Analysis of hospital reviews through sentiment analysis: An approach to aid patients in the times of COVID-19 pandemic

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Abstract. The COVID pandemic had over-stressed our healthcare system. This has affected the lives of both COVID and non-COVID patients, in the worst possible way. The patients are facing difficulty in getting proper medical care in time. The reason being the already stressed situation of hospitals and lack of proper information in the general population. The lack of information is amplified in the environment of fear and panic in the pandemic. We aim to use sentiment analysis of hospital reviews to provide relevant and important information about the operating conditions and current status of hospitals to the general public. Sentiment analysis applied to patient's reviews to quantify the direction and/or magnitude of the emotive content. Patient comments are segregated into different sections and analysis is done on these sections to quantify the positive or negative aspects of the reviews. This will allow us to give an overall rating to the hospital-based on key parameters that will help people to understand the hospital's current condition. The results established a strong relationship between the online reviews and the overall recommendation percentage of the hospitals. This information provides great value to the patients by allowing them to compare and select the best option. The information is more reliable and robust due to its dynamic nature.

Keywords: Sentiment analysis, Natural language processing, lemmatization, web scrapping, COVID-19 outbreak

1. Introduction

The end of the year 2019 has seen a spread of COVID-19 coronavirus in China which infected a large number of people all over the country [1]. However, China was soon able to control the outbreak, while COVID-19 spread to other countries.

At present, many countries can control the further spread of COVID-19, from the pandemic, the healthcare industry being one of them. while few countries are still struggling to adopt efficient and effective The study by Bartik et al. 2020 shows that pandemic has led to a massive dislocation of small businesses [4].

In contrast, there have been few sectors that have benefited. In the difficult times of COVID-19 Pandemic, our healthcare system has been continuously operating above its capacity and is in a stressed situation [5]. This has not only affected the healthcare workers but also patients who are in immediate need of medical care. Patients have faced great difficulty in getting access to hospitals. The primary reason being overcrowding of hospitals but another significant reason that can be resolved is the lack of information about the hospitals among the general populous. This problem has serious consequences on not only COVID-19 patients but also other non-COVID patients who are required to take extra precautions in this pandemic as their current health puts them at higher risk [6]. The non-COVID patients are also finding serious difficulties in getting treatment due to a lack of proper information about hospitals and details regarding their current status [6]. To get the precise information about hospitals like the availability of beds, availability of ventilators, and any other such data, people generally follow the traditional process of question-answers where they ask from their friends, acquaintances, and other people who might have used the facilities of the particular hospital or may know about the hospital. Nowadays, the more popular method is to read

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reviews of the hospitals posted by the patients and other stakeholders on various blogs and social networking websites which are easily accessible on the internet [7]. Patients share their opinions, suggestions, and other thoughts, which may be either favorable or unfavorable on various review sites. However, these reviews are largely unstructured, contain sarcasm, language slangs, etc. Hence, it becomes necessary to understand these reviews properly to derive meaningful insights from them, which is the basic idea behind Sentiment Analysis [8]. Sentiment analysis is a domain that classifies reviews, comments, or opinions into two basic and intrinsic emotional indicators namely positive and negative [9]. Sentiment analysis means the understanding of the emotional essence of any text and the evaluation of the nature of opinion of the text [10]. Nature can be either on the extremes of good and bad or just neutral [11]. Sentiment analysis has been used on the reviews of movies, hotels, restaurants, etc. to help customers to choose according to their requirements, but work on the application of sentiment analysis on the reviews of hospitals is not much and thus it is an area to explore. The manual way of filtering out reviews associated with a hospital's status and the condition is not scalable and also has reliability issues. To automate the process of categorizing the sentiment from reviews or posts, we analyze the text then perform natural language processing along with various computational techniques [12].

In this paper, the authors have developed a methodology to extract reviews on 184 hospitals from **mouthshut.com** and thereby apply sentiment analysis on the reviews to gain meaningful insights. In other words, the authors aim to conclude the patient's reviews collected from some review specific sites. In this work, the authors have

From this study, the authors found that the sentiment analysis of online reviews can provide reliable information on hospitals. This information can be very useful for patients as it helps them compare and choose what's best for them. The analysis result also helps hospital administration to improve the current services according to the needs of the patients. Sentiment analysis is a very useful tool for gaining insight into a patient's opinions. This can also be generalized for consumers. A large number of companies including the health sector as well are using this tool for providing a better service to their customers. After analysis of the review, we

addressed the task of classifying given reviews as positive, negative, or neutral. The task is complex in nature due to the inherent complexity of the natural language constructs as there are many ways to indicate positive and negative views in natural language.

