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The Study on Sentiment Analysis of Customer Reviews on Food Delivery Applications

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Abstract:
Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique used to determine the sentiment or emotional tone expressed in a piece of text. The goal of sentiment analysis is to identify whether the sentiment conveyed in the text is positive, negative, or neutral. NLP is to enable computers to understand, interpret, and generate human language in a way that is both meaningful and contextually relevant. The primary objective of sentiment analysis is to understand and interpret the sentiment or emotional tone expressed in a piece of text. Sentiment analysis is widely used in various industries and businesses to gain insights into public opinion, customer feedback, and market trends. This helps in improving product recommendations, managing inventory, and enhancing the overall shopping experience. Social media and Marketing use sentiment analysis in social media platforms to gauge the success of marketing campaigns, track brand sentiment, and identify trends. Social media sentiment analysis helps in shaping marketing strategies and maintaining a positive brand image. In Healthcare organizations use sentiment analysis to analyse patient feedback, reviews, and comments about healthcare services. This can assist in improving patient satisfaction, identifying areas for improvement, and enhancing overall healthcare delivery. In conclusion sentiment analysis serves as a powerful tool for extracting meaningful information from textual data, offering a deeper understanding of human expressions and opinions. Its widespread adoption across industries reflects its transformative impact on decision-making, customer relations, and overall business strategies.
Keywords: Sentiment analysis, natural language processing, customer feedback, decision-making, reviews, and comments.

Background of the Study:
The goal of sentiment analysis is to identify whether the sentiment conveyed in the text is positive, negative, or neutral. This process is valuable for businesses, researchers, and individuals to understand public opinion, customer feedback, and social media sentiments.The background of sentiment analysis can be traced back to the broader field of natural language processing (NLP) and the growing need to understand and interpret human emotions expressed in text. NLP is basically the Natural Language Processing. It is a subfield of artificial intelligence (AI) that focuses on the interaction between computers and humans through natural language. NLP involves a range of tasks related to language, including text analysis, machine translation, sentiment analysis, and speech recognition.Here are some specific objectives and goals of sentiment analysis is to understand the public opinion , customer feedback analysis, social media monitoring, market research, product development and improvement, customer service optimization etc.
Here are some areas where sentiment analysis finds application. Sentimental analysis includes various industries like retail and ecommerce where retailers and e-commerce platform use sentiment analysis to understand customer opinion about customer and services. For Example in Healthcare organizations use sentiment analysis to analyse patient feedback, reviews, and comments about healthcare services and Telecommunications companies use sentiment analysis to analyse customer

sentiments expressed in reviews, social media, and customer service interactions. This information aids in improving services, addressing customer concerns, and reducing churn. Hence, sentiment analysis serves as a powerful tool for extracting meaningful information from textual data, offering a deeper understanding of human expressions and opinions.Wang, Z, et.al (2023), this study delves into the evolution of sentiment analysis research over the last two decades, aiming to uncover both established methodologies and unexplored territories. The primary goal is to assist researchers in discovering novel techniques and approaches, while also highlighting the existing limitations in sentiment analysis. The research findings reveal that current hotspots in the field encompass social media platforms, diverse sentiment analysis techniques, user comment or opinion mining, and sentiment analysis for non-English languages. Notably, the paper emphasizes the emergence of new trends driven by advancements such as deep learning technology and innovative methods for analysing sentiments in non-English languages. These breakthroughs have not only reshaped the landscape for researchers but have also influenced the overall trajectory of sentiment analysis research.

Nandwani, Pansy & Verma, Rupali(2021) this study delves into the challenge posed by the rapid influx of unstructured data on social networking sites. Given that people often express their emotions on these platforms, there is a need for applications that can accurately analyse these sentiments. In the course of the research, various algorithms and methods were explored to address this need. The study's findings highlight the efficacy of Lexicon-based methods in accurately analysing emotions and sentiments. Lexicon-based approaches rely on predefined dictionaries or word lists to associate words with specific emotions, proving to be a reliable method in this context. Throughout the investigation, several other algorithms and methods were discovered, presumably in an attempt to find the most effective approach based on the volume of data.
