DATA VISUALIZATION FOR ONLINE FOOD REVIEW

A PROJECT REPORT

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ABSTRACT

The visualization of online food reviews provides a comprehensive method to analyze customer feedback, offering valuable insights for both researchers and businesses in the food delivery industry. This project focuses on utilizing various data visualization techniques to explore a dataset of online food reviews. Key areas of analysis include the distribution of ratings, trends in review frequency over time, sentiment analysis, and the correlation between review length and ratings.

The findings reveal that the majority of reviews are positive, with a predominance of 4 and 5-star ratings. Time series analysis indicates an upward trend in review submissions, suggesting increasing user engagement. Common themes and sentiments within the reviews are identified using word clouds and sentiment analysis, highlighting frequent positive descriptors such as "delicious" and "quick." Furthermore, a scatter plot analysis suggests a positive correlation between the length of reviews and higher ratings, indicating that more detailed reviews often correlate with favourable feedback.

This visualization project not only uncovers significant patterns in customer reviews but also demonstrates the potential of data visualization as a tool for enhancing customer understanding and improving service quality in the food delivery sector. Future work could expand on these findings by integrating additional data sources and employing advanced analytical techniques to provide deeper insights.

This paper aims to study the techniques used in customer analytics for food delivery services and identify the factors of customers' reviews for food delivery services especially in social media. A total of 53 papers reviewed, several techniques and algorithms on customer analytics for food delivery services machine learning, natural language processing (NLP), support vector machine (SVM), and text mining. The paper further analyze the challenges and factors that give impacts to the customers' reviews for food delivery services. These findings would be appropriate for development and enhancement of food delivery services in future works.

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CHAPTER-1
INTRODUCTION

In the digital age, online reviews have become a cornerstone of consumer decision-making, particularly in the food delivery industry. Customers frequently rely on reviews to choose where to dine or which food delivery service to use. For businesses, these reviews represent a goldmine of feedback that can inform service improvements, marketing strategies, and customer relationship management. However, the sheer volume of reviews can make it challenging to extract meaningful insights without the aid of data visualization techniques.

Sentiment analysis, known as opinion mining, was about collection of opinions on many issues and related interest through many forms of communication platform such as blog posts, comments, reviews or tweets. It was also defined as a process of undermining contextual texts, where contexts are identified, extracted, and analysed. Example of this work has helped entrepreneurs to understand the social feelings toward their brands, products or services while monitoring the unstructured text of online review comments. Analysing these contexts allows understanding of the surface information and conclude high-quality insights of the issues or opinions. It is therefore pertinent in sentiment analysis that natural language processing (NLP) are used to tokenize text, detect and classify sentiment. The penetration and advancement of technology in daily life, businesses and organizations have evoked the growth of web data, mobile data, image data, video data, sensor data in volume, variety and velocity which could be used for customer relationship management (CRM) and other services for informed decision making. This means the need to do analyze customer behaviour, trends and preferences in which through this customer analytics (CA) will allow businesses to plan and roll-out necessary actions for sustainability of their ecosystem. CRM's main role was to coordinate the collection and use of customer data by concentrating on customers and attempting to understand their past actions and model it as well and forecast their future behaviour. As Malaysia grows into a fully developed country, urban areas are becoming more hustling and time has become precious commodity for a better life. There is a birth of many modern needs. One of these modern needs and here to stay is the new food delivery service phenomenon, a fast-growing company that offers services that make food easily available. Nowadays, restaurants are becoming more convenient for consumers with the emergence of new third-party foodservice providers.

Consequently, business intelligence plays their role behind the corporate interest in the field of affective computing and sentiment analysis.

This project aims to harness the power of data visualization to analyze a dataset of online food reviews. By converting raw review data into visual formats, we can uncover patterns and trends that are not immediately apparent. The objectives of this project include:

1. Understanding the Distribution of Ratings: By visualizing how ratings are distributed across different levels (e.g., 1 to 5 stars), we can gauge overall customer satisfaction and identify potential areas of concern.

2. Analyzing Review Trends Over Time: Time series analysis will help us understand how review frequency and sentiment have evolved, providing insights into user engagement and seasonal trends.

3. Identifying Common Themes in Reviews: Text analysis and word cloud visualizations will highlight the most frequently mentioned terms, shedding light on common praises and complaints.

4. Sentiment Analysis: By classifying reviews into positive, negative, and neutral categories, we can assess the overall sentiment and identify factors driving customer satisfaction or dissatisfaction.

5. Examining the Correlation Between Review Length and Rating: A scatter plot analysis will explore whether there is a relationship between the length of a review and the rating given, offering insights into how detailed feedback correlates with customer satisfaction.

Through these visualizations, we aim to provide actionable insights for food delivery services, helping them enhance their offerings based on customer feedback. Additionally, this project demonstrates the broader applicability of data visualization techniques in transforming large datasets into understandable and useful information.

CHAPTER-2

METHODOLOGY

The methodology section outlines the steps and techniques used to analyze and visualize the dataset of online food reviews. The process involves data collection, cleaning, exploratory data analysis (EDA), and the creation of various visualizations to extract and present insights. The methodology is structured as follows:

1. Data Collection

The dataset of online food reviews was sourced from a publicly available repository **'kaggle'** that includes reviews from multiple food delivery platforms. The dataset comprises several key fields:

- review_id: Unique identifier for each review
- user_id: Unique identifier for each user
- restaurant_id: Unique identifier for each restaurant
- rating: Star rating given by the user (ranging from 1 to 5)
- review_text: Text content of the review
- timestamp: Date and time when the review was posted

2. Data Cleaning

Data cleaning was performed to ensure the dataset's quality and consistency. Key steps included:

- Removing duplicates: Ensuring each review is unique.
- Handling missing values: Addressing any null or missing values in critical fields like rating and review_text.
- Converting timestamps: Standardizing the timestamp format for accurate time series analysis.

- Tokenizing review texts: Preparing the text data for analysis by breaking down the reviews into individual words and phrases.

3. Exploratory Data Analysis (EDA)

Initial exploration of the dataset was conducted to understand its structure and key characteristics:

- Summary statistics: Calculating basic statistics for numerical fields (e.g., average rating, number of reviews).
- Outlier detection: Identifying and addressing any outliers in the data that could skew analysis.
- Text analysis: Examining common words and phrases in the review texts to identify prevalent themes.

