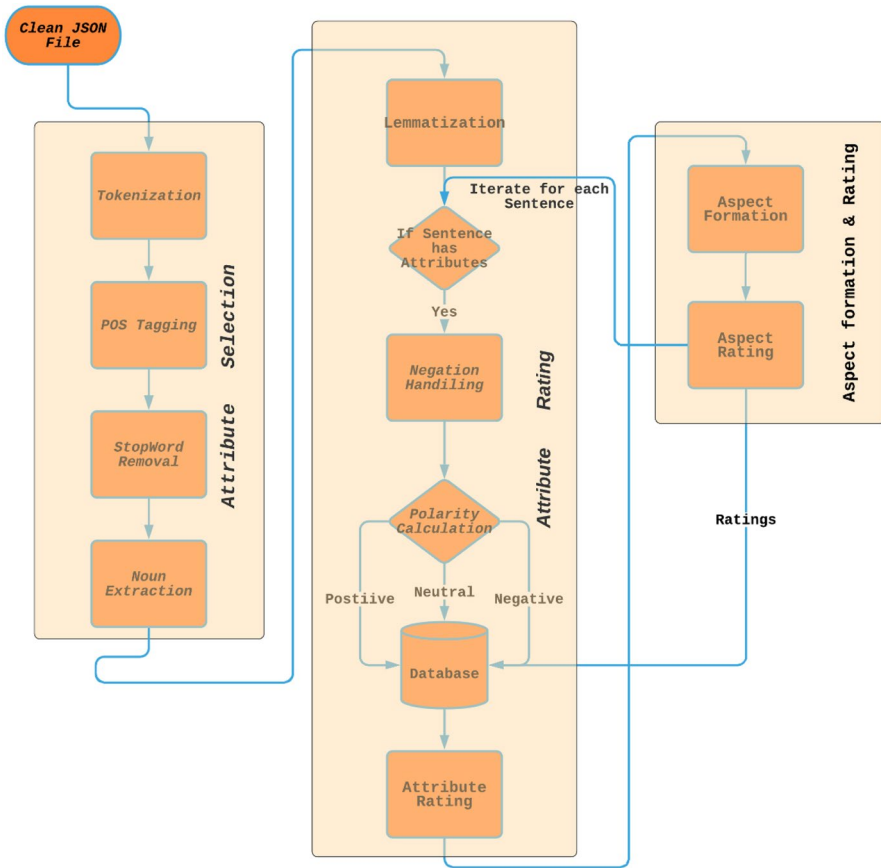
Fig. 2 Flowchart of the proposed algorithm

We used the tagged_list that contains all the tokens along with their POS tags (obtained from step 2) to create a new list that contains all the nouns along with their frequency of nouns (noun_list). Then, we sorted the noun_list according to the frequency of occurrence of nouns in descending order and created a new list of attributes (attribute_list) by selecting the most occurring nouns from the sorted list.

Step 5: Selection of relevant attributes based on the frequency of noun and domain-specific heuristic (healthcare domain). This step involves filtering nouns based on their frequency in reviews and then manual selection. In this project, we have selected 50 attributes.

Following is an illustration to elaborate the understanding of an attribute and how they are extracted.

Review:"[Title]: Neat and clean rooms; [Body]: Overall neat and clean facility. Their ambiance and services are Excellent. Staff, nurses, all are very kind and helpful."

From this example review, we extract the following nouns and their associated adjectives:

[Title]:
Rooms → Neat and clean
[Body]:
Facility → Neat and clean
Ambiance, Services → Excellent
Staff, Nurses → Kind and helpful

Rating of Attributes

After selecting a proper set of attributes, the next step is to provide the rating to all these attributes individually based on the context of the sentence in which these attributes are present. Following algorithm is used to provide rating to the attributes.