However, the study concludes that, among the explored methods, Lexicon-based approaches stand out as more significant for accurate sentiment analysis. The study also underscores the importance of pre-processing and feature extraction techniques in influencing the performance of different sentiment analysis approaches. Pre-processing involves cleaning and preparing the data, while feature extraction focuses on selecting relevant elements for analysis. In summary, the research emphasizes the need for applications to analyse the abundant emotions expressed on social networking sites. It identifies Lexicon-based methods as particularly accurate for this purpose, even after exploring various other algorithms and methods. The study also highlights the critical impact of pre-processing and feature extraction techniques on the overall performance of sentiment analysis approaches.
Kawade, Dipak(2017) this study delves into the realm of Twitter discussions surrounding the URI Attack, focusing specifically on tweets related to the incident. Despite the abundance of tweets, the study selectively considers 5000 for analysis. The primary objective is to explore the polarity within these tweets, employing text mining techniques for in-depth examination. The key discovery of the research lies in the identification of various emotions expressed in the tweets. These emotions are further categorized into three polarities. Notably, the study envisions the potential application of big data analysis techniques in the future to classify emotions on a larger scale, encompassing a substantial volume of tweets. The present study is lauded for its accurate classification of emotions, aligning with human psychology. Its utility extends to uncovering opinions and sentiments expressed by individuals through tweets, facilitating the identification of tweet polarities. The entire analysis is conducted using R Studio and its text mining packages.
Kommaraju, V., Gunasekaran, Ket.al., (2020) this study investigates how machine learning and natural language processing play a crucial role in shaping strategies across various industries. The paper conducts a comparative and comprehensive analysis of current trends and techniques in these fields. The findings of the study reveal that sentiment analysis, a common application of natural language processing, faces challenges in certain sectors such as politics and healthcare, where its success is limited. However, the study notes that these technologies prove valuable in predicting market trends. In conclusion, the paper highlights the effectiveness of lexicon-based methods in providing accuracy in sentiment analysis. Additionally, it suggests that there are unexplored areas in these fields, and machine learning approaches can be applied to investigate and understand market

trends more thoroughly. Overall, the study underscores the significant impact of these technologies on shaping strategies in various industries.
Drus, Zulfadzli& Khalid, Haliyana(2019) this study investigates the realm of social media and its applications, focusing on the data generated in the form of text and videos uploaded by users. The core premise lies in developing applications based on this user-generated content. The primary findings stress the importance of selecting suitable methods for effective analysis. This involves identifying prevalent social media platforms and demonstrating the application of sentiment analysis. A notable aspect highlighted in the paper is the adaptability of techniques based on the nature of the data. Tailoring methods to the specific format of content not only optimizes time and effort but also yields benefits across various sectors. The study underscores the significance of employing lexicons and machine learning methods to enhance accuracy and quality in sentiment analysis applications.
Medhat, W., Hassan, A. and Korashy, H(2014) this paper highlighted the ongoing developments in sentiment analysis within the field of text mining. The research emphasized that sentiment analysis is a dynamic area with numerous applications and methods still in need of exploration. The survey provided updated insights into the applications and techniques employed in sentiment analysis. The key findings of the study indicated a growing interest in languages other than English in the field of sentiment analysis. The researchers noted a deficiency in resources and research related to these languages, highlighting the need for further exploration. The study revealed that WordNet is the most commonly used lexicon source, and it is available in languages beyond English. Despite this, the research emphasized the ongoing requirement for building resources specific to sentiment analysis tasks for various natural languages. The study showcased sophisticated categorizations of numerous recent articles, shedding light on the latest trends in sentiment analysis and its associated areas. The researchers stressed the need for continued efforts in building resources and conducting research to address the evolving landscape of sentiment analysis, particularly in languages other than English.
Murthyet.al (2020) this paper focuses on deep learning applications in sentiment analysis, specifically highlighting methods such as Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN). The main emphasis is on sentiment classification using LSTM for text data. The paper acknowledges the global trend of users expressing and sharing their opinions on diverse topics, making manual analysis of such extensive data challenging. Consequently, there's a growing need for computer processing to handle this large-scale data efficiently. The findings of the study reveal that employing deep learning methods, particularly LSTM, yields a superior performance in sentiment classification. Specifically, when there is a larger volume of training data, LSTM demonstrates an impressive 85% accuracy in sentiment classification. This suggests that deep learning methods, particularly LSTM, can effectively handle the complexities of sentiment analysis in text data. In conclusion, the paper advocates for the continued exploration of deep learning methods in sentiment analysis. The researchers express their intention to extend the study to a broader scope, incorporating different embedding models and diverse datasets. This expansion aims to further enhance the understanding of the performance and versatility of deep learning techniques in sentiment analysis across various applications and contexts.