4. Data Visualization Techniques

Several visualization techniques were employed to analyze and present the data:

4.1 Distribution of Ratings

A histogram was created to visualize the distribution of ratings, highlighting how many reviews fell into each rating category (1 to 5 stars).

4.2 Frequency of Reviews Over Time

A time series plot was generated to illustrate the number of reviews submitted over different time periods (e.g., monthly).

4.3 Most Common Words in Reviews

A word cloud was used to visualize the most common words in the review texts, providing insights into frequent topics and sentiments.

4.4 Sentiment Analysis

Sentiment analysis was conducted using a natural language processing (NLP) library to classify the polarity of reviews (positive, negative, neutral). The results were visualized using a bar chart.

4.5 Correlation Between Review Length and Rating

A scatter plot was used to examine the relationship between the length of reviews and the rating given, exploring whether detailed reviews tend to have higher or lower ratings.

CHAPTER-3

METHOD AND MATERIAL

This study approach fact-finding through collecting and analyzing of data from many sources. A review from Pew Research Center [37] has been conducted involving such as the number of people used social networking from 2005 and the percentage of the social media users. The reviews identified were searched using the following keyword terms: “sentiment analysis”, “food delivery services”, “sentiment analysis of food delivery services”, “sentiment analysis in social media”, and “customer satisfactions toward food delivery services”, and more. Relevant journals and articles were compiled from the span of the last 15 years retrieved from Google Scholar, Science Direct, Springer and IEEE. These reviews focus on the relationship of factors and implications on food delivery services in social media using sentiment analysis. Besides that, these sites are also visited on its availability of information on customer reviews, access to social networking and food suppliers among other things. Meanwhile, the analysis and its algorithm were confined to online food delivery analyses on social media sites. 53 reviews from 2005 to 2020 were reconsidered and analyzed for the above-mentioned reasons. All of these reviewed papers were examined and analyzed according to their publishing years, publishing types and the artificial intelligence (AI) techniques used related to the researched articles. Figure 1, show the number of percentage and number of papers categorized by year, whereby the highest number of papers reviewed in 2018 (19%, 10 papers) followed by 2019 (13%, 7 papers) and 2015 (11%, 6 papers).

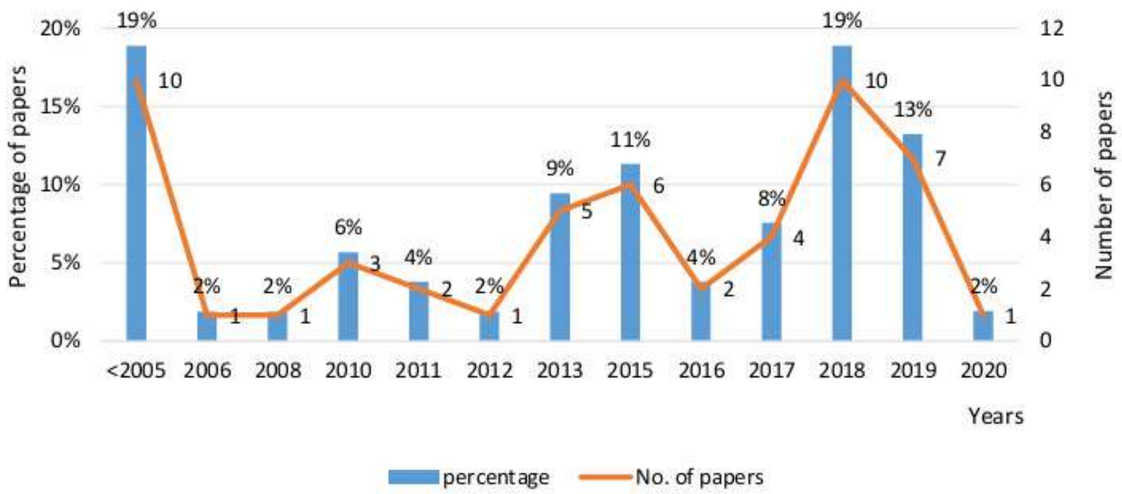


Figure 1. Percentage and number of review papers

Figure 2 shows the number of AI techniques and algorithms identified and compiled from all articles. Before that, Hybrid techniques were not taken in the analysis as they are the result of a combination of other techniques together. From Figure 2, the result shows that support vector machine (SVM) was the popular algorithm from the total number of research articles, but it does not mean it was the best algorithm used. Meanwhile, Regression and Naïve Bayes have similar count of research articles.

