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Consumer sentiment analysis of heritage hotels' online reviews, using text mining: A multi-language approach (A case study of Noor mahal palace, Karnal)

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Abstract
Purpose: In business, online reviews have an economic impact on firm performance.
The study is an analysis of the online reviews written by customers about Noor Mahal palace, a heritage hotel in karnal, Haryana. It aims to analyze reviews with polarity classification and to identify the overall sentiment of the collected reviews.
Design/methodology/approach: A total of 1,000 online reviews about the hotel were collected from the TripAdvisor website and web scraping was done by using a beautiful soup package in Python. Orange data mining software was applied to pre- process and analyze the data. VADER sentiment analysis is used to generate the polarity and overall sentiment of the reviews. The study categorizes the emotions of reviews as positive, neutral, and negative.
Findings: Results revealed that 99.9% or 999 out of 1000 responses have a compound sentiment of positive and only 0.01 or 1 out of 1000 responses have a compound sentiment of negative. Reviews that have received a rating of 5 or 4 are regarded as being favorable reviews, whereas reviews that have received a rating of 1 or 2 are regarded as being negative reviews.
Originality/value: The study is a rare attempt to examine online customer reviews of Noor Mahal palace using a text mining approach and to identify the sentiment scores of the online reviews to know the satisfaction and dissatisfaction.

Keywords: Text mining, online reviews, sentiment analysis, customer satisfaction, polarity classification

Introduction

Over the course of the past few decades, consumers' ways of building opinions and making decisions have undergone substantial shifts as a direct result of the rise of the Internet. Consumer choices are greatly affected by online reviews written by others and shared by others about their experiences. The development of reliable Internet access as well as the meteoric rise in the number of people using smartphones are further factors that have contributed to the shift in the approach in which customers get information regarding products and services. This also resulted in a significant rise in the number of various products and services that may be accessed through the medium of the internet. Therefore, it is more common for people in these modern times to rely on online data sources for info on services. (Xu *et al.*, 2013) [49] The term "electronic word-of-mouth" (sometimes abbreviated as "eWOM") refers to "any informal communications directed at customers through internet-based technologies relating to the usage or features of certain goods and services, or their sellers." (Chittiprolu *et al.*, 2021) [50]. Customer reviews can be seen on websites, blogs, forums, mobile applications, and social networking sites. These reviews are where customers share their thoughts, experiences, and suggestions regarding a product or service. (Wong *et al.*, 2020) [53].

As a result of reading internet reviews, consumers gain access to a wealth of information in the form of advice, insights, and perspectives from their peers that can inform their buying and decision-making processes. This is made possible by the accessibility with which the network and information are available. (Chittiprolu *et al.*, 2021) [50].

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This user-generated content (UGC) allows businesses have access to a large amount of trustworthy data, which in turn enables organizations to obtain trustworthy assessments of customer satisfaction and service quality. (Chatterjee *et al.*, 2022) [51].

A direct correlation exists between the number of reviews and ratings received by a company and the increase in Reviews that have high ratings, on the other hand, indicate that customers are satisfied with the service in the form of praise. Reviews that have low ratings, on the other hand, convey customer displeasure in the form of complaints. in that firm's revenue. However, evaluations with low ratings have a detrimental impact on the performance of the firm (Ahmad & Guzmán, 2021) [52]. Failures that occur repeatedly can result in "churn" in client relationships, which indicates that consumers who are dissatisfied with the service they receive are willing to switch to other companies (Knox & Oest, 2014) [22].

The influence of online reviews has significantly altered the decision-making process in practically every business and sector. The travel and tourism industry is not an exception; online reviews play an important part in the purchasing decisions of customers in this area as well. The tourism sector is one of the leading players in the adoption of new technologies and consistently implements innovative techniques in the business. (HBI, 2018) [12] Before arriving at their destination, 90 percent of travelers said that reading online evaluations helped them get more familiar with the area's attractions, alternatives, and new ideas. (Gretzel & Yoo, 2008) [11].