Algorithm for Rating of Attributes

Step 1: Lemmatization

The grammar of almost all languages allows one to use multiple forms of a single word due to various reasons such as to express the plurality of nouns or to express tense. For example, multiple forms of a base word 'organize' can be 'organizes', 'organized', 'organizing', etc. However, such multiple forms of a single word do not contribute in sentiment analysis. Thus, it is advisable to consider the base word only. In this study, we have found the base word by lemmatization which reduces any form of a word to its base word. We used 'WordNetLemmatizer' from 'nltk.stem' module to perform this task.

lemmatizer = WordNetLemmatizer()
For example,
'are', 'is', 'being' → 'be'
'car', 'cars', 'car's' → 'car'

Step 2: Repeat steps 3–5 for each sentence of the review one by one

Step 3: For each sentence, check if any of the nouns in the sentence is there in the final list of extracted nouns (attributes). This list is referred to as attribute_list (step 4 in Algorithm for attribute extraction). For all such sentences in which any of the nouns are also present in the attribute_list, we proceed with the next step else we do not process the sentence.

Step 4: Negation handling

Negation is used when we have to express the opposite meaning of a particular word or sentence. Negations are expressed by words like 'not', 'no', and 'never'. Negation has three types of scopes, it can be localized, it can be generalized or it can be a subject negation. We need to analyze such sentences differently because negative words reverse the polarity of the sentence. All the sentences with negation words are processed using the function: nltk.sentiment.util.mark_negation(sentence).

For example, consider the following original sentences and their negation analysis:

Original sentence("polarity") →Sentence after negation analysis("polarity")

not good("positive") →not good_NEG ("negative")

does not look very good("positive") →does not look_NEG very_NEG good_ NEG("negative") no one thinks that it's good("positive") → no one_NEG thinks_ NEG that_NEG it's_NEG good_NEG("negative")

Step 5: Polarity calculation

Next, we perform a polarity calculation of the selected sentences. We used synsets() from SentiWordNet for calculating the polarity of the sentences which could be positive-valued (for good opinion) or negative-valued (for bad opinion) of zero (for neutral opinion). We used three counters to count all the positive, negative, and neutral sentences corresponding to each attribute of the hospital. We updated the database after analyzing every selected sentence and stored all the counters based on different attributes for each hospital.

Step 6: Attribute rating

For each attribute, amongst all the sentences associated with them, we count the sentences with positive, negative, and neutral polarity. Using these counts, we finally give a rating to the attributes individually according to Eq. 1, where the rating of an attribute (Ai) (where 'i' represents the attribute number) is calculated by dividing the number of positive sentences with the total number of sentences and then multiplying by 100.

$$\text{Rating}(Ai) = \frac{\text{Number of positive sentences}}{\text{Number of total sentences}} * 100 \qquad (1)$$

Aspect Formation

We have divided the set of attributes into multiple subsets, where each subset contains attributes that have a similar meaning. This subset of attributes represents a particular aspect. Aspects are used to make the final summary of the hospital more comprehensive and easier to compare. As a hospital can have a number of attributes, it might be difficult for a patient to make a decision based on the attributes alone as he may be required to compare a large number of attributes of multiple hospitals. Thus, aspect-based rating will be beneficial as the patients have simpler and fewer parameters to compare different hospitals.

In this paper, we have identified four such aspects for the summarization of hospitals. These are 'Doctors' services', 'Staff's services', 'Hospital facilities', and 'Affordability'. The aspects 'Doctors' services', 'Staff's services' comprise of all those attributes which tell about the qualifications, experience, behavior, etc. of the doctors and staff, respectively. The aspect 'Hospital facilities' comprise of all those attributes which tell about the factors such as room service, food, lab-testing, etc. Whereas, all the attributes which tell about the economical aspect of the hospital and combined under 'Affordability' aspect.

Some of the attributes associated with the aspects are as follow: -

Doctors' services =

["knowledge", "qualified", "qualification", "doctor", "punctual", "operation", "specialist"]

Staff's services = ["nurse", "talk", "receptionis" "call", "wardboy", "manager", "speak", "spoke", "speaks", "etiquette"].