The contributions of this paper are:

1. Development of a general approach towards Sentiment Analysis for any product or services based on online reviews.

2. Collection of nearly 14121 reviews from **mouthshut.com** of 184 hospitals.

3. Established a relationship between the patient's review for the hospital and overall recommendation for the hospital.

4.Classification of a given review as positive, negative, neutral.

5. Provide the overall rating (recommendation percentage) of each of the hospitals so that the customers/patients can draw a comparison amongst them.

The task of Sentiment Analysis of hospital reviews mainly includes the following steps in sequence – preprocessing [13], feature extraction which is followed by the selection of the relevant features [14], classification [15], and finally the result analysis. Preprocessing includes removing any error present in the review which is very important for the task of proper and accurate classification of text. Feature Extraction identifies the features that are essential and then these features are stored in the feature array. Different types of feature extraction methodologies exist and in this paper, the authors have used machine learning-based feature extraction methods. Finally, the analysis involves the overall calculation of the percentage for the hospital. This percentage is based on the polarity of all the reviews of the particular hospital.

can classify the consumer's emotions about the product or service in question [16,17,18].

The paper is organized in a total of ten sections. The next section discusses some works already done in the field of sentiment analysis along with other works related to the analysis of hospital reviews. Following this, section 3 describes the collection and structuring of the dataset for the hospital and its reviews. Section 4 discusses the methodology of the work. The results are presented in section 5. The next section discusses the practical implications of the work. The final section contains the epitome of paper and future work is discussed.

2. Related Work

Sentiment Analysis is popularly used for providing ratings to movies, hotels, restaurants based on the reviews provided by the customers on different review websites, blogs, online groups, etc. For example, many approaches involve the use of using a tree kernel-based model for the classification of the polarity for Twitter tweets into three classes namely: positive, negative, and neutral. This can also be used for gauging public sentiment regarding any particular event, news, etc. The random forest method is often used to attain a very high accuracy for predicting the overall reception and popularity of books by the reviews. In addition to this, few studies have used sentiment analysis in the field of healthcare. For example, the authors of paper [8] demonstrated the use of sentiment analysis for analyzing a person's online posts, tweets, remarks, etc. regarding their experiences in a hospital or any health-care-related institution. And the new approach might be a better alternative than the traditional methods such as surveys that were previously associated with measurements regarding customer satisfaction and feedback.

From this survey, we appreciated the importance of our proposed work which is based on the idea of using sentiment analysis on hospital reviews to collect reliable and dynamic data on working conditions of hospitals.

The gathered results will be very beneficial for the general public who are facing a serious lack of reliable and dynamic information on the condition of hospitals. The current virus-pandemic situation had amplified the problems faced by the public. Reliable information will help both COVID and non-COVID patients. This will also reduce the stress on our healthcare system which might face problems because of false information in public. This work opens up a new dimension of possibilities where sentiment analysis can not only be used as feedback by the healthcare system but also provide public reliable and right information on hospitals and other such infrastructures. The dynamic nature of information ensures future reliability and also makes our results more robust.

3. Data collection and preprocessing

Data collection is done by the method of web scraping. It is a method used to fetch large volumes of data from multiple websites. Web scraping automates the process of data gathering and data can be gathered in multiple formats. We extracted the hospital reviews data from India's largest review website mouthshut.com. Python was used for data extraction as it has efficient tools for web scraping.

Web scraping is done using the Beautifulsoup library and the Request library of python. We have extracted the review data from the website and stored it in a JSON file. Thus, the process of data collection can be summarized in three main steps: (1) pairing of HTML websites, (2) extraction of required data, and (3) storing of data. A total of 14121 reviews of 184 hospitals are collected from well-known and established review sites.After gathering data, we generally need to clean and reorganize the data as the collected data is not well structured and needs some processing before it becomes ready to use. We organized the raw data after cleanup into a key-value pair where key - attribute indicates the Hospital's name and the value - attribute represents the reviews of the particular hospital.