Many of India's historic buildings, including palaces, forts, and mansions, are currently undergoing restoration so that they may function as hotels. This is due to the fact that after independence, many of these estates were deserted after the breakup of princely federations. This led to the current situation. These properties were changed by the government of India into heritage hotels, which are presently run by the respective royal families as well as the most well-known hotel corporations in India. Owning heritage sites comes with a variety of benefits, some of which include the preservation of cultural arts, the providing of work possibilities for locals, the maintenance of historic monuments' architectural integrity and aesthetic appeal, and the creation of employment opportunities overall (Piramanayagam, Rathore, & Seal, 2020) [36] (Rasoolimanesh, Jaafar, Kock, & Ahmad, 2017) [39]

Many tourists, both domestic and international, are drawn to India's heritage hotels because they provide guests with a taste of royal life while also illuminating the nation's past and present (India, 2017) The services provided by heritage hotels contrast with those provided by commercial hotels (See & Goh, 2019) [42] According to the study note that was written by (Henderson, 2013) [14] the primary distinction between historic hotels and commercial hotels should be understood in terms of the heritage features that are present and the commercial activities that take place in the hotel. Heritage hotels that are considered to have commercial worth differentiate themselves from other hotels by providing stylish bars and fine dining restaurants.

In karnal, Haryana, the Noor Mahal palace palace hotel is among the most well-known names in the category of luxury heritage hotels. It opened its doors to the public as a heritage hotel that was full of splendor. The interior was exquisitely decorated with traditional pieces of furniture and upholstered with exquisite hand-woven tapestries for a truly grand look. The Noor Mahal palace is one of the very few heritage palaces in India, and it has a long and illustrious history dating back to the regal era. The palace was the official royal seat of Nawab Sadiq Khan IV and represents a priceless bequest from the princely state of karnal, Haryana, which was located in British India. "Like the beauty of goddess" or "iman ki roshni ka sarchashma" is what the phrase "NOOR" means when translated from the Urdu language.

In the course of our research, we demonstrated how we can extract useful information from the textual components of online customer evaluations to determine the level of happiness of our clients. We have used text mining and sentiment analysis to extract relevant data from online reviews to know customer satisfaction.

Objectives of the study
To produce sentiment analysis results, the responses were pre-processed and inputted into a machine learning tool. Specifically, this study aims to achieve the following:
1. Through a word cloud, the study will identify the frequently occurring words in the document collection.
2. Determine the Overall Sentiment of the reviews by Utilizing a Heat Map with the Valence Aware Dictionary for Sentiment Reasoning (VADER) model.

Literature review
Online reviews" Online customer reviews (OCR's) can be described as peer-generated product reviews that are placed on the company's website or the websites of third parties" (Mudambi & Schuff, 2010) [31] and Customers rely heavily on online reviews as their primary source of product and service information due to the accessibility of big data and the ease with which they may use the internet. Customers look at online reviews to avoid being confused about what to buy and to save time (Hennig-Thurau, Groth, M, Paul, & Gremler, 2006) [16] (Tan, 2018) [43]. Clients spread their expertise through the writing of reviews, the publishing of videos and photographs on a variety of internet channels such as web blogs, social network sites, and third- party websites such as TripAdvisor and Ctrip, amongst others (e.g., Facebook, Twitter, Instagram, YouTube, etc.). Studies have shown that online reviews bring in new customers (Hennig-Thurau, Groth, M, Paul, & Gremler, 2006) [16] assist consumers in making purchasing decisions (Ye, Li, Wang, & Law, 2014) [46] and influence consumers' trust (Filieri, "What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM ", 2015) in websites that are operated by third parties. Customers post reviews online for a variety of different reasons. To come in first is a delight. Consumers have fun while posting online reviews about their experiences, and they truly appreciate what they do (Oliveira, Brochado, Moro, & Rita, 2019) [33] Two, the concepts of altruism and reciprocity. Customers submit feedback in the form of online reviews to assist both other tourists and service providers in making necessary improvements (Pourfakhimi, Duncan, T, & Coetzee, 2020) [37] (Gretzel & Yoo, 2008) [11] (Jelodar, *et al.*, 2019) [19] Third, the satisfaction of psychosocial demands. Customers may voice their contentment or discontentment with a hotel's services through the writing of online reviews. These reviews may be positive or negative in nature. A personal