Jayasanka, Sachiraet.al (2013) this paper delves into the intricacies of sentiment extraction from diverse social media platforms, aiming to discern whether user reactions are neutral, positive, or negative. The primary focus lies in understanding customer perspectives, desires, and responses. To achieve this, the study employs SentiWordNet, a lexical data source, to identify the positivity or negativity associated with words in sentences. The essence of the findings revolves around comprehending how individuals of specific demographics, such as age, location, and profession, perceive and react to a product or service. The model developed in this research analyses sentiments by scrutinizing user comments and reviews on social media. In essence, the paper provides insights into the sentiment dynamics of people, shedding light on their opinions and emotions concerning a particular product or service based on their social media interactions.

Fang, X., Zhan, J(2015) the paper delves into the challenges associated with polarity categorization in sentiment analysis, which involves the identification of sentiments as positive, negative, or neutral within text. The research conducts experiments at both sentence and review levels, yielding encouraging results. The findings suggest that the models employed in the study demonstrate promise in effectively categorizing sentiments. The conclusion of the paper addresses the overarching issue of polarity categorization in sentiment analysis, summarizing the key insights and contributions made throughout the research.

Sirimevan, Naadun&Mamalgaha et al(2019) this research paper delves into the prediction of stock market prices, aiming to create a practical system to guide investment decisions. The distinctive feature of our approach lies in combining both sensex points and Really Simple Syndication (RSS) feeds for enhanced prediction accuracy. Through our algorithm for sentiment analysis, we establish a correlation between stock market values and sentiments expressed in RSS news feeds. The key contribution of our study is the integration of common people's sentiments, as reflected in news feeds, with sensex data to predict stock market behavior. Unlike traditional stock market prediction systems, our innovative method leverages sentiment analysis to analyse the emotional tone in news feeds and combines it with sensex data for forecasting. The results indicate that this combined approach yields efficient predictions for stock market trends, providing valuable insights for investors on when to buy or sell their stocks. In conclusion, the fusion of sentiment polarity from news feeds and sensex points proves to be a robust and effective method for stock market forecasting.

Investigating the temporal dynamics of sentiment on Zomato could reveal how sentiments towards restaurants or cuisines change over time, considering factors such as seasonality, trends, or external events.Comparing sentiment across different restaurant types, cuisines, or geographical regions could reveal interesting patterns and disparities. Understanding why certain establishments or cuisines elicit more positive or negative sentiments compared to others could inform marketing strategies and business decisions.There is a gap in understanding how user behavior and demographics influence sentiment expression on Zomato. Research could delve into differences in sentiment based on factors such as age, gender, location, or frequency of reviews, shedding light on the diversity of opinions and preferences among users.There are opportunities to develop or refine sentiment analysis methodologies tailored specifically to user-generated content on platforms like Zomato. This could involve addressing challenges such as sarcasm, slang, or language variations to improve the accuracy and reliability of sentiment analysis results.

Research Methodology

The research methodology for sentiment analysis on food delivery applications entail a systematic approach to extract meaningful insights from user-generated content. Beginning with clear research objectives, the process involves collecting a substantial volume of data from Zomato's platform, encompassing user reviews, ratings, and comments. Subsequently, this data undergoes rigorous pre-processing to eliminate noise and standardize text. Sentiment labels are then assigned, followed by feature extraction to capture relevant information for analysis. Various machine learning models, such as Support Vector Machines or neural networks, are trained on the labelled data to predict sentiment. Evaluation metrics assess the model's performance, guiding the interpretation of results which uncover trends, influences, and sentiments towards restaurants and cuisines. Ethical considerations remain paramount throughout, ensuring responsible handling of user data and transparent reporting of findings. For the main objectives to find the sentiments of the model by using LSTM model and to find the accurate customer reviews from data.In a Jupyter notebook, regression analysis is employed to write code for conducting sentiment analysis research on Zomato.