Hospital Facilities = ["scan", "xray", "room","radiology","insurance","parking", "cafeteria","cafe","tidy","tidiness"]

Affordability (of hospital) =

["cost", "costly", "loot", "payment", "pricey", "cash", "affordable", "bill", "fees"].

Rating of Aspects

Finally, we calculate the rating of each aspect based on the rating of all the attributes that constitute an aspect, i.e., for 'Doctor's services' we take the average of the rating of those attributes ("knowledge", "qualified", "qualification") that form the aspect of 'Doctor's services'.

Thus, aspect rating is equal to the average of the rating of all attributes that are in that aspect. Equation 2 is used in this step, where aspect rating (Xj) (where 'j' represents the aspect number) is calculated by dividing the sum of all the attribute ratings (Ai) (where 'i' represents the attribute number) by the total number of attributes (*n*).

$$\text{Aspect Rating}(Xj) = \frac{\sum_1^n A_i}{n}. \tag{2}$$

Result Evaluation

In this section, we evaluate and analyze the experimental results. For the purpose of demonstration, we have represented the results of only 20 hospitals, the names of which are given in Table 2. The serial numbers corresponding to each hospital as given in Table 2 are used for further analysis of results.

Table 3 presents aspect-wise results, where the first four columns represent aspect ratings of each of the four aspects for all the 20 hospitals. The aspect ratings are calculated using Eq. 2. These aspects serve as parameters for the customer to compare hospitals and make choices based on the aspect of their priority. Consider a patient for whom the high expenses are not an issue, so he might ignore the aspect of 'Affordability' and compare the hospitals based on the other three aspects. The patients who require a longer stay at a hospital might give more weightage to the aspect of 'Affordability' and 'Hospital facilities' as for them comfort during the stay will be an important factor for choosing a hospital. Similarly, a patient who has been moving from one doctor to another would give more consideration to the aspect of 'Doctors' services' as for him the quality of service given by doctor matters more than any other factor.

We can also rank hospital-based individual aspects to figure out which hospital is best for which aspect; this will allow patients to make better decisions. For example,

Table 2 Hospitals used for result analysis

S. No	Hospital name
1	Kumaran Hospital—Kilpauk—Chennai
2	ARC International Fertility & Research Centre—Chennai
3	Columbia Asia Hospital—Salt Lake—Kolkata
4	Disha Eye Hospital and Research Centre—Barrackpore—Kolkata
5	Prince Aly Khan Hospital—Mazgaon—Mumbai
6	Star Hospitals—Banjara Hills—Hyderabad
7	Bombay Hospital—Marine Lines—Mumbai
8	Parvathi Hospital—Secunderabad
9	Narayana Nethralaya—Rajaji Nagar—Bangalore
10	Deenanath Mangeshkar Hospital—Erandawane—Pune
11	Asian Institute of Gastroenterology—Somajiguda—Hyderabad
12	Sri Ramachandra Hospital—Porur—Chennai
13	Holy Family Hospital—Delhi
14	Sirohi Hospital—Meerut
15	Bellevue Clinic and Nursing Home—Loudon Street—Kolkata
16	Asian Institute of Medical Sciences—Faridabad City—Faridabad
17	Renai Medicity—Cochin
18	Paras Hospital—Ghaziabad
19	Continental Hospitals—Nanakramguda—Hyderabad
20	Health Point—Bhawanipur—Kolkata

considering the aspect of 'Doctors' services', we can conclude from Table 3 that hospitals no. 9, 10 and 11 are the highest rankers and hospitals no. 7 and 19 are the lowest rankers. Consider the aspect of 'Affordability' whose rating is 50 for hospital no. 2. This implies that half the number of people who have mentioned this aspect in their reviews have said positive or good things about this particular aspect. Similar inference can be drawn from the other ratings. In this way, the aspect-based results would be more helpful for the patients than simple average ratings given to hospitals based on the sentiment analysis of whole reviews. The last four columns of Table 3 represent results related to normal sentiment analysis of hospital reviews, where we simply count the number of positive (good), negative (bad), and neutral (neither good nor bad) reviews and rate the hospital based on these data. The 'Net rating' (last column) is calculated according to Eq. 3, where Total Reviews are the sum of all the positive, negative, and neutral reviews.