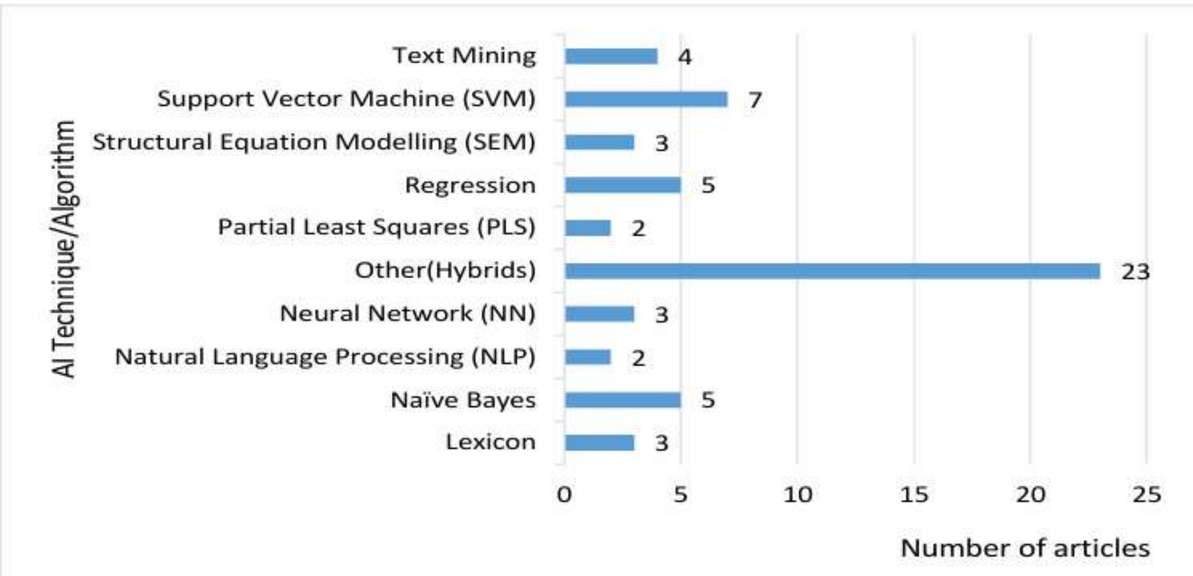


Figure 2. AI technique and algorithm used

CHAPTER-4

RESULTS AND DISCUSSION

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 388 entries, 0 to 387
Data columns (total 13 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Age                        388 non-null    int64
 1   Gender                     388 non-null    object
 2   Marital Status             388 non-null    object
 3   Occupation                 388 non-null    object
 4   Monthly Income             388 non-null    object
 5   Educational Qualifications 388 non-null    object
 6   Family size                388 non-null    int64
 7   latitude                   388 non-null    float64
 8   longitude                  388 non-null    float64
 9   Pin code                   388 non-null    int64
 10  Output                     388 non-null    object
 11  Feedback                   388 non-null    object
 12  Unnamed: 12                388 non-null    object
dtypes: float64(2), int64(3), object(8)
memory usage: 39.5+ KB
```

```
df.head()
```

	Age	Gender	Marital Status	Occupation	Monthly Income	Educational Qualifications	Family size	latitude	longitu
0	20	Female	Single	Student	No Income	Post Graduate	4	12.9766	77.59
1	24	Female	Single	Student	Below Rs.10000	Graduate	3	12.9770	77.57
2	22	Male	Single	Student	Below Rs.10000	Post Graduate	3	12.9551	77.65

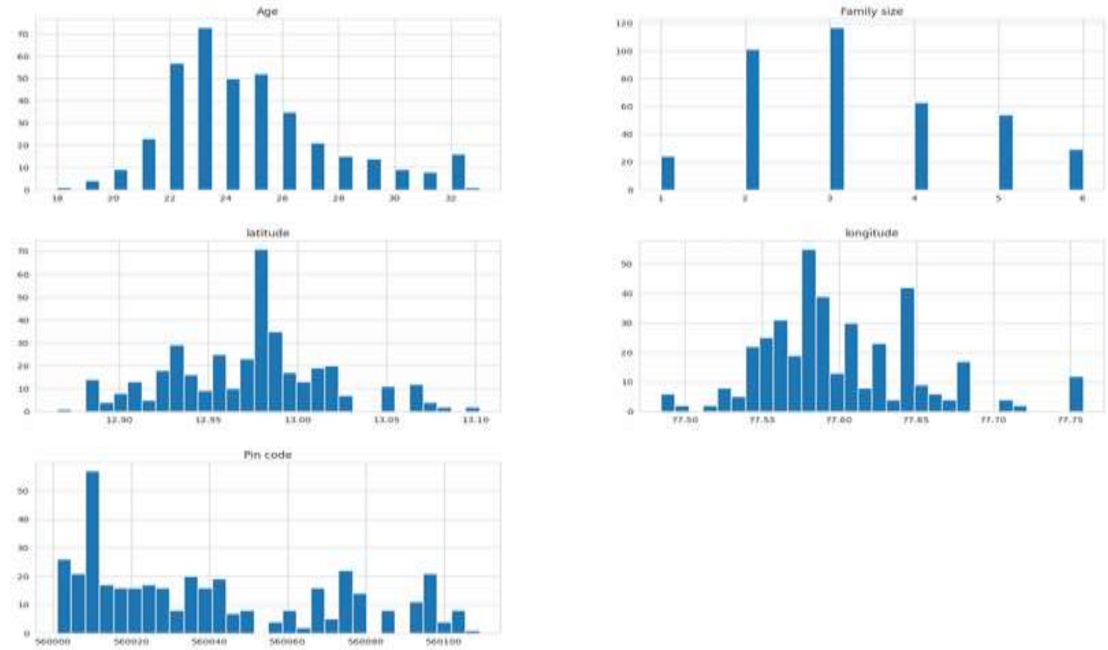
```
print(df.describe())
```