In this study, preprocessing of the data is done by (1) Removing HTML tags and URLs, (2) Correcting spelling errors. Reviews may contain bold /underlined/ italic words to emphasize the meaning of some words or sentences. Different tags in HTML are used for this purpose, <b> for bold, <u> for underline and <i> for italics. However, while analyzing the reviews, such emphasizing is of no use as they do not provide any useful information towards the sentiment, thus, they are removed. Similarly, punctuation marks, special characters, white spaces, stop words, etc. are also removed during preprocessing. In addition to this, there may be some spelling errors in the review which can result in deviation from correct analysis. TextBlob is a Python library for processing textual data.

We used the correct () method in the TextBlob library to attempt spelling correction. After removing all the unnecessary HTML tags and correcting the spelling mistakes, the whole review is separated into two parts, viz. the review title & the review body.

The review title gives the whole gist of the review and hence can be used to get the whole sentiment of the review. So to analyze the sentiment of the review we first find the polarity of the review title and if and only if the polarity is neutral then we process the review body for finding the polarity.

4. Methodology

If we delve into the Sentiment analysis, it also involves the understanding of different emotions conveyed by the patient. These emotions can be regarding any of the following feelings such as anger, gloom, joy, confidence, shock, pity, panic, and expectation. In the following section, we explain in detail, the algorithm used for polarity calculation and assigning the positive, negative, and neutral rating to each hospital.

The coding has been done in Python using the module NLTK (Natural Language Toolkit) which is used for natural language processing. Figure 1 represents the main processing that is applied to the preprocessed data. It involves the polarity calculation to find the sentiment of the review. The output is organized and stored in a database that is analyzed for the final results and conclusion.