Analysis and Interpretation

The data analysis is done using the LSTM Model. Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is particularly effective for modelling sequential data, such as text. In sentiment analysis, LSTM models are used to analyse and understand the sentiment expressed in a piece of text, such as a review or comment.LSTM models excel in capturing long-term dependencies in sequential data by maintaining a memory cell that can retain information over extended periods. This capability is crucial for sentiment analysis tasks where the sentiment expressed in a text may depend on the context of previous words or phrases. In the context of sentiment analysis, an LSTM model typically takes in a sequence of words or tokens as input and processes them sequentially. At each step, the model updates its internal state based on the current input and the information stored in its memory cell. Finally, the model produces an output, which could represent the sentiment of the entire text or of individual words.

First of all the EDA is done that is exploratory data analysis. It's an approach to analysing datasets to summarize their main characteristics, often employing visual methods. EDA aims to uncover patterns, spot anomalies, test hypotheses, and check assumptions, all with the goal of better understanding the dataset and the underlying structure of the data.In the data of Zomato Study targeting the state Bangalore and from there analysis have to do that how many chains are there in Bangalore.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51717 entries, 0 to 51716
Data columns (total 17 columns):
url                            51717 non-null object
address                        51717 non-null object
name                           51717 non-null object
online_order                   51717 non-null object
book_table                     51717 non-null object
rate                           43942 non-null object
votes                          51717 non-null int64
phone                          50509 non-null object
location                       51696 non-null object
rest_type                      51490 non-null object
dish_liked                     23639 non-null object
cuisines                       51672 non-null object
approx_cost(for two people)    51371 non-null object
reviews_list                   51717 non-null object
menu_item                      51717 non-null object
listed_in(type)                51717 non-null object
listed_in(city)                51717 non-null object
dtypes: int64(1), object(16)
memory usage: 6.7+ MB
```

Figure No: 1

These are the head of data and by using them analyse have done on the basis of location, dish liked, review list, online orders, table booking, ratings etc.
This is showing the details of the table that what does table contains how many heads and rows. By using this we can further do our EDA part well.

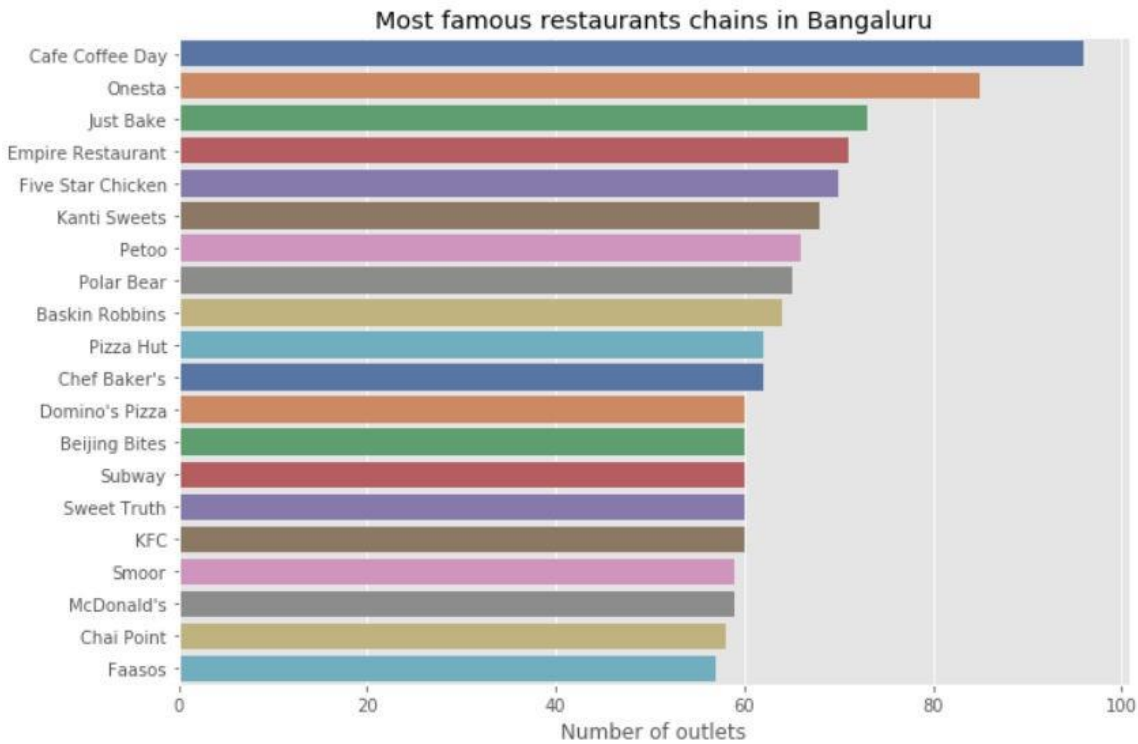

Figure No: 2

This chart 2 shows that the Café Coffee Day, Onestaand Just Bake are the most number of outlets which are in Bangalore.