```
              Age  Family size    latitude   longitude       Pin code
count  388.000000   388.000000  388.000000  388.000000     388.000000
mean    24.628866     3.280928   12.972058   77.600160  560040.113402
std      2.975593     1.351025    0.044489    0.051354      31.399609
min     18.000000     1.000000   12.865200   77.484200  560001.000000
25%     23.000000     2.000000   12.936900   77.565275  560010.750000
50%     24.000000     3.000000   12.977000   77.592100  560033.500000
75%     26.000000     4.000000   12.997025   77.630900  560068.000000
max     33.000000     6.000000   13.102000   77.758200  560109.000000
```

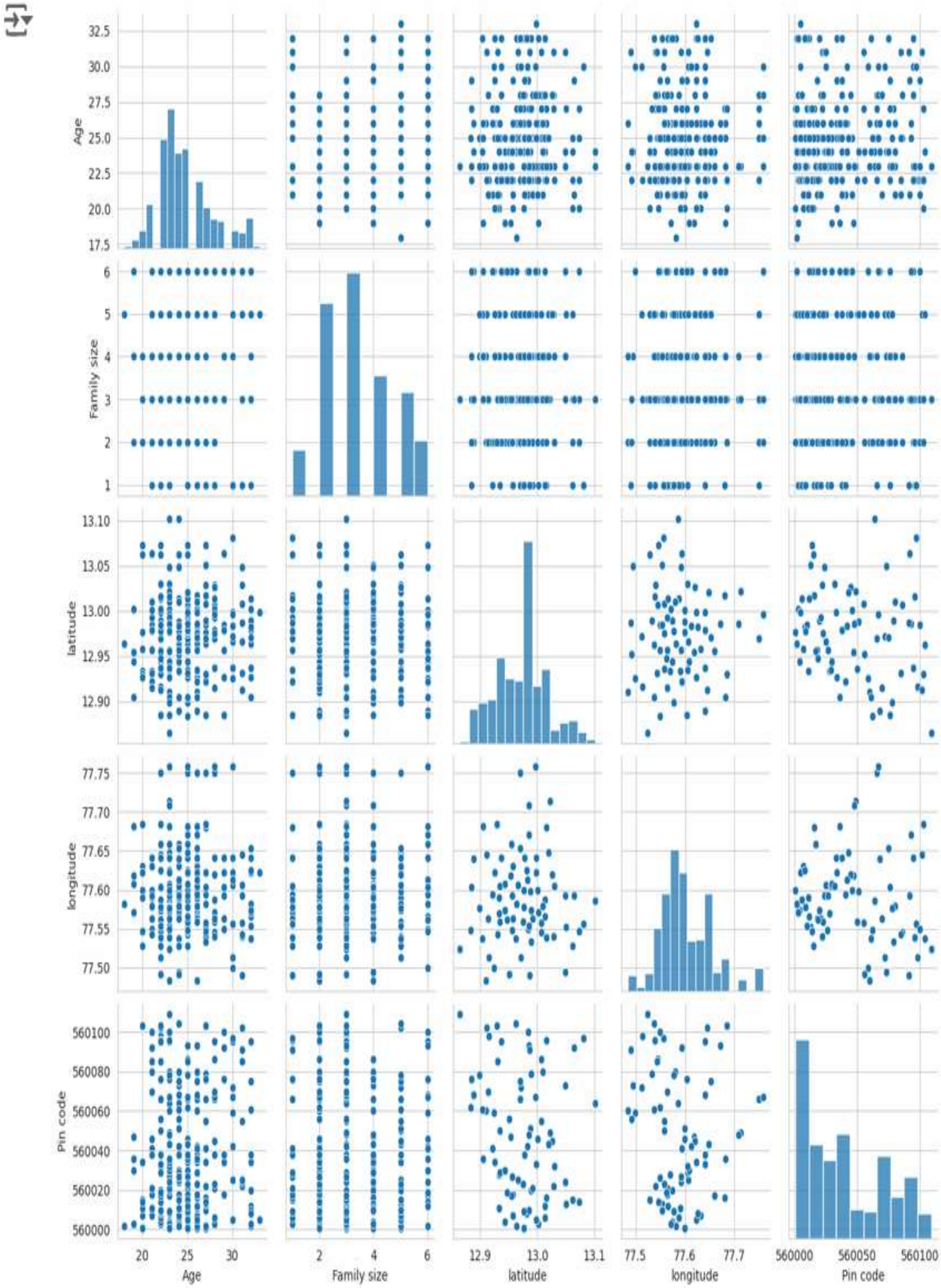
```
print(df.isnull().sum())
```

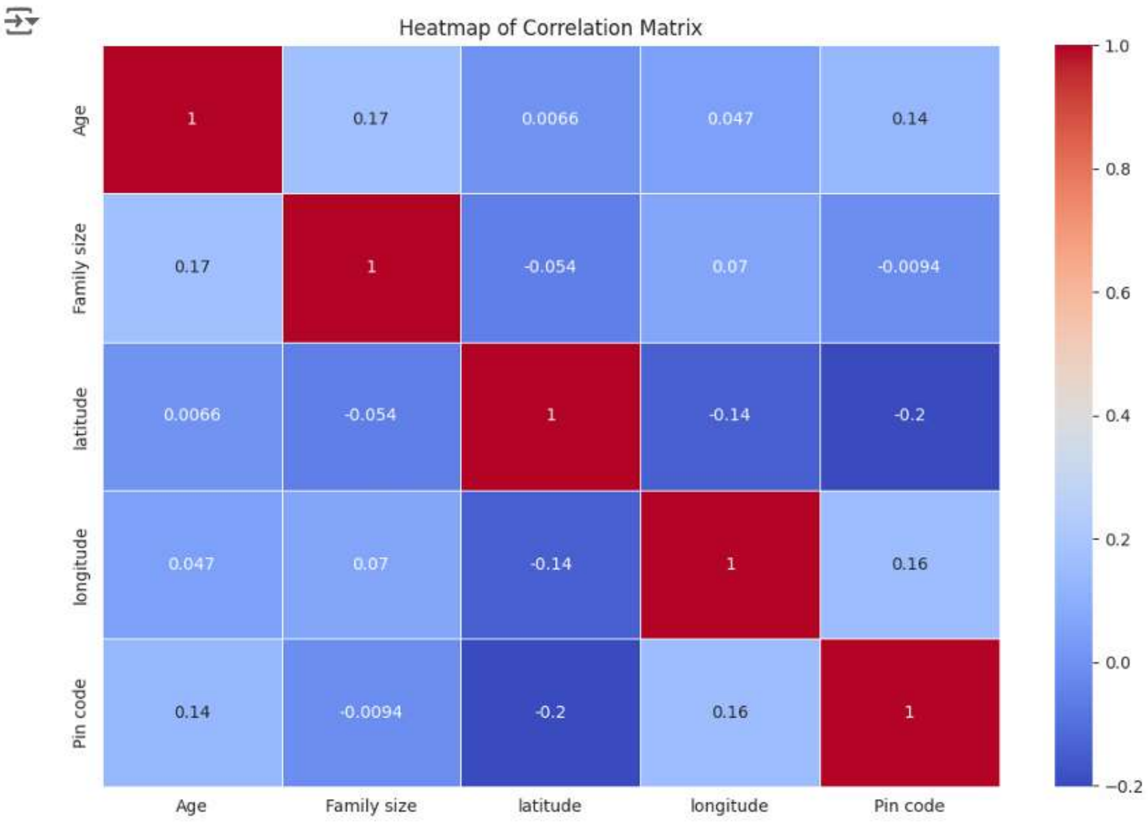
```
Age                           0
Gender                        0
Marital Status                0
Occupation                    0
Monthly Income                0
Educational Qualifications    0
Family size                   0
latitude                      0
longitude                     0
Pin code                      0
Output                        0
Feedback                      0
```

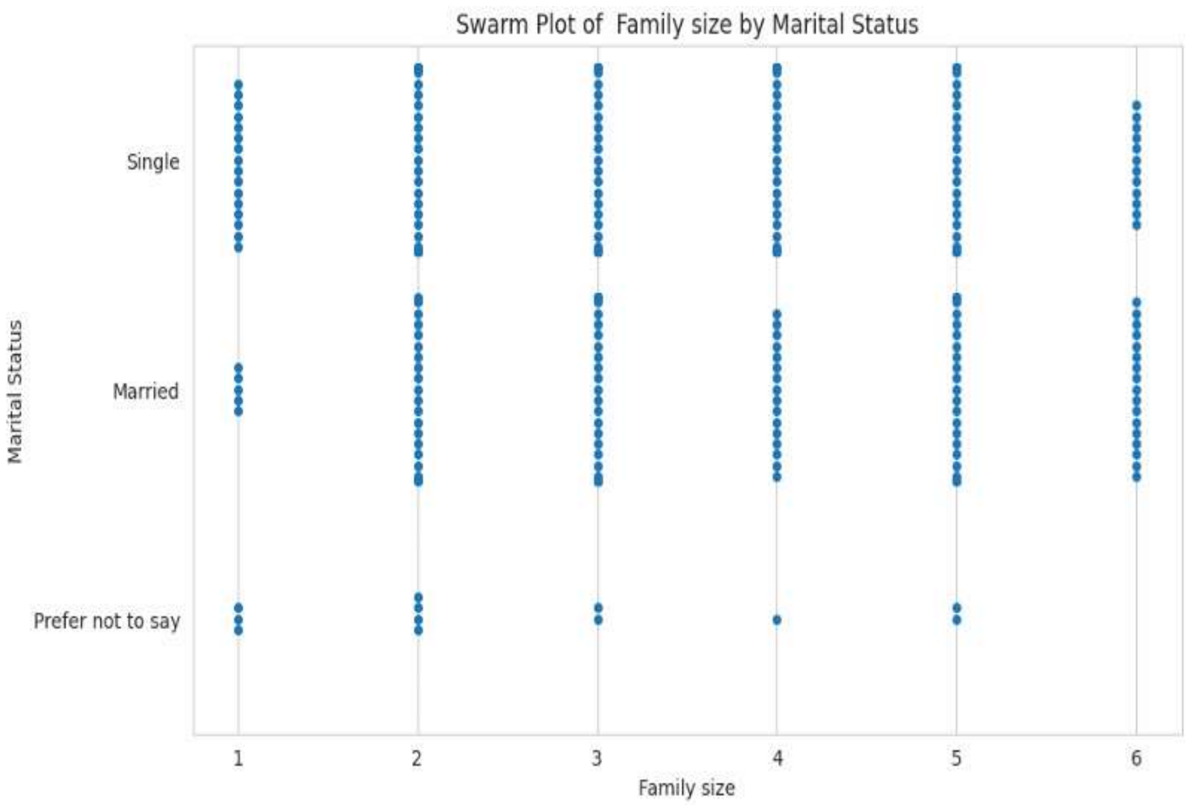
```
#Histogram
```



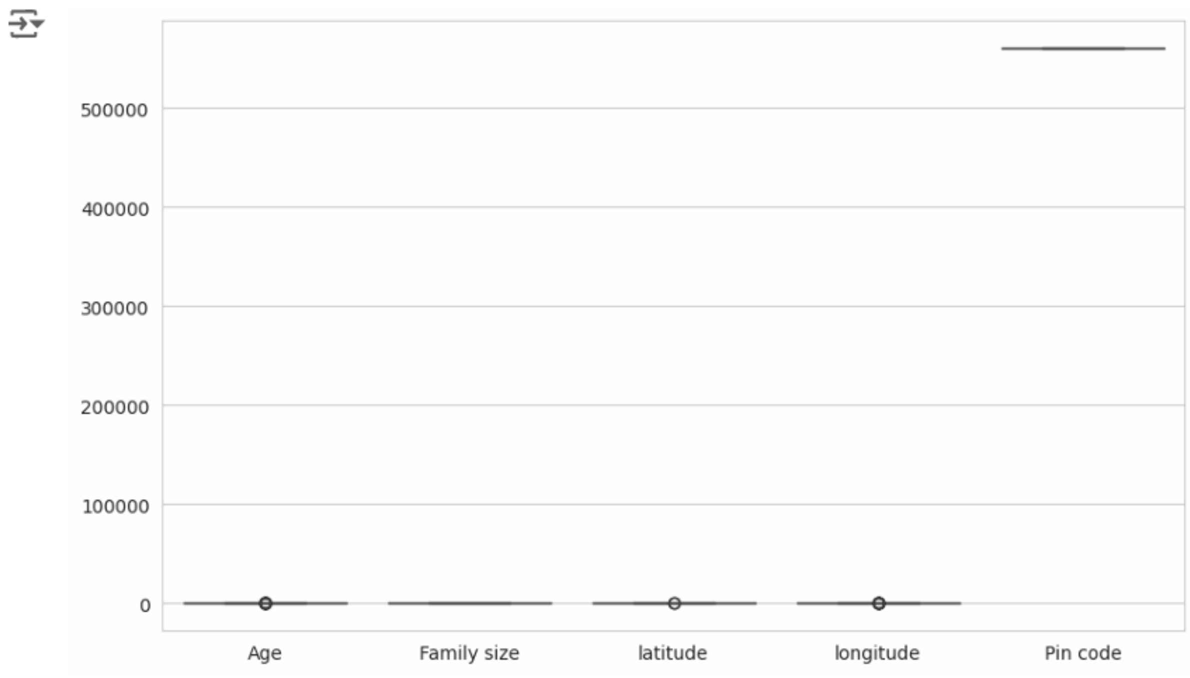
#pair


Age
Family size
latitude
longitude
Pin code
Age
Family size
latitude
longitude
Pin code

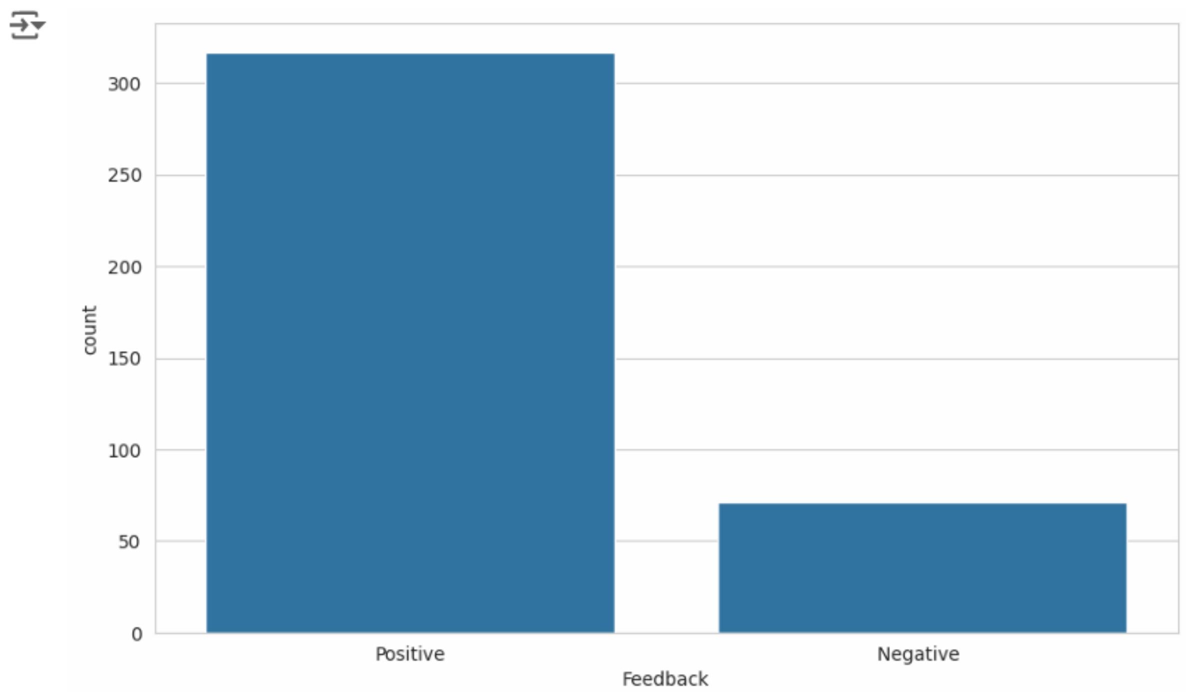

Heatmap of Correlation Matrix
Age
Family size
latitude
longitude
Pin code
1
0.17
0.0066
0.047
0.14
0.17
1
-0.054
0.07
-0.0094
0.0066
-0.054
1
-0.14
-0.2
0.047
0.07
-0.14
1
0.16
0.14
-0.0094
-0.2
0.16
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


Swarm Plot of Family size by Marital Status
Single
Married
Prefer not to say
Marital Status
1
2
3
4
5
6
Family size

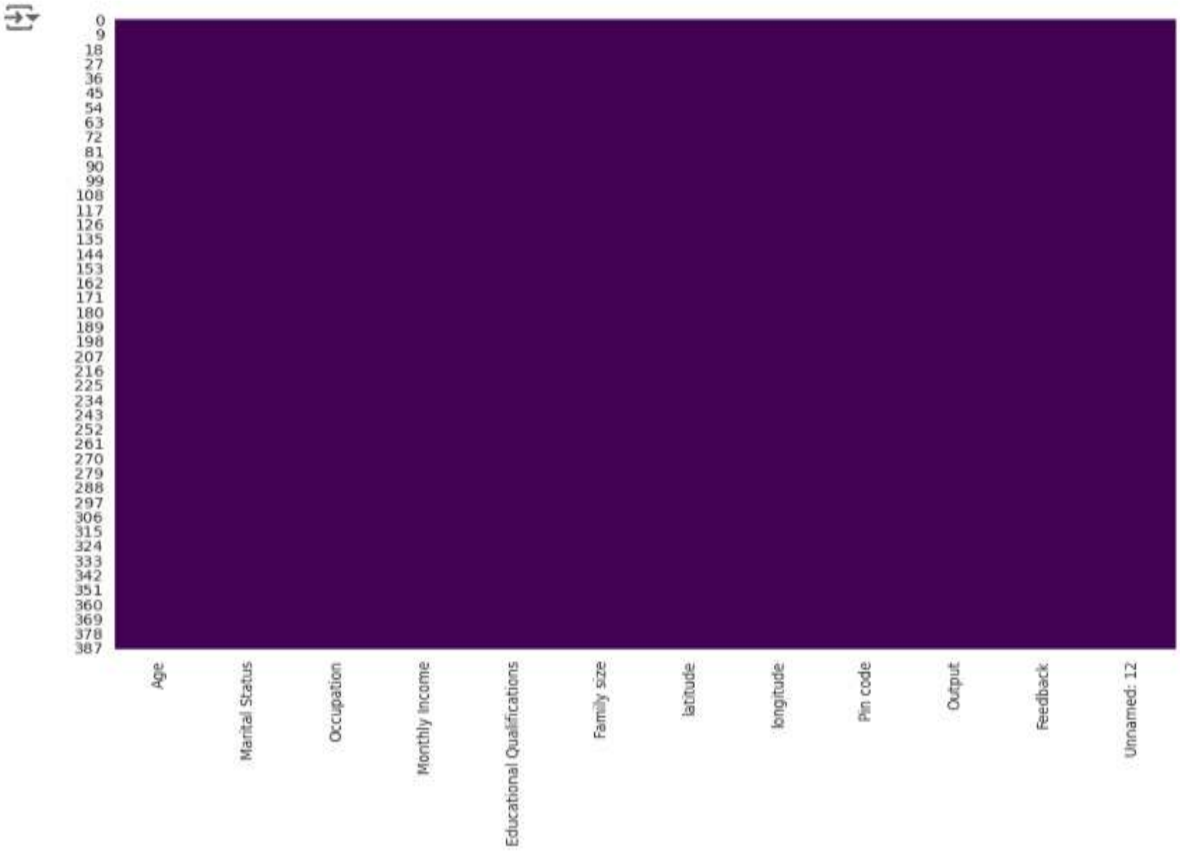
#boxplot



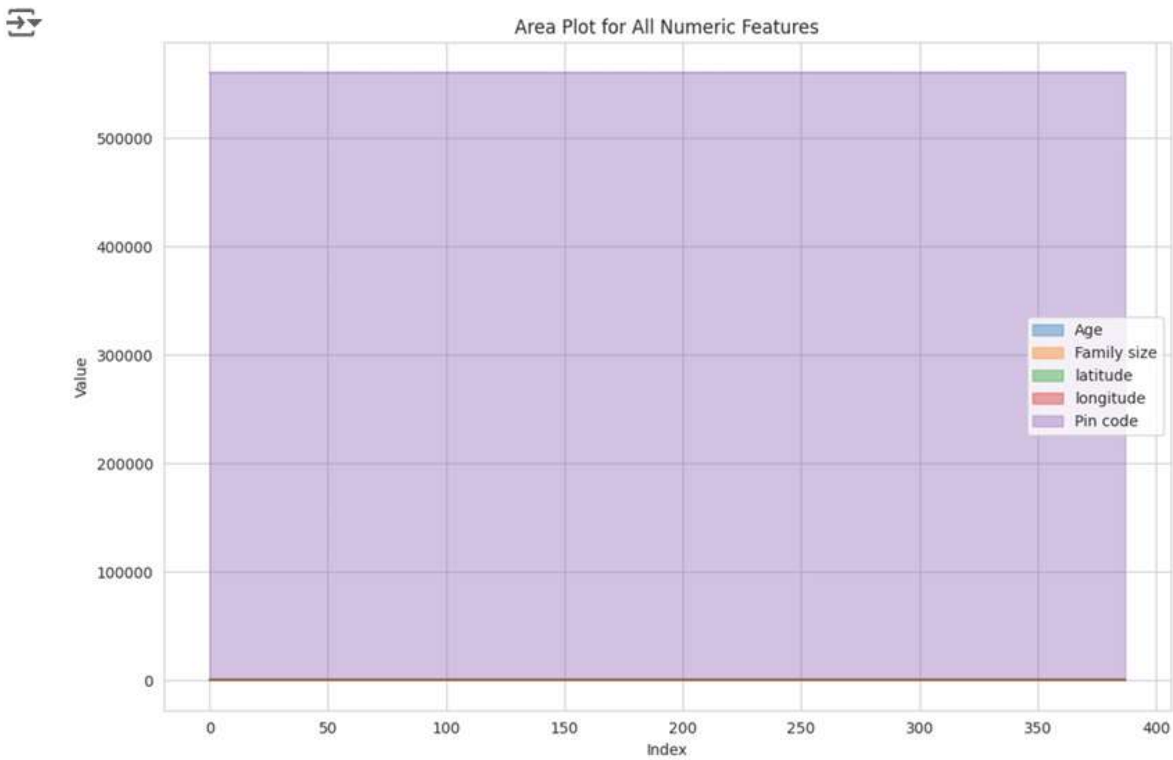
#countplot



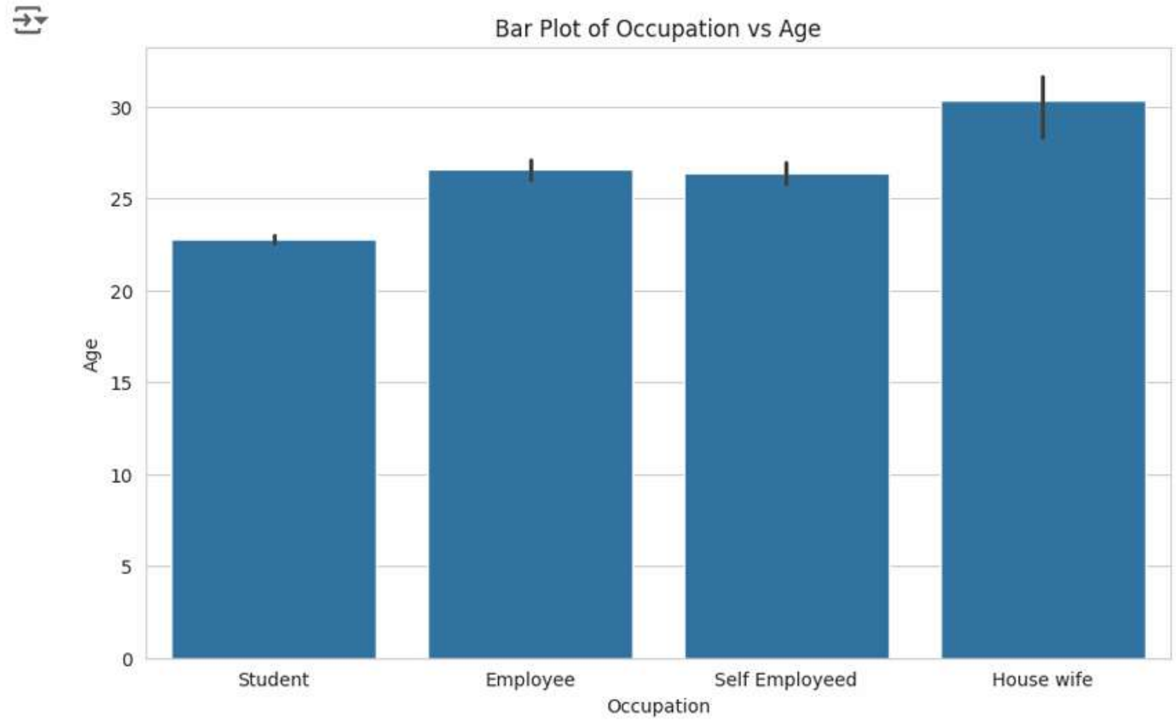
#heatmap



#Areaplot