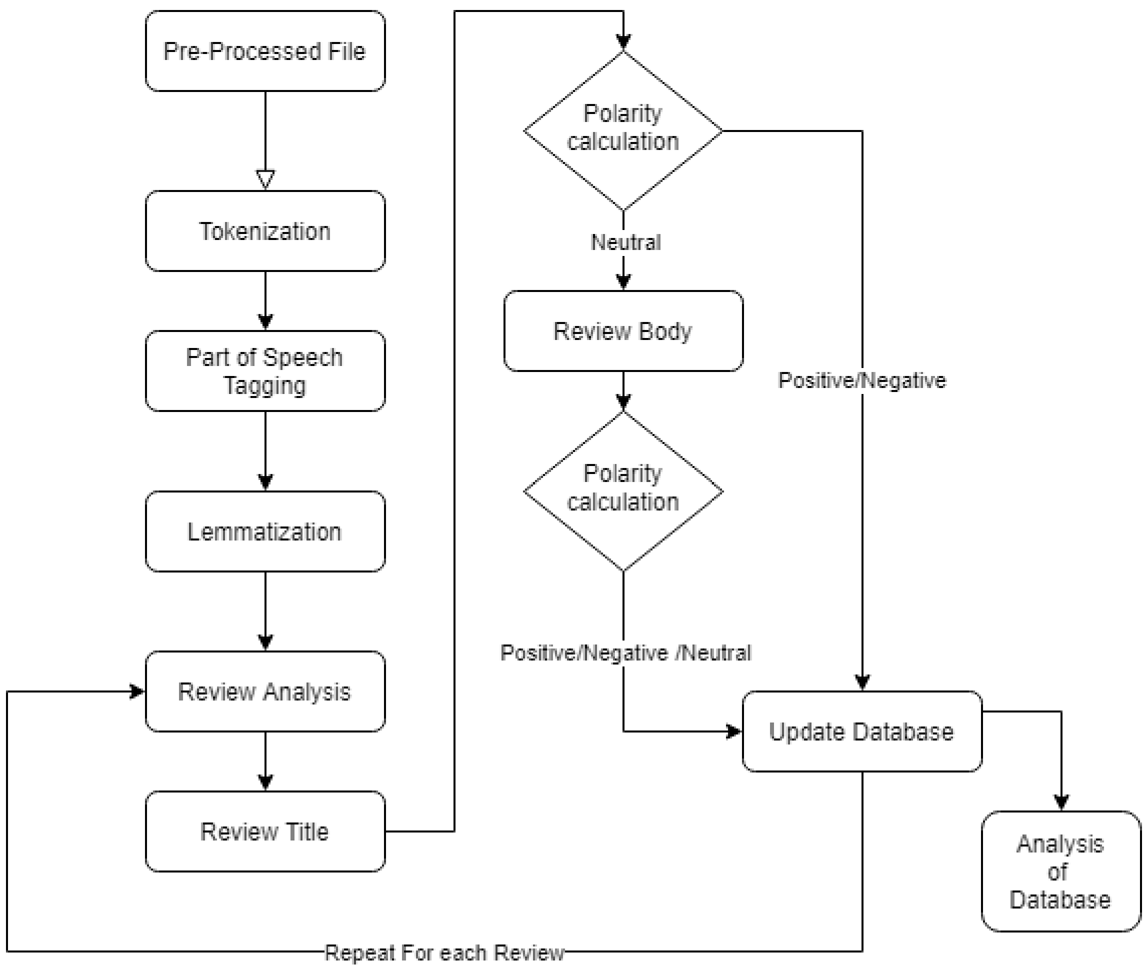

Fig. 1. The proposed methodology of the work

4.1 Steps used to conduct the review analysis

The proposed algorithm is represented by the following steps:

Step 1: Break the review into sentences i.e. Tokenization.

By our methodology, the sentiment analysis can only be done for each sentence of the review and therefore we need to break the review into sentences. We Apply the SentenceTokeniser() to break each review into sentences as follows:

nltk.tokenize.punkt.PunktSentenceTokenizer()

Step 2: Analyzing the negation sentences

For sentiment analysis, the algorithm must know the structure of the sentence. For example, the sentence can be complex and may include comparison, contradiction, negation, or irony. Negation can be of a localized nature, it can of long-range or it can be the negation of the subject. To analyze these sentences, we mark the words which have changed their meaning due to the tone of the sentence. For eg. If the sentence is stated as “The hospital is not good” the sentiwordnet will give this a positive polarity due to the presence of "good" in the sentence. After marking the negation of the sentence it will become "The hospital is not good_NEG” now the sentiwordnet will give this sentence a negative polarity due to the presence of “good_NEG”. The interpretation of the word changes for the sentiwordnet after it is marked as negation. Negation analysis is done as follows:

nltk.sentiment.util.mark_negation(sentence)

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

Original Sentence ⇒ Sentence after negation analysis(“polarity”)

not good ⇒ not good_NEG (“negative”)
does not look very good ⇒ does not look_NEG very_NEG good_NEG(“negative”)
no one thinks that it’s good ⇒ no one_NEG thinks_NEG that_NEG it's_NEG good_NEG(“negative”)

Step 3: Tagging words by their syntactical nature

Part of Speech (POS) tagging involves tagging the word in a corpus to a congruous part of a speech tag based on its grammatical definition. We have attached the PosTag such as adjective, noun, adverb & verb with the word in the sentence. The noun phrases generally correspond to product features, adjectives refer to opinions, and adverbs are generally used as modifiers to represent the degree of expressiveness of opinions.

Step 4: Lemmatization

It is a text normalization technique in the domain of Natural Language Processing that is used to prepare text & words for further processing. It refers to performing things in the right way along with the use of a vocabulary and morphological analysis of words, aimed for the elimination of inflectional endings only and to return the base form of a word, which is called a lemma. For example:“playing”-> Lemmatization -> “play”
“plays”-> Lemmatization -> “play” and “played”-> Lemmatization -> “play”.

Step 5: Repeat steps 6-7 until each sentence of the review is iterated.

Step 6: Maintain three counters: the first counter stores the positive reviews count, the second counter stores the negative reviews count, and the third counter stores the neural reviews count.

Step 7: Polarity Calculation using SentiWordNet

The sentiment analyzer uses words, their meanings, alternative words, polarity of each word, and association intensity level with each word words in a sentence. The polarity of the sentence is usually based on the meaning of words. However, the negation (for negative sentences only) changes the meaning of the words and polarity of the sentence in reverse order. Now check the orientation of the review title using SentiWordNet. If the orientation is positive or negative, then update the respective counter. If the orientation is neutral, then check the orientation of the review body and update the respective counter.

Step 8: Calculating the final results

The polarity data is calculated for every review and a final polarity value of each hospital is computed by taking the summation of the polarity value of all the reviews for a particular hospital. Then using this data, we finally calculate the recommendation percentage of every hospital according to the reviews. Recommendation percentage is calculated by dividing the number of positive reviews by the total number of reviews and then multiplying by 100 for percentage.

5. Results analysis

Here we evaluate and analyze the results. The results are represented in the terms of quantity of positive ratings, the number of negative ratings, the number of neutral ratings, and the recommendation percentage in Table 1. The amount of positive rating represents the number of good ratings given by the user in their review and the number of the negative rating represents the quantity of poor rating given by the user in their review. Then finally the recommendation percentage is indicated for the hospital-based on the polarity of overall reviews of the hospital. Recommendation percentage is calculated by dividing the number of positive reviews by the total number of reviews and then multiplying by 100 for percentage.