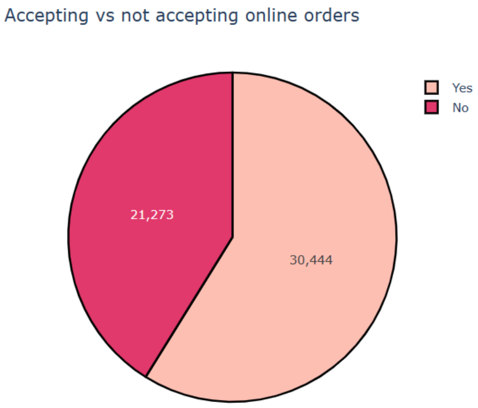

Figure No: 3

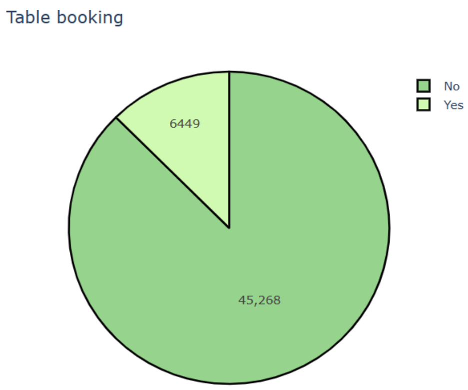

Figure No: 4

The above figure 3 indicates whether outlets in Bangalore are accepting online orders, showing that around 60% of restaurants are doing so. One potential reason for this could be that these restaurants might find it financially challenging to afford the commission fees charged by platforms like Zomato for facilitating online orders.
To address this issue and potentially increase the number of restaurants offering online services through their platform, Zomato could consider providing additional benefits or incentives to these establishments. This might encourage more restaurants to join their online ordering system, thereby expanding their customer base and improving overall service accessibility.
The above mentioned chart 4 is showing about table booking around 90% of restaurants in Bangalore do not offer table booking facilities. In India, it's uncommon for average restaurants to provide this service; typically, only five-star establishments offer table booking. Further investigation into this trend is warranted.

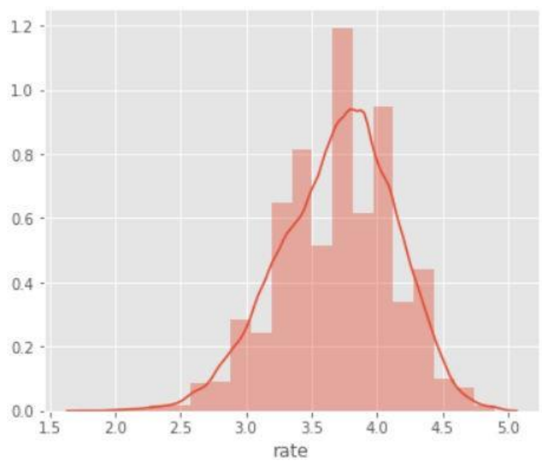

Figure No: 5

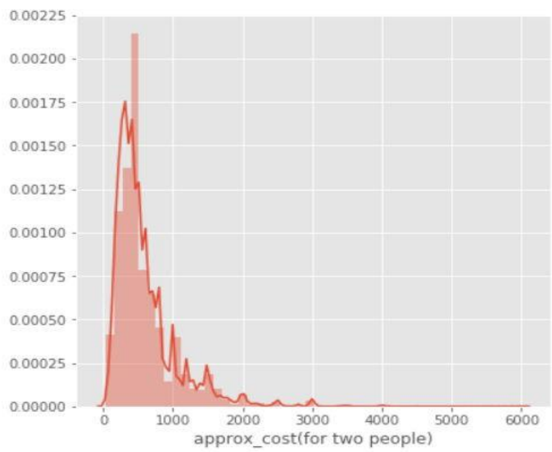

Figure No: 6

The chart 5 shows about rating of the restaurant and this is the rating distribution curve in the form of bell shaped curve showing that almost 50% of the restaurant having the rating between3 to 4. Restaurant which are having ratings more than 4.5 is very less.