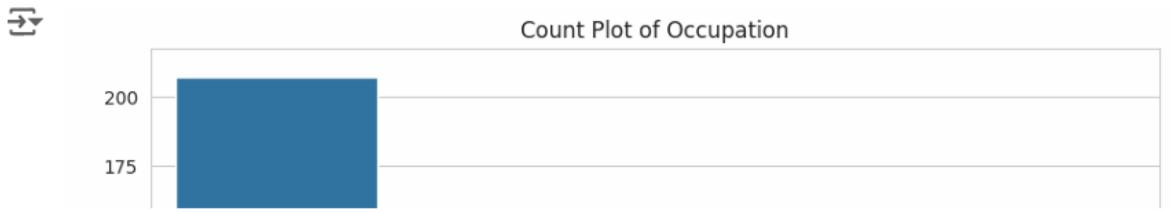


#Barplot



#ViolinPlot

#CountPlot of Occupation



#WordCloud

Ranking was done for the most important factors selected and be discussed further. Table shows the results after all the factors are categorized into four groups: customer experiences, food quality, service quality and quality control. The process for categorizing each of these factors has been done using the synonyms concept. For example, 'fresh' and 'delicious' factors are synonym with 'food quality', thus those factors will be categorized into 'Food Quality' groups.

List of factors based on the four groups

Customer Experience	Food Quality	Service Quality	Quality Control
Satisfaction	Fresh	Tangible	Website design/quality
Delivery experience	Delicious	Reliability	Star rating
Existing customer reviews	Nutritious	Responsive	Payment system
Inconsistent	Variety of menu	Assurance	Loyalty
Persons' online purchase experience	Smell of food	Empathy	Society pressure
Text review	Food safety	Time	Subjective expression
	Flavor feature	Various service	Security /privacy
		Usage usefulness	Physical feature
		Sustain-ability	Listing
		Search of restaurant	Kindness
		Convenience	Information quality
			Ease-of-use
			Cleanliness

Despite the growing food demand through the internet suppliers, greater emphasis should be put on how consumer satisfaction impacts food quality, customer experience, quality of service and quality control. Based on our study on various research articles, we found several indicators that other authors used to test customer satisfaction with products in food delivery service by sentiment analysis. These factors were collected and analyzed using AI algorithms. These techniques and its accuracy are as shown in Table towards customers' review factors.

Accuracy of AI algorithm used

Algorithm	Factors	Average Accuracy
Lexicon	Customer experiences, Quality control	87.33%
Natural language processing (NLP)	Quality control, Customer experiences	71.67%