$$\text{Net Rating} = \frac{\text{Total Positive reviews}}{\text{Total Reviews(Positive + Negative + Neutral)}} * 100. \quad (3)$$

Figures 3, 4, 5, 6 show the histogram plot of the four aspects, viz. 'Doctors' services', 'Staff's services', 'Hospital facilities' and 'Affordability', respectively, where the distribution of hospitals based on the rating of every aspect is depicted. The X-axis of the plot indicates the aspect rating divided into intervals for better

Table 3 Aspect-wise result evaluation

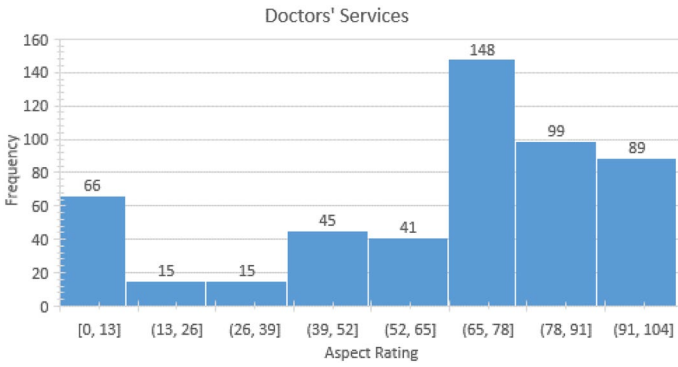| S. No	Doctors' services	Staff's services	Hospital facilities	Affordability	Total positive reviews	Total negative reviews	Total neutral reviews	Net rating
1	15.38	10	10	10	10	24	11	22.22
2	16.66	10	10	50	62	71	42	35.42
3	50	10	66.67	10	55	105	50	26.19
4	42.85	10	33.34	50	17	22	9	35.41
5	28.57	50	50	10	28	36	26	31.11
6	28.57	14.28	33.34	10	50	66	24	35.71
7	10	28.57	33.34	40	10	134	86	31.25
8	50	66.67	40	25	14	29	10	26.41
9	66.67	10	50	45.45	320	138	145	53.06
10	66.67	50	28.57	16.67	132	148	97	35.01
11	66.67	66.67	10	25	193	218	130	35.67
12	40	31.57	55.56	10	139	124	113	36.96
13	28.57	80	50	71.42	98	92	53	40.32
14	50	10	50	50	10	11	6	37.03
15	46.15	10	33.34	25	39	52	16	36.44
16	25	66.67	75	50	220	188	134	40.59
17	42.85	40	10	80	39	30	20	43.82
18	50	40	10	10	24	24	19	35.82
19	10	50	10	50	127	114	73	40.44
20	50	50	10	50	15	18	6	38.46

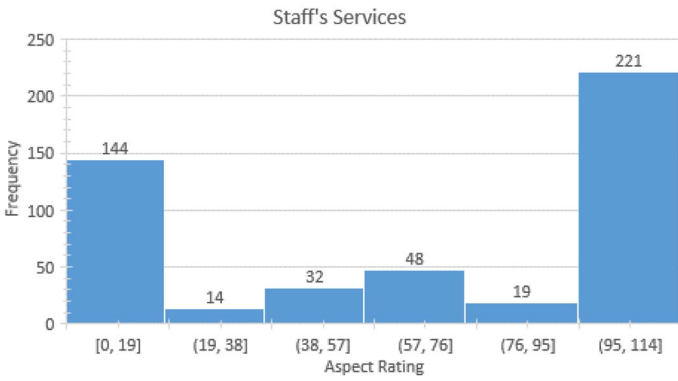**Fig. 3** Histogram depicting rating of Doctors' services