The graph 6 represents the cost analysis of the two people going in restaurant and this graphs tells about the approximate cost for two people when they go to restaurant the graph is skewed left which

tells that in less than Rs.1000 people are getting their food. It means that 90% of the people having their food below the Rs.1000.

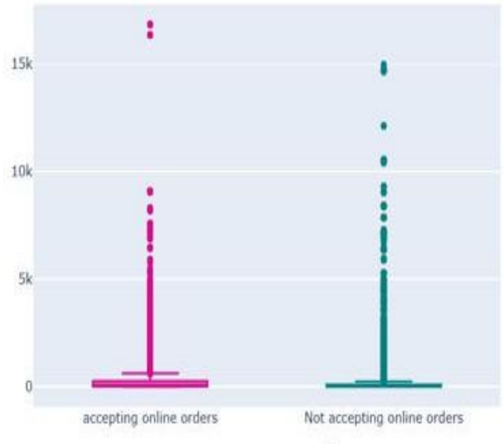

Figure No: 7

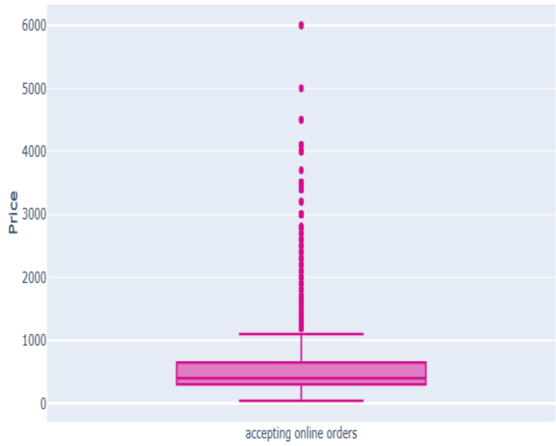

Figure No: 8

The figure 7 shows that the median number of votes differs between the two categories. Restaurants that accept online orders tend to receive more votes from customers.

This could be because the Zomato application prompts users to rate their experience after each order, leading to higher engagement and more ratings for these establishments.

The chart 8 represents that the median approximate cost for a meal for two people is around 400. This means that if you were to look at all the restaurants' prices for a meal for two people and line them up from least to most expensive, the one right in the middle, where half of the restaurants charge more and half charge less, would be around 400.Additionally, about 50 percent of restaurants fall within the price range of 300 to 650 for a meal for two people. This suggests that a significant portion of restaurants offer meals within this range, catering to various budgets and preferences.

	level_0	rest_type	name	count
59	27	Casual Dining	Empire Restaurant	58
60	27	Casual Dining	Beijing Bites	48
61	27	Casual Dining	Mani's Dum Biryani	47

Figure No: 8

	level_0	rest_type	name	count
41	19	Cafe	Cafe Coffee Day	96
42	19	Cafe	Smally's Resto Cafe	54
43	19	Cafe	Mudpipe Cafe	39

Figure No: 9

The above table 8 shows that most popular casual dining in Bangalore that is Empire restaurant, Beijing bites and Mani's Dum Biryani are the most popular casual dining restaurant chains in Bangalore.

Table 9 represents that top cafes in Bangalore and it's not unexpected to see Café Coffee Day emerge as the dominant café chain in Bangalore. With a staggering 96 outlets across the city, Café Coffee Day has firmly established itself as a go-to destination for coffee lovers. Its roots trace back to 1996 when the first CCD outlet opened its doors on Brigade Road in Bengaluru, Karnataka. Since then, Café Coffee Day has grown exponentially, solidifying its presence and popularity among Bangalore People.