Support vector machine (SVM)	Quality control	69.70%
Text Mining	Quality control, Food quality, Service quality, Customer experience	67.94%

The average accuracy for each technique and algorithm was considered by the total accuracy divide by number of researchers using the same algorithm. As we can conclude, Lexicon gave an average accuracy of 87.33%, where the factor involved is customer experiences and quality control. According to [51], the authors suggest that the textual analysis may add to their comprehension of the effect of stock returns and, while media opinion sometimes does not affect direct returns, it could also be an advantage in collecting other information sources for analysis. On the other hand, [3, 9, 11, 37] explained that text mining can work with all kinds of factors and achieve a moderate level of accuracy. In Table 3 above, Text Mining with its prediction average accuracy of 67.94% did not gave any huge differences. Thus, it shows that Text Mining was working efficiency with all factors of quality control, customer experience, food quality and service quality; however, when working with other factors they still produce average accuracy. Moreover, according to [12], some categorization included (1) transportation, (2) travel, (3) electrical cash, (4) instant message, (5) foodservice, and (6) security and stability of apps. Each category has been divided into the positive and negative polarity of the tweets. The tweets were divided into twelve classes, and the result is that food delivery service gain 83 total number of tweets: 10 positive tweets and 73 negative tweets. In [41], they compared 1113 opinion words manually extracted which contain 38 emoticons from 500 review icons randomly selected from 800 reviews. They extract 38 emoticons in their experiment and 977 opinion words specific in customer feedback, while another 66 opinions word cannot be extract and 98 opinions