sense of accomplishment and self-actualization comes in fourth. Gaining recognition in the community of fellow travelers and on social media is something that many travelers strive for. Travelers have the opportunity to earn more helpful votes and contributor points by publishing more reviews (Oliveira, Brochado, Moro, & Rita, 2019) [33] The fifth point is financial incentives. Reviewers can receive monetary rewards from service providers or third-party review websites in exchange for their feedback (Yoo & Gretzel, 2011) [11] (Oliveira, Araujo, B, & Tam, 2020) [34] (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004) [15]

Hotel customer sentiment
Customer sentiments are the feelings that customers express about a product or service in an online review (Geetha, Singha, & Sinha, 2017) [10] It could have either a positive or negative connotation, or it could be neutral. The feedback received from customers answers informational questions regarding the characteristics of the product under consideration (Liu & Sangwon, 2015) [27] As a result, sentiment drivers are recurrent factors that urge customers to leave online reviews (Xie, Chen, & Wu, 2016) [45].

The owners and operators of hotels were strongly reminded to be mindful of the influence that the opinions expressed in reviews can have on the selection of a hotel by potential guests (Gavilan, Avello, & Martinez-Navarro, 2018) [9] They are required to evaluate the credibility of the testimonials provided by the customer (Noone & Mcguire, 2016) [31]. According to (Lo & Yao, 2019) [28], good emotions have a direct linkage to persuading customers to visit a company's website and a high possibility of converting those customers into sales. They also found that this linkage is directly proportional to the level of customer satisfaction. As a result, hotel operators need to have an accurate and comprehensive image of the feelings expressed by consumers on the numerous platforms available for customer reviews. Previous research has established that the opinions of hotel guests play an important part in determining the level of revenue generated by hotels (Kim, 2013) [21] (Uddin, 2015) [44] (Lee & Cheng, 2018) [23].

It has been determined that one of the most important criteria in the creation of useful marketing intelligence is the feelings of the customer (Li, Li, Zhang, & Hu, 2019) [25] For instance, (Zhao, Xu, & Wang, 2019) [48] highlighted the fact that customer sentiment was a prominent factor in forecasting hotel customer happiness. The perceived value of a service to the customer is a major factor in the customer's willingness to pay for a specific product or service. According to (Mattila & O'neill, 2003) [30] price is a significant factor in both the value and the quality of the items. In a similar vein, (Dube & Renaghan, 2000) [5] highlighted the opinions of customers on value for money while selecting a hotel. This is in line with (Atkinson, 1988) [2] argument that the perceived value of a product or service to a client influences the decisions that they make. The direct association between customers' perceived value and customers was confirmed by a study that was carried out on three-star hotels in Malaysia.

Customers' increased evaluations of the hotel's amenities led to higher ratings overall, which in turn led to a rise in revenue for the establishment (Salehan & Kim, 2016) [41] (Geetha, Singha, & Sinha, 2017) [10] For instance, clients evaluate the quality of services by comparing their impressions of the service delivery to the actual service they

were provided with (Uddin, 2015) [44] The attitudes of hotel guests have always been a leading indicator of hotel client retention (Liang, Li, Yang, & Wang, 2015) [26] (He, Tian, Chen, & Chong, 2016) [13] (Park, Ashihara, & Lu, 2016) [35] According to (Bilgihan, Nusair, K, Okumus, & Cobanoglu, 2015) [4] consumers' intentions to book the same hotel again depend on the experiences they've had there in the past.