Figure 10 shows that analysing a word cloud can provide valuable insights into the key aspects of customer experiences, preferences, or complaints associated with Zomato restaurants or services. It can help identify popular dishes, positive attributes, areas for improvement, or common issues mentioned by customers across different reviews.

	name	rating	review
0	Jalsa	4.0	A beautiful place to dine inThe interiors take...
1	Jalsa	4.0	I was here for dinner with my family on a week...
2	Jalsa	2.0	Its a restaurant near to Banashankari BDA Me a...
3	Jalsa	4.0	We went here on a weekend and one of us had th...
4	Jalsa	5.0	The best thing about the place is its ambiance...

Figure No: 10

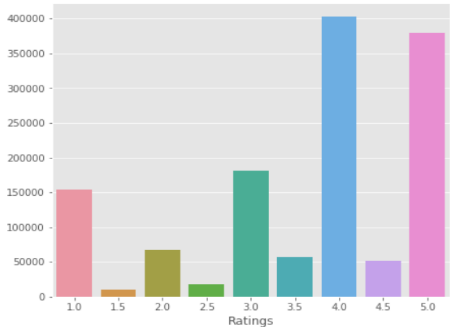

Figure No: 11

After doing this next will be the topic modelling which means that comments will be divided into positive and negative comments on the basis of ratings provided. Comments below 2.5 rates as negative comments and above 2.5 considered as positive comments (Figure 11).

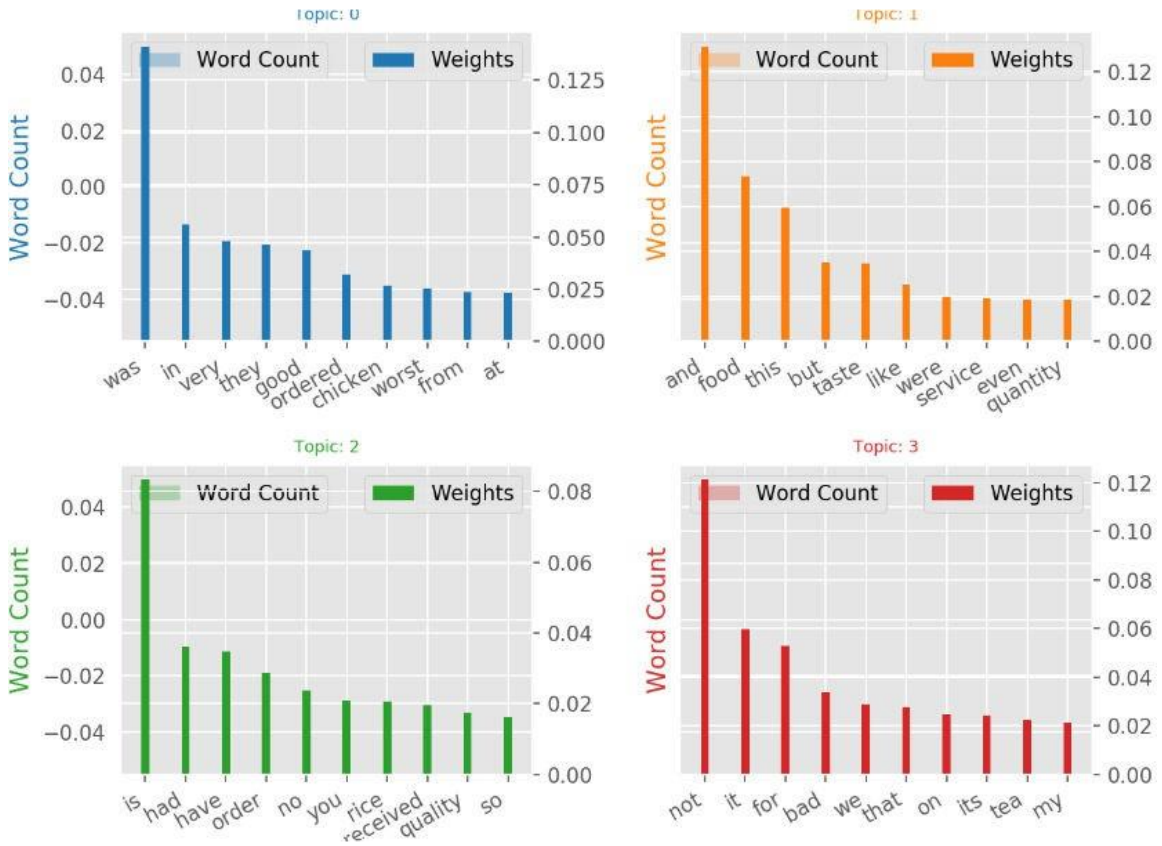

Figure No: 12

The above charts 12 shows that Word Count Analysis and there's a clear distinction between the two types of comments. Negative comments typically contain critical language, while positive comments tend to express appreciation. This differentiation is evident in the choice of words used in each type of comment.To perform sentiment analysis on user reviews, study need to structure our data appropriately. Categorize the reviews as either positive or negative based on the ratings given by users. If a user rates a review lower than 2.5, study will classify it as negative. Conversely, if the rating is 2.5 or higher, study will classify it as positive. This mapping allows us to label each review accordingly, forming the foundation for sentiment analysis.