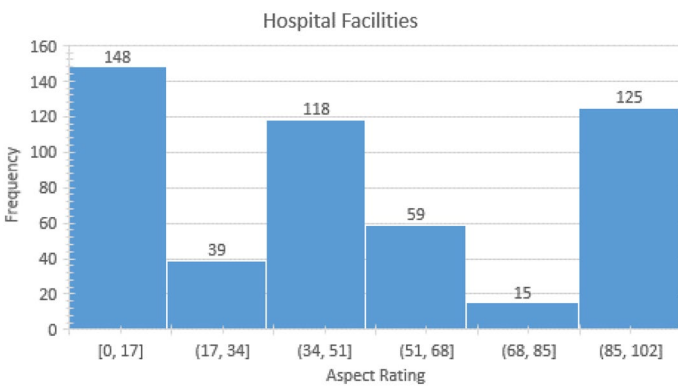**Fig. 4** Histogram depicting rating of Staff's services

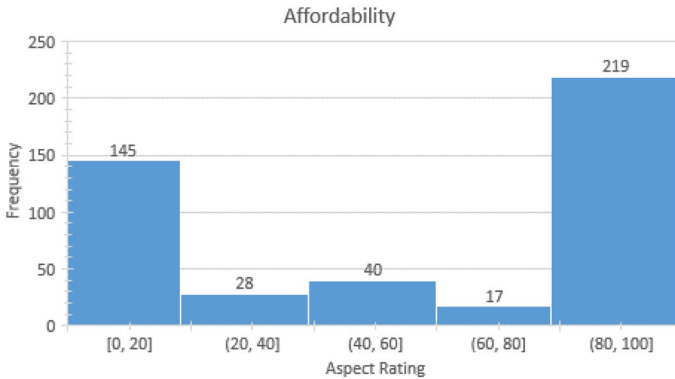**Fig. 5** Histogram depicting rating of Hospital services

Fig. 6 Histogram depicting rating of Affordability

representation of data and the Y-axis indicates the number of hospitals that are in a particular aspect-rating interval.

Figure 3 shows that a highest number of hospitals (i.e., 148) share the rating from the interval of 65(excluded) to 78(included) for the aspect of 'Doctors' services'. This indicates that average rating for this aspect lies in the interval of 65(excluded) to 78(included). Thus, the average aspect rating can be used as benchmark to compare other hospitals in aspects of doctors' quality, expertise etc. and hospitals above this average are among top rated ones.

Figure 7 represents the Net rating of the hospital calculated according to Eq. 3 and indicates the result for the normal sentiment analysis of hospital reviews. The data from Table 3 in the last column with the title 'Net Rating' is corresponding to the scatterplot of Fig. 7. As we can observe from Fig. 7 that majority of hospitals have the average net rating in the interval of 60–80. Thus, the average net rating can be used to filter the above average rated hospitals from the rest. Figure 7 only represent single data point for each hospital based on sentiment analysis
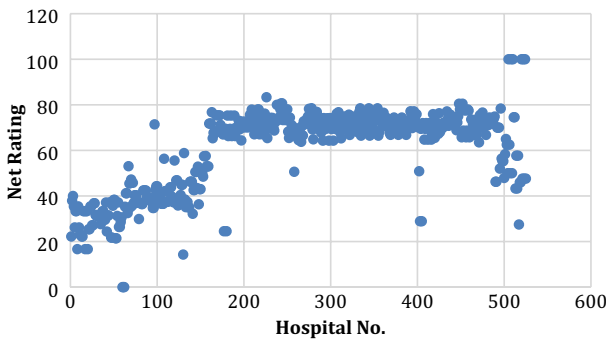

Fig. 7 Scatter plot depicting the net rating

(sentence level) of reviews, which lack the extra details that we can extract from the reviews using aspect-based sentiment analysis.

Figure 8 shows the net deviation of the results derived in this study (using sentiment analysis) with the actual average rating of the reviews for each of the hospitals. The deviation indicates the overall accuracy of the methodology used for sentiment analysis of reviews. The blue line indicates the calculated net ratings and the orange line indicates the average ratings of all reviews extracted from the review site. The deviation is minimum for hospitals with a rating of approx. range of 60–80% and the deviation increases for lower and higher rated hospitals.