Hotels integrate business intelligence techniques to internet reviews in order to acquire a competitive advantage by providing innovative services and goods (Kandampully & Solnet, 2019) [20] (Leung, 2019) [24] Because of TripAdvisor's prominence in the travel and tourism sector, we decided to use it as a source of information for this research (Filieri, Alguezaui, & Mcleay, "Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth", 2015) One of the most comprehensive review websites, TripAdvisor, has more than 760 million reviews covering a variety of topics, including restaurants, hotels, attractions, activities, travel experiences, cruises, and airlines (TripAdvisor, 2019). Before making the reviews of customers publicly available, TripAdvisor screens them by confirming the customers' email addresses and Internet protocol addresses and making an effort to identify any potentially fraudulent tendencies (Zhao, Xu, & Wang, 2019) [48] According to (Marine-Roig & Clave, 2015) [29] consumer review websites are accessible data sources that may be used to analyze consumer behavior destination image, and service quality in a variety of scenarios.

Research process
Data and sample
The Noor Mahal palace, a heritage hotel in karnal, Haryana, was selected as the sample for this research. A total of 1,000 online reviews about the hotel were collected from the TripAdvisor website and web scraping was done by using a beautiful soup package in Python. Orange data mining software was applied to pre-process and analyze the data. VADER sentiment analysis is used to generate the polarity and overall sentiment of the reviews. The study categorizes the emotions of reviews as positive, neutral, and negative.

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The ratings given by customers are based on a Likert scale that has five points, with one representing "awful" and five representing "great." This scale is provided by TripAdvisor. Reviews with ratings of 5 and 4 are considered to be positive reviews, but reviews with ratings of 1 and 2 are considered to be bad reviews (Berezina, Bilgihan, Cobanoglu, & Okumus, 2016) [3] choose the reviews that

have a rating of "5" as satisfied customers and a rating of   "1" as dissatisfied customers.
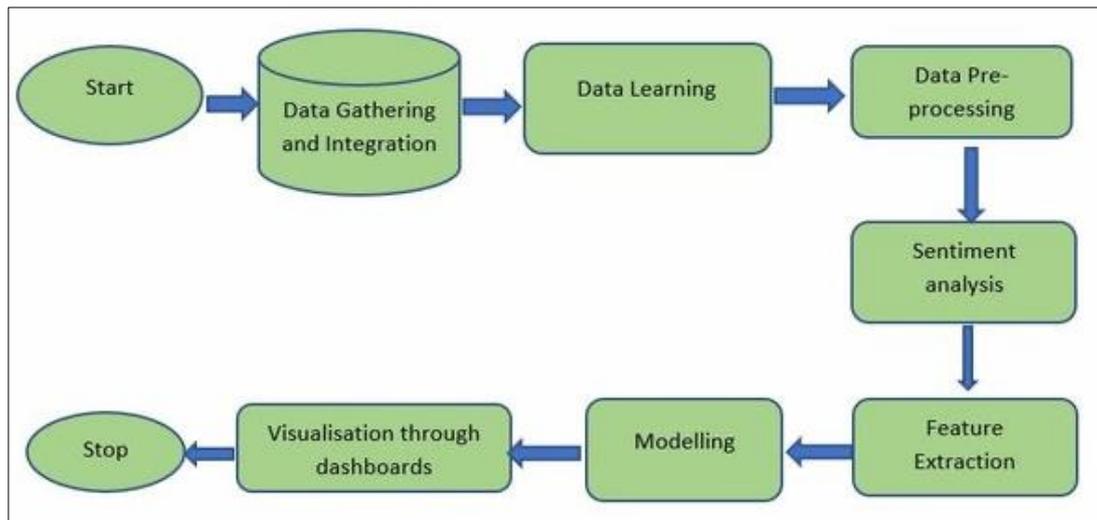

Fig 1: Aspect Based Sentiment Analysis Process Flow Diagram

Data analysis

Text Pre-processing and Cleaning

After that, the responses are saved in an Excel document and imported into Orange Data Mining Software. Textual pre-processing and cleaning were performed on each and every response. During the pre-processing stage, information is extracted from the documents in order to locate keywords and associations within the text. This procedure, which is also referred to as pattern matching, is undertaken in order to accomplish this. The following are the pre-processing and cleaning procedures that were carried out for this research:

Elimination of Stop words

Stop words Elimination: Within natural language, there is a category known as stop words. The reason that analysts recommend deleting stop words from a text is because they give the content a heavier and less relevant appearance to the reader. When stop words are eliminated from the term space, the dimension of the space becomes less complex. Even though articles, prepositions, and pronouns make up most of the words found in written texts, they do not contribute to the overall meaning of the text. (S. Vijayarani, 2015) [40].

