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Sentiment Analysis of Patients' Opinions in Healthcare using Lexicon-based Method

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Abstract: The rapid increase in technology made people across the world use social networking sites to express their opinions on a topic, product or service. The success of a healthcare service directly depends on its users. If a majority of users like the service then it is a success otherwise, the service needs to be improvised. For improvising the service, the users' opinions need to be analyzed. Manually extracting and analyzing the content present on the web is a tedious task. This gave rise to a new research area called Sentiment Analysis. It is otherwise known as opinion mining. It is being used by many health organizations to make effective decisions on their service. This paper presents the sentiment analysis of patients' opinions on hospitals which is mainly used to improve healthcare service. This is implemented using a lexicon-based methodology to analyze the sentiment.

Keywords: Healthcare, Opinion mining, Patient Opinions, Sentiment Analysis.

I. INTRODUCTION

All we love about the advancement in technology is a result of artificial intelligence. Artificial Intelligence (AI) is being used in various domains of life. Machine Learning and Natural Language Processing are subfields of artificial intelligence.

AIML (Artificial Intelligence Mark-up Language) and LSA (Latent Semantic Analysis) are used to build artificially intelligent systems like a chatbot that interacts with the user using text or voice responses [1]. In health-care, AI uses complex algorithms to analyze and predict results. Heart disease prediction can be done effectively using Artificial Neural Network (ANN) when compared to SVM which is a machine learning algorithm [2].

Nowadays doctors and patients are using social media for conveying their opinions. According to a recent United States survey, 52 million adults have used the World Wide Web (WWW) to obtain health or medical information. The percentage of individuals switching to the internet to look for a variety of health-related topics remains to expand. Online reviews play a crucial role in social voting. This helps in building recommender systems using a collaborative filtering method [3]. People are abstract creatures and feelings are significant. Having the opinion to interact with individuals on that level has numerous advantages.

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There are some benefits of using social media and blogs because individuals can choose the finest hospital according to the views of the other patients. This analysis won't just support patients or people however utilizing this analysis the medicinal services division will likewise improve their treatment.

Sentiment analysis has various applications, this paper is about the slant examination on patients' opinions on medicinal services. To extract, identify and characterize the sentiment of a text is called Sentiment analysis. Phrases are the building blocks of sentiment expression. Sentiment Analysis is the way toward deciding if a bit of content is positive, negative or neutral. The applications of sentiment analysis are wide and capable. The ability to draw out experiences from social information is a training that is extensively embraced by associations over the world. With the help of sentiment analysis, this unstructured information could be subsequently changed into composed data of general sentiments about any topic or service that people can express decisions about.

In this paper, we focused on extracting sentiments from social media and perform sentiment analysis using lexicon-based approaches. There are various lexicon-based sentiment analysis tools available in python. This paper is composed in the following way. Section II briefly presents the other related works of sentiment analysis. Section III discusses the methodology implemented. Section IV contains the implementation and results. In Section V performance measures used are explained. Section VI contains the conclusion. Finally, references are represented.

II. RELATED WORK

The sentiment is a significant part of the information that is conveyed in a natural language. There are several tasks studied such as identification of subjectivity, such as identification of subjectivity, recognition of emotions or extraction of opinion. This paper focuses on analyzing which lexicon-based approach is best, based on the classification of polarity and intensity which are one of the important tasks of Sentiment Analysis. This paper focuses on analyzing which lexicon-based approach is best, based on the classification of polarity and intensity which are one of the important tasks of Sentiment Analysis. The research and growth of Sentiment analysis methods have risen in latest years owing to several aspects such as the accessibility of data sets produced by the extraction of internet reviews of customers, the application of automatic learning methods in NLP and the huge interest in automatically evaluating views [4]. In this research work, the authors applied supervised learning and lexicon-based sentiment analysis techniques over two different corpora of the Spanish language.

One Corpus is COPUS, it contains patients' opinions about physicians. The other one contains the opinions of patients on various drugs. From their work, it is concluded that reviews about physicians are characterized easily because of the use of informal language while the reviews on drugs are difficult to characterize because of the use of a combination of informal language and medical terminology with a greater variety of lexicons.