As discussed, we collected 14121 reviews of 184 hospitals from **mouthshut.com** a well-known and established review site. Due to space constraints, it is not feasible to represent the result values of all the 184 hospitals. Therefore, concerning all the reviews of 184 hospitals, we report the overall negative, positive and neutral ratings which are 11427, 2545, and 149 respectively. To show the results corresponding to the hospital names, we selected a few hospitals out of a total of 184 hospitals. For selecting a few hospitals, we have divided the hospitals into 3 categories and have represented the results for only the hospitals which fall in these categories. Hospitals are categorized based on their recommendation percentages as follows:

Category 1: Hospitals with a recommendation percentage between 80 to 100

This category represents the ‘Best’ class which includes the most recommended hospitals.

Category 2: Hospitals with a recommendation percentage between 70 to 79 This category represents the 'Average' class.

Category 3: Hospitals with the recommendation percentage between 0 to 69 This category represents the ‘Poor’ class which includes the least recommended hospitals.

The hospitals are divided into three categories according to the scatter plot shown in figure 2 which represents the overall distribution of the hospitals over the recommendation percentage. This trend line can further be used as a benchmark that can be tested against other hospital’s recommendation percentages. This benchmark also allows us to further categorize hospitals based on their relative recommendation percentage which can also be used to generate relative ranking for the hospitals in the dataset. Since the ranking in general, it can also be used on newly included data to expand the scope of the dataset and also increase the reliability of the methodology.

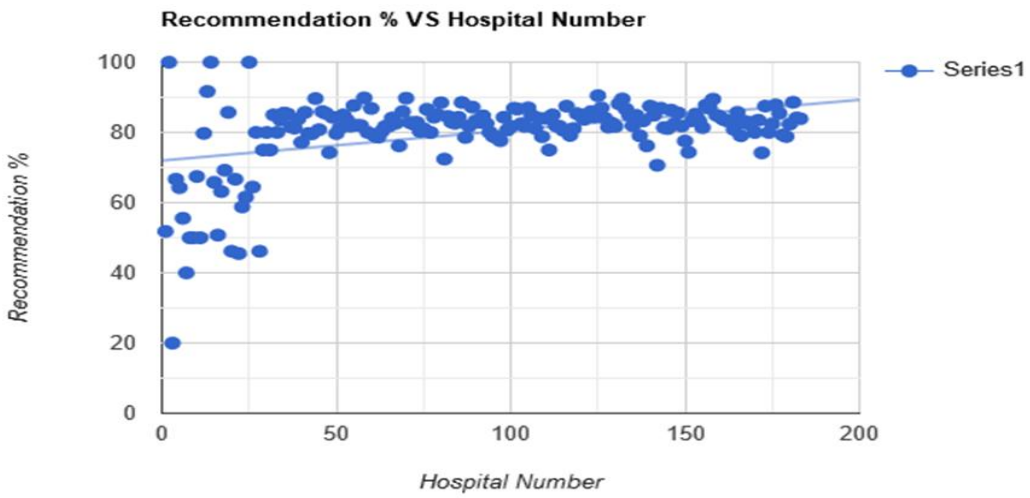

Fig. 2. Scatter plot indicating the overall distributions of hospitals over the recommendation percentage

Table 1. Recommendation percentage of the selected hospitals

S. No.	Hospital Name	Number of +ve ratings	Number of -ve ratings	Number of neutral ratings	Recommendation %
Class1 Hospitals with the highest recommendation percentage					
1	C T Hospital - Thergaon - Pune	11	1	0	91.66
2	Mody General Hospital - Kadodara - Surat	11	0	0	100.00
3	Alpha Hospital & Research Centre - Mela Anupannady - Madurai	76	8	0	90.47
4	Jayam Hospital - Chokikulam - Madurai	52	6	0	89.65
Class2 Hospitals with an average recommendation percentage					
5	Baava Medicals - Madurai Main - Madurai	57	13	1	80.28
6	Shyama Heart Care Centre - Chargawan - Gorakhpur	76	22	0	77.55
7	Shukla Hospital - Betiahata - Gorakhpur	58	19	1	74.35
Class3 Hospitals with the least recommendation percentage.					
8	Padaav: Speciality Ayurvedic Treatment Centre - Dehradun	1	4	0	20.00
9	Fortis Hospital - Kangra	2	3	0	40.00
10	Columbia Asia Hospital - Malleshwaran - Bangalore	91	104	5	45.5
11	Park Hospital - Gurgaon	18	21	0	46.15
12	Iswarya Fertility Test Tube Baby and Research Centre - Coimbatore	11	11	0	50.00