Stemming

This method is used to determine a word's root/stem. For example, the term "connect" is the origin of the phrases connected, connecting, connecting, and connections (Ramasubramanian & Ramya, 2013) [38] Connect is also the root of the word linked. This tactic intends to accomplish the mentioned objectives by doing away with multiple suffixes, reducing the number of words, making certain that stems are accurately matched, as well as saving both time and memory space (S. Vijayarani, 2015) [40].

Frequency-Inverse Meaning of the Term Document Frequency

TF-IDF is a numerical statistic that demonstrates how important a term is to a collection of documents. This statistic compares the frequency of a word to its inverse document frequency. The TF-IDF is commonly applied as a weighting factor in the context of information retrieval and

text mining. The value of the TF-IDF increases in proportion to the number of times a word appears in the document; however, the frequency with which the word appears in the corpus counteracts this effect (S. Vijayarani, 2015) [40].

Sentiment Analysis

VADER (Valence Aware Dictionary for Sentiment Reasoning) is a sentiment analysis model used to determine the polarity (positive/negative) and intensity (strength) of the emotion of a corpus or set of documents. In 2014, the VADER model was first made available to consumers. It employs a human-centered methodology that blends qualitative analysis and empirical validation by employing human evaluators and crowdsourcing. VADER relies on a vocabulary that maps words to varying degrees of emotional intensity known as sentiment scores in order to quantify the feeling that a word evokes. A text's score is determined by adding up the intensity values of every word that appears in a collection of documents known as a corpus. The intensity of an emotion can be measured on a scale that extends from -4 to +4, with -4 representing the highest negative score (the most negative) and +4 representing the most positive score. In the meantime, the value 0 (the midway) is deemed to be neutral.

A normalization procedure is used to the total emotion intensity, and then the score is mapped onto a range that goes from - one to + one (Hutto & E, 2014) [17]. In a study conducted at the Georgia Institute of Technology, VADER and several other widely used and well-respected sentiment analysis tools were compared and evaluated based on their capacity to classify emotions. The results of the study showed that VADER performed well and was generally superior to the performance of the other sentiment analysis tools (Hutto & E, 2014) [17]. (Al-Shabi, 2020) [1] came to the same conclusions as well with his research. This is the primary justification for why VADER was used in the investigation.

Text processing, sentiment analysis, and the development of word clouds were all carried out with the assistance of Orange Data Mining Software in this investigation. Orange is open- source software that may be used for both machine learning and data visualization. Visually constructing

processes for data analysis is one of its primary functions, and it comes with a comprehensive toolkit.

Results

Word Cloud

In order to identify the words that were used most frequently in the responses given by the customers in reviews a word cloud was created.

When using a Word Cloud, the data that was acquired is presented in a more understandable manner. It displays the tokens that are contained inside the corpus, with the size of the words representing the frequency with which they are used. The words that appeared most frequently in the pool were palace, heritage, Noor Mahal palace, staff, stay etc.

Fig 2: word cloud of reviews(sentiments)

Sentiment Analysis Result: For the Analysis, textual reviews were taken and after applying the VADER sentiment analysis model, the reviews were classified into positive, negative, neutral and compound. Results revealed that 99.9% or 999 out of 1000 responses have a compound sentiment of positive and only 0.01 or 1 out of 1000 responses have a compound sentiment of negative. In Fig (3) the highlighted review shows the negative sentiment.