C.J. Hutto and Eric Gilbert [5], these authors discussed the development, validation, and performance of VADER (Valence Aware Dictionary for sEntiment Reasoning) lexicon. VADER lexicon is developed from traditional sentiment lexicons. This study also describes sentiment orientation lexicons, sentiment intensity lexicons, and machine learning approaches for sentiment analysis.

Haseena Rahmath P, Tanvir Ahmad, these authors in the research paper [6] discussed the sentiment analysis techniques and compared those techniques. They compared the same technique with different datasets. They concluded that SVM works comparatively better than other techniques but it too has some limitations. The authors also mentioned finding a better technique than existing algorithms to overcome all the limitations.

In this research paper [7] authors have applied the sentiment lexicons to detect the violence in the videos by using the transcript of that video. The authors compared the performance results of the ESWN and VADER. They concluded that VADER performs better than ESWN.

Abdullah Alsaeedi, Mohammad Zubair Khan [8] presented their study on sentiment analysis for twitter data. They discussed various methods for the analysis of twitter data. Their research results established that machine learning techniques like SVM and MNB created the greatest precision when there are different features. The authors presumed that the ensemble and hybrid-based twitter sentiment analysis algorithms performed superior to the supervised learning techniques.

In this research paper [9] authors discussed the sentiment analysis for Chinese patients' experience. The authors collected the data from the two hospital's E-survey tools. They used five algorithms like the random forest, SVM, GBDT, XGBoost, and LSTM and concluded that LSTM works better for that data.

In this research paper [10] authors predicted sentiment from movie reviews using the lexicon-based model. They considered SWN, VADER and Affin lexicons for analysis.

III. METHODOLOGY

A. Lexicon-Based Sentiment Analysis: Lexicon based approach for sentiment analysis is a simple and viable approach to analyze sentiment. This approach needs a sentiment lexicon which is a lexical asset of words and expressions that are typically used to express positive and negative notions. It doesn't require any kind of training data. These methods consider linguistic features and provide sentiment scores which are used to analyze the sentiment. Most of sentiment analysis methodologies take one of two structures: polarity-based, where bits of text are named either positive or negative, or valence-based, where the strength of the sentiment is considered.

In this paper, we used the sentiment analysis tools like Vader and Text blob in python for sentiment classification.

B. Vader: VADER (Valence Aware Dictionary and sEntiment Reasoner) is indeed a lexicon and rule-based system for identifying the opinions communicated in social platforms. VADER utilizes a combination of a sentiment lexicon as a list of lexical features usually marked as either positive or negative according to their semantic orientation Not only VADER tells us about the rating for Positivity and Negativity, but it also informs us how positive or negative an opinion is. It takes the intensity of the expressed sentiment into account. VADER approach gives positive, negative, neutral and compound scores. Installation: pip install vaderSentiment

Table I: Sentiment Type Based On Compound Score

Sentiment	Compound Score
Positive	> = 0.05
Neutral	> - 0.05 and < 0.05
Negative	< = 0.05

C. TextBlob: Textblob is a library available in python accessible for text handling operations and moreover utilized in sentiment analysis. The *sentiment function* of the text blob library gives two properties polarity and subjectivity.

Polarity: Polarity is used to identify the sentiment. It could be drift esteem that lies within the run of [-1,1]. Subjectivity: Subjectivity usually refers to personal opinions whereas objectivity refers to factual information. It lies in the range of [0,1]

Installation: pip install text blob

IV. IMPLEMENTATION

Fig 1: Block Diagram

The series of steps needed to implement this model is

1. Data Collection
2. Data pre-processing
3. Extraction of patient opinions (features)
4. Application of lexicon-based algorithms and results

1. Data Collection:

We have collected the data from the URL https://www.scoi.com/about-us/patient-reviews which contains patients' opinions on Southern California Orthopaedic Institute which is located in California, USA. This URL contains 92 web pages where each web page contains patient opinions. For extracting required data i.e patient opinions from a website we used a package called beautiful soup in python.

Beautiful Soup: It is a library that is available in python used to parse HTML and XML files. This process of extracting data is useful for web scraping. This library is available for python 2.7 and python 3.