After Doing the Exploratory data analysis next step is to convert the data into train and test data in the form of 77% and 33% ratio in training and testing data respectively to see the accuracy of the data and the model. Further, the score: 0.11 typically refers to a metric such as precision, recall, F1-score, or some other evaluation measure specific to the task. Without more context, it's difficult to determine exactly which metric is being referred to. However, a score of 0.11 suggests that the model's performance on that particular metric is relatively low. Accuracy: 0.96 refers to the accuracy of the model, which is the proportion of correctly classified instances out of the total instances. An accuracy of 0.96 indicates that the model is performing well overall, correctly classifying approximately 96% of the instances.0.96 says that data is 96% accurate and it is overall performing well and all the predictions which has been done is correctly predicted.

Discussions and Conclusion

LSTM, a deep learning method, achieves a notable 85% accuracy in sentiment classification when trained on a larger volume of data. Deep learning techniques, particularly LSTM, are adept at handling the complexities inherent in sentiment analysis tasks involving textual data.In above interpretation and analysis we have find that our data is showing 96% of accuracy it means that what we have predicted has been actually right.The study also tells about the computational efficiency of the LSTM model instead of using the other techniques. LSTM model is successful in trained data set, unseen dataset. LSTM model provides the further insights for strategic decision maker on customer perception.

Through sentiment analysis, companies can effectively gauge customer sentiment, enabling them to bolster customer relations, enhance offerings, and refine service quality. This profound analysis transcends mere statistical modeling, encompassing a holistic examination of customer feedback and sentiment trends. While LSTM models undoubtedly contribute to this analysis, their role is just one aspect within a broader framework of analytical methodologies. Through diligent application of sentiment analysis tools and techniques, companies can authentically connect with their customer base and continually improve their offerings.Through rigorous implementation and refinement, Zomato achieved an impressive accuracy rate of 96% with this model. Such a remarkable feat underscores the effectiveness and reliability of LSTM in the realm of customer sentiment analysis.Zomato's success story serves as a testament to the transformative power of LSTM in extracting actionable insights from textual data. It effectively summarizes the key findings and insights derived from the study, emphasizing the significance of LSTM in extracting valuable insights from textual data and its role in enhancing customer satisfaction.

Future Scope for the Study

The scope of a study based on these recommendations would encompass several key areas of inquiry. Firstly, researchers could delve into the practical implementation and evaluation of sentiment analysis tools across various industries to ascertain their efficacy in gauging customer sentiment and enhancing overall satisfaction. Additionally, the study could analyze the impact of sentiment analysis on crucial business performance metrics such as customer retention, sales, and brand reputation, thereby illuminating the tangible benefits of integrating sentiment analysis into organizational strategies. Furthermore, comparative analyses of different analytical methodologies, including LSTM models and alternative techniques, could be conducted to determine the most effective approach in different business contexts. Qualitative examinations of customer feedback would provide deeper insights into not only sentiment but also the underlying motivations and preferences guiding customer perceptions. Longitudinal studies tracking changes in customer sentiment over time would offer valuable insights into the effectiveness of organizational efforts to improve satisfaction based on sentiment analysis insights. Moreover, ethical considerations surrounding data collection and analysis, as well as best practices for safeguarding customer privacy, would be essential focal points to ensure responsible implementation of sentiment analysis techniques.

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