Review	Sentiment	Sentiment Category
The hotel was fantastic with great service	0.65	Positive
I had a terrible experience, the room was dirty	-1.00	Negative
Amazing ambiance and very friendly staff	0.65	Positive
The food was mediocre and the service was slow	-0.35	Negative
An exceptional place with beautiful decor	0.85	Positive
Not worth the price, very disappointing	-0.40	Negative
A wonderful stay, highly recommend	0.70	Positive
The amenities were poor and not as advertised	-0.10	Neutral
Worth visit	0.5	Positive
Parking	0.5	Positive

Heat map: It is a visualization of information that takes the form of a map or diagram, and the data values are shown as different colors in the representation.
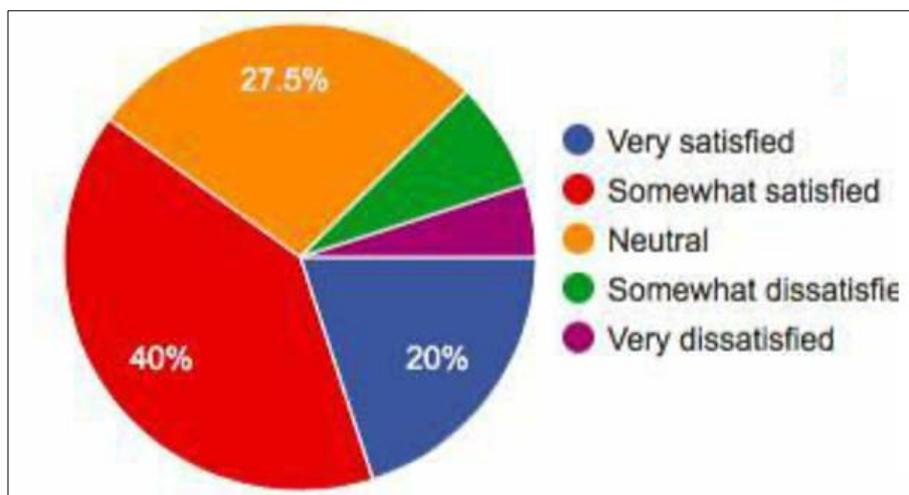
Fig 3: Pie chart showing the satisfaction with the recovery process.
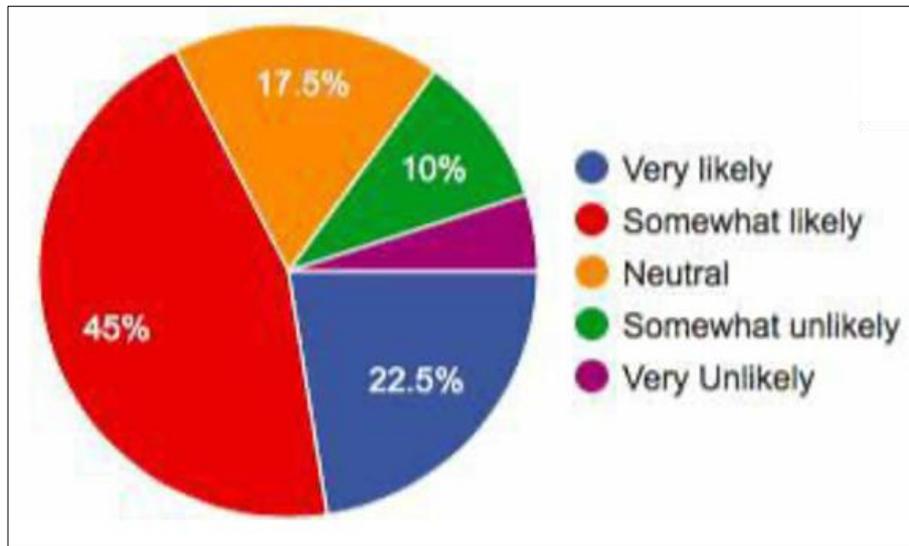
Fig 4: Pie chart showing the likelihood of recommending a hotel to another guest.