The results are also represented in the form of a pie chart in figure 3. The pie chart is used for the representation of sentiment distribution of reviews. The chart indicates that neutral reviews are only a very small fraction which completely coincides with the general nature of opinions and reviews in the online community and also with commonly observed patterns of distribution of sentiments of opinion by the general populous. The large percentage of positive reviews also is following our average recommendation percentage of the hospitals. Both scatter plot (for distribution of hospitals on the recommendation percentage) and pie chart (for distribution of sentiment of the reviews) validated the integrity and reliability of the dataset used in this paper to demonstrate the methodology for sentiment analysis on the hospital reviews by the patients.

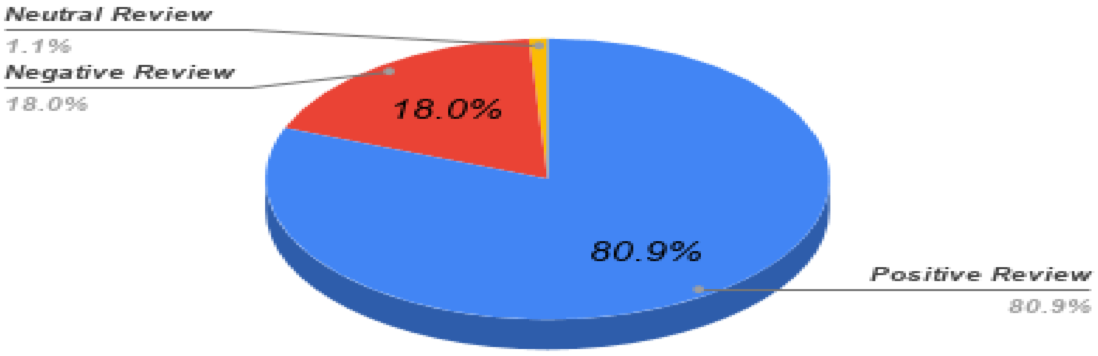

Fig. 3. Pie chart indicating the overall distributions of reviews on sentiments of the review.

6. Conclusion & Future Work

Sentiment analysis is an ever-expanding field and it needs a lot of work to mature as a domain of study This paper has emphasized the importance of review analysis for a multitude of benefits for both patients and the healthcare sector itself. It can help patients by providing relevant and reliable data for both COVID and non-COVID patients. It also helps in revealing the weak links of the overall system which need immediate improvement. These improvements will not only help patients but also allow hospitals to increase their operational ability in stressed pandemic situations. The general method involves three main sections namely: data collection, pre-processing, sentiment analysis of reviews, and finally analysis for the recommendation rating of the hospitals. The data collection is done through web-scraping using python and preprocessing involves the removal of non-essential components of the collected data. Then using sentiment analysis, we find the sentiment of the review which can be positive, negative, or neutral. Then in the final step, we calculate the final recommendation rating of the hospital by finding the percentage of positive ratings based on the total no of reviews.

Fig. 2 gives us a benchmark to compare the hospitals based on the patient's perceived quality of service and personal experience. This benchmark can also be used to compare any other hospital. The reliability of ratings is ensured by the large data -set and its dynamic nature. This result can also provide hospital administration with the patient's valuable feedback which will allow them to improve the quality of service at the hospital.

The approach discussed in this paper also has some implications for other sectors especially the service sector where the quality of services and its perception is the most important metric for the company involved. This paper established a strong relationship with the online reviews and how its analysis has applications for both the consumers and the company which is providing the services. And for the provider company, the analyzed data can provide important insight for upgrading the standard of the facility. The approach may be further extended to analyze the different aspects of the service or product in question. This may be achieved with slight modification in the methodology and the same dataset provided that the dataset has diverse reviews covering the different aspects of the product or service. This can give us more detailed insight into different aspects or attributes of the product.

Considering the healthcare industry as an example we can modify the approach and try to find the aspect-based rating for different attributes of the hospital. Different aspects related to hospitals such as infrastructure, food quality, economic expense, etc. can also be categorized and rated. One drawback is that this method will need a more diverse dataset or extra dataset to augment the analysis

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