2. Data pre-processing:

It is a basic step to obtain good results by decreasing noise. The pre-processing steps performed after crawling required data from a website are:

i. Counting the number of words and characters in a review
ii. Removal of Stop words that are unnecessary for analysis. They are the words that contain simply no importance and we need to evacuate them. We have done this effectively, by putting away a rundown of words that we considered as stop words by using the NLTK corpus.

3. Extraction of patient opinions: The pre-processed patient reviews are now extracted and are ready for analysis.

4. Application of lexicon-based algorithms: Two approaches VADER and Text Blob sentiment analysis is applied to extract features.

VADER is applied by importing SentimentIntensityAnalyzer from vaderSentiment which is installed as in section III. A method, polarity_scores() from SentimentIntensityAnalyzer(x), where x is a patient opinion, gives sentiment scores as output. It gives positive, negative, neutral and compound scores.
Based on the compound score we can decide the sentiment orientation. The Compound score is a measure that is obtained by calculating the sum of all the standardized lexicon scores between -1 (most negative) and +1(most positive). These scores are in the form of a dictionary in python language and only compound scores are extracted. After extraction of compound scores for each patient's opinions, based on the values given in the table in section 3, the number of positive, negative and neutral opinions is computed. We represented the results in the form of a pie chart using the matplotlib.pyplot in python.

Table II: Results of the Vader Algorithm

Total Reviews	914
Positive Reviews	823
Negative Reviews	68
Neutral Reviews	23

Table III: Percentage Results of the Vader Algorithm

Positive percent	90.0
Negative percent	7.4
Neutral percent	2.5

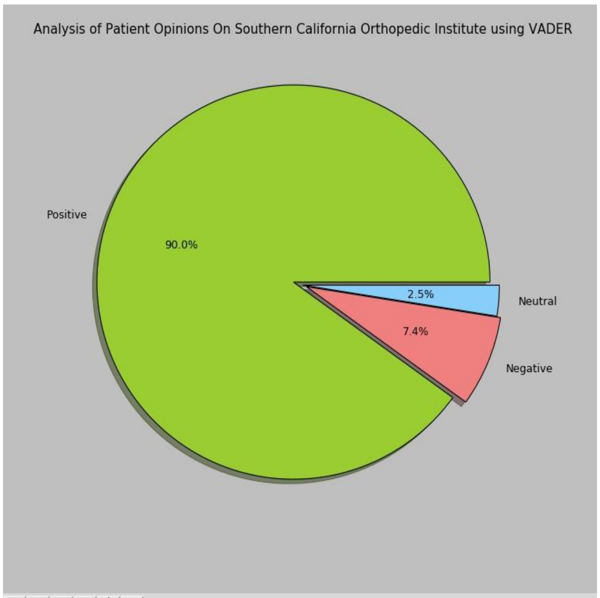

Fig 2: Graphical Representation of Vader Analysis

TEXT BLOB is applied by importing TextBlob from the text blob package. A method, sentiment () from TextBlob() gives polarity and subjectivity scores for each patient opinion. TextBlob(x) takes argument x where x is a patient opinion.
In Text Blob based on the polarity scores, we can analyze sentiment orientation.

If the polarity score is > 0 then it is a positive sentiment.
If the polarity score is < 0 then it is a negative sentiment.
If the polarity score is = 0 then it is a neutral sentiment.

Table IV: Results of the TextBlob Algorithm

Total Reviews	914
Positive Reviews	867
Negative Reviews	24
Neutral Reviews	23

Table V: Percentage Results of the TextBlob Algorithm

Positive percent	94.9
Negative percent	2.6
Neutral percent	2.5

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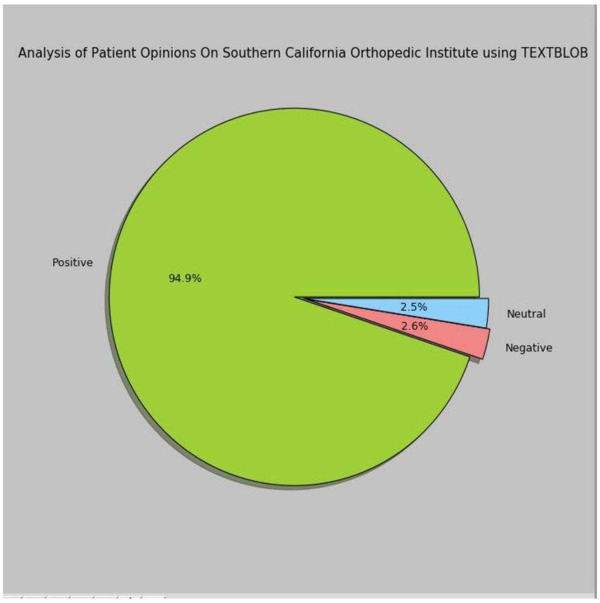