Distributions
Displays value distributions for a single attribute such as positive, negative, neutral sentiments and rating. In classless domains, the bars are displayed in blue. We used the Housing dataset.

Positive sentiment Negative sentiment
Neutral sentiment
**Discussion and Conclusion**
Rating
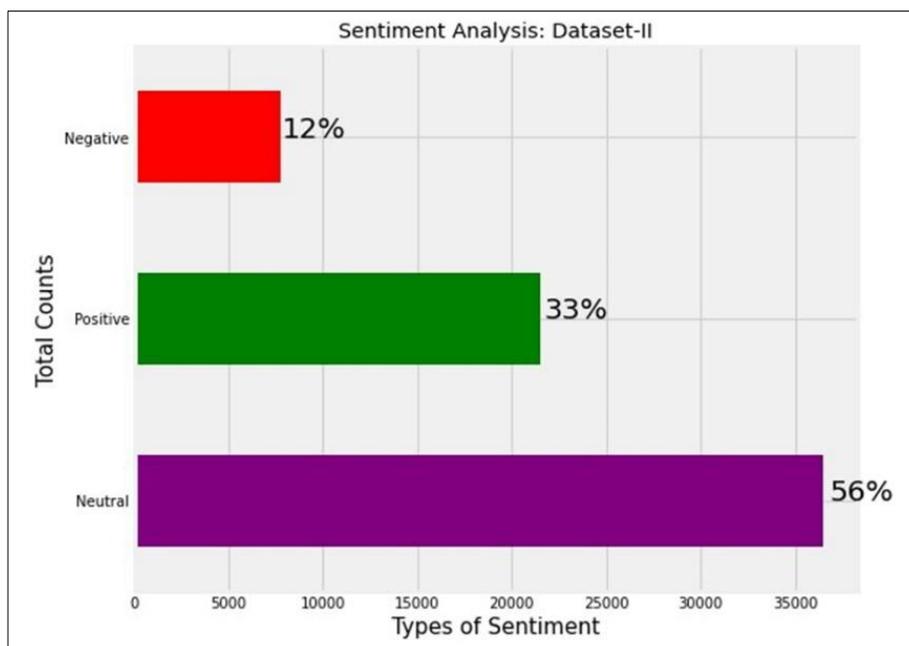
Fig 5: Graphical Bar chart for the count of Positive, Negative & Neutral

The current study focuses on the application of text mining and sentiment mining techniques to retrieve insights from the textual part of the consumer reviews about Noor Mahal palace a heritage hotel in karnal, Haryana extracted from tripadvisor.com.

This study aimed at determining the sentiment analysis of online reviews. Results revealed the most frequently occurring words in the responses of the palace, Noor Mahal palace, hotel, tour, tea, staff, heritage, etc. Results revealed that 99.9% or 999 out of 1000 responses have a compound sentiment of positive and only 0.01 or 1 out of 1000 responses have a compound sentiment of negative. It clearly states that 99 percent of the customers are satisfied with the hotel's services. Reviews that have high ratings, on the other hand, suggest that customers are pleased with the service

provided in the form of praise for the business. Reviews that have low ratings, on the other hand, indicate customer dissatisfaction in the form of complaints about the product or service. Direct correlations exist between the Reviews and customer satisfaction. We know that dissatisfied customers are likely to tell many more friends about their negative experiences than satisfied customers are about good experiences.

Additional research could be carried out on a massive scale with all of the heritage hotels located in India and other nations. The current study is based on just one review of a heritage hotel, and those reviews were taken directly from the TripAdvisor website. The findings of subsequent research can be compared by gathering data from many websites, such as booking.com, Expedia, Agoda, and

Trivago, among others, and analyzing the data. We did not take into account the cultural features of the reviewers, which include their age, gender, country of origin, and type of traveler. Additional research could also concentrate on reviewer aspects; the data might be helpful to the service provider in personalizing the products and services they give. In the future, it would be fascinating to investigate studies on a large scale conducted with hotels located in a variety of nations.

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