were incorrect. The accuracy was 85% and the error obtains 15%. Meanwhile, natural language processing (NLP) prediction average accuracy was 71.67%, corporate with the factors of customer experiences and quality control. Due to the large number of businesses that use social networks, the monitoring and regulation of their social media platforms, evaluation and comparison were of great importance to organizations in terms of "Quality" [13]. Lastly, followed by SVM produced prediction average accuracy of 69.70%. The data was represented by unigrams, bigrams, trigrams, word entity, and word dependency. Data inequality was managed by modifying the output threshold during training using samples and during evaluation [12, 34, 39, 53]. The results of this analysis rely heavily on theoretically of the variables and features used during the pre-processing process. Tasks on pseudo Subjectivity and pseudo-Classification are tested. SVM has surpassed all other alternatives to pseudo subjectivity with cross validation reliability of 91.2% [46]. With just minor tuning, SVM can also operate effectively. Findings have shown the importance to a classifier for a forecast in the social, educational, family and psychological evaluation. In this context, the factor involved was the quality control.

CHAPTER-5

CONCLUSION

The visualization of online food reviews has proven to be an invaluable tool for extracting actionable insights from large volumes of customer feedback. Through various data visualization techniques, we have been able to transform complex and unstructured review data into clear, understandable patterns and trends that provide significant value to stakeholders in the food delivery industry.