Fig 3: Graphical Representation of Text Blob Analysis

V. PERFORMANCE MEASURES

A confusion matrix is the measurement of the effectiveness and performance of our algorithm. It is a table with a combination of actual observations and predicted observations and it is useful for measuring Accuracy, Precision, Recall, and F1score.

We used four performance measures like True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

True Positive means you anticipated positive and it is true

True Negative means you anticipated negative and it is true.

False Positive means you anticipated positive and it is false. False Negative means you anticipated negative and it is false.

Accuracy, in general, tells about how regularly is our algorithm or model is correct and it is the proportion of correctly estimated observations to the total observations.

$$\text{Accuracy} = \frac{(T_P+T_N)}{(T_P+F_P+F_N+T_N)} \quad (1)$$

Precision tells about when the algorithm estimates positive, how frequently it is right.

It is the proportion of effectively anticipated perceptions of the total anticipated positive perceptions.

$$\text{Precision} = \frac{T_P}{(T_P+F_P)} \quad (2)$$

Recall is also called as a sensitivity which ascertains what number of the Actual positives our algorithm or model catch through marking it as True Positive

$$\text{Recall} = \frac{T_P}{(T_P+F_N)} \quad (3)$$

F1 score considers both precision and recall. It is the harmonic mean of precision and recall.

$$\text{F1 score} = \frac{2*(\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})} \quad (4)$$

Table V1: Confusion matrix of VADER

N=914	**Predicted Positive**	**Predicted Neutral**	**Predicted Negative**	**Total**
Actual Positive	634	15	49	**698**
Actual Neutral	34	5	0	**39**
Actual Negative	155	3	19	**177**
Total	**823**	**23**	**68**	**914**

This confusion matrix shows that the number of actual positive opinions is 698, the number of actual neutral opinions is 39 and the number of actual negative opinions is 177. The total number of opinions collected is N=914. This actual number of different classes of opinions is calculated based on the sentiment score using online sentiment analysis tools like MonkeyLearn. By using the VADER lexicon, the algorithm predicted that the number of positive opinions is 826, the number of neutral opinions is 26 and the number of negative opinions is 62.

Table VII: Confusion matrix of TEXT BLOB

N=914	Predicted Positive	Predicted Neutral	Predicted Negative	Total
Actual Positive	660	20	18	**698**
Actual Neutral	37	2	0	**39**
Actual Negative	170	1	6	**177**
Total	**867**	**23**	**24**	**914**

The number of actual positive opinions, neutral opinions, and negative opinions and total opinions i.e. N is the same as in the case of Vader. By using TextBlob the algorithm it is predicted that the number of positive opinions is 871, the number of neutral opinions is 19 and the number of negative opinions is 24.

Table VIII: Results of performance measures

Lexicon-based approach	Accuracy %	Precision %	Recall %	F1-score%
VADER	71.9	42.2	38.1	40
TextBlob	73.0	36.5	34.3	35.36

Table VIII shows that the accuracy of TextBlob is more than that of VADER. But on considering the other performance measures which are calculated using the equations in section V VADER obtained the best performance on the dataset.

VI. CONCLUSION

The confusion matrix of two different algorithmic approaches depicts that our data is imbalanced as the number of observations for each class is not uniformly distributed. So, standard classification metrics such as accuracy is alone not sufficient to assess the performance of the model. Hence, we calculated other measures such as precision, recall, and F1-score. From section V table VIII, it is seen that the accuracy of the VADER lexicon-based approach is 71.9% and the TextBlob lexicon-based approach is 73.0%. But on performing comparative analysis considering precision, recall, and F1-score we concluded that VADER lexicon-based approach performs the best.

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