Future Work

The proposed work in this paper when used in combination with other artificial intelligence-based technologies can have other types of applications in the healthcare sector. For example, in the current pandemic, a lot of emphasis has been given to proper diet by all kinds of health experts to stay healthy [38]. A healthy body is the first line of defence against a viral disease. Thus, the authors plan to propose a diet recommendation system based on the reviews of the patients and doctors. In addition to healthcare sector, the methodology discussed in this paper can be further extended to any product or service due to the general nature of the implementation. This also ensures the commercial viability of deploying such methods for any product or service in a variety of sectors. The ability to focus on the different features can greatly help any business to refine the said product very rapidly and in a data-based approach rather than shooting blindly.

The dynamic nature of this approach will also help companies to use this method in almost real time that will give them a competitive edge over any rivals that are not using this methodology extensively. This will not only direct the afford towards the features that are not doing well but will also give hints about the features or aspects that are doing well.
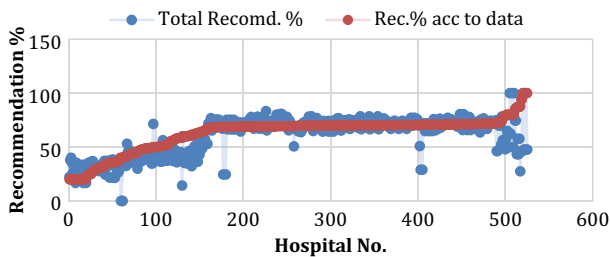

Fig. 8 Scatterplot depicting the deviation

Conclusion

In today's time, people are increasingly using social media platforms and other forums which allow them to vocalize their perspective, opinion or experience about any particular product or service. Therefore, a large amount of data containing reviews and opinions are generated on the internet through various platforms. This data has a great financial potential and can be of great value to any business. These reviews play a significant role in determining the decision of a potential buyer. Hence, these online reviews are crucial not only for the buyers/customers but also for the sellers as these reviews can have a huge impact on their revenue. Sentiment analysis provides us with the required tools to process and analyze a large amount of user-generated reviews from multiple platforms.

Although a lot of work has been already done in the field of sentiment analysis, the domain still is a long way from its maturity. The ever-expanding reaches of the internet is still pushing the boundaries of applications of sentiment analysis which presents a lot of opportunity for research and study in this field. This study represents one such application which is based on aspect-based review analysis in the domain of healthcare. In this work, we have focused on the different aspects related to hospitals which include the quality of infrastructure of hospitals, the affordability, the quality of services provided by the doctors and the staff of all the hospitals (considered in this study). Aspect-based review analysis helps to analyze and compare various hospitals based on these aspects. We have quantified these aspects based on the positive or negative polarity of attributes present in the reviews.

The general method involves four main steps namely: data collection and cleaning, pre-processing for natural language processing, identification of attributes of hospitals, and then the final step includes giving each hospital aspect-based ratings. For this work, we have collected approximately 30,000+ reviews from more than 500 hospitals. A database consisting of the comprehensive summary of all the aspect-based ratings for all the hospitals is maintained. The result/comprehensive summary which includes various quantified parameters can be used in making comparisons among various hospitals. This will be beneficial for both patients and hospital staff and administration. For patients, this will save the hassle of reading online reviews from multiple sites, which many times are unstructured. The administration can use these results as a feedback mechanism that is superior in terms of numbers from other contemporary feedback systems such as surveys.

The approach discussed in this paper also has implications for other sectors especially the service sectors where the quality of services and their perception is the most important metric for the company involved. This paper showed that aspect-based analysis is advantageous to both the both the consumers and the company which is providing the services. This can help consumers in making more informed decisions and, thus, lead to better selection of the services. For the provider company, the analyzed data can provide important insights and feedback which help the company to address the gaps.

Declarations

Conflict of Interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

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