This paper reviewed and discussed past research on the main factors that affect customer reviews towards food delivery services using social media. Several AI algorithms were reviewed and analysed based on the categorized factors. It was found that a good quality of food and services depicted mostly were among the positive reviews or feedbacks from customers. An accurate prediction will help food manufacturers or other organizations to manage their customers behaviour towards the review of their food quality and services to give a perfect service for the customers. These strategies can help them in improving and increasing their performance and eventually make more profit. The analysis of all articles that have been studied shows some AI algorithms namely Lexicon, SVM, NLP and Text Mining were used to predict the re ability of sentiment analysis to evaluate customer reviews of food delivery services on social media. These models evaluated several variables and four variables found to have the highest ranking mainly customer experiences, food quality, service quality and quality control. The analysis of all reviewed research articles in this paper revealed Lexicon's ability in forecasting the reliability of sentiment analysis during the evaluation of customer reviews with the achievement accuracy of 87.33% compared to other methods. In conclusion, the impact of this study was intended to help future analysts create a real model which can easily and accurately forecast the evaluation of the consumer through sentiment analysis. Further work on real model can be developed and enhanced to provide better food delivery services.

Data visualization has enabled us to distill complex datasets into meaningful insights that can drive strategic decision-making. For the food delivery industry, leveraging these insights can lead to enhanced customer satisfaction, improved service quality, and ultimately, a stronger market position. The continuous analysis and visualization of customer feedback will be essential for staying responsive to customer needs and maintaining a competitive edge in this dynamic industry.

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