

# **Jaypee Institute of Information Technology, Noida**

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING AND INFORMATION  
TECHNOLOGY



**Project Title:** Yelp Review Analysis

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## **1. ABSTRACT:**

In the digital age, where information is at our fingertips, online reviews have become a powerful influence on consumer decisions. Review analysis, the systematic examination of user-generated feedback, has emerged as a crucial aspect of understanding customer sentiments, preferences, and overall satisfaction. This practice involves employing various techniques, often rooted in natural language processing and machine learning, to extract valuable insights from the vast pool of reviews available on the internet.

Review analysis provides a panoramic view of how products, services, or experiences are perceived by the public. In e-commerce, for instance, potential buyers heavily rely on reviews to gauge the quality and reliability of a product. Similarly, in the realm of hospitality, restaurants, hotels, and other establishments thrive or falter based on the feedback they receive. Review analysis enables businesses to comprehend the dynamics of customer satisfaction, identify areas of improvement, and capitalize on strengths.

Review analysis empowers businesses to adopt a customer-centric approach. By delving into the language and sentiments expressed in reviews, companies can gain a nuanced understanding of their customers' needs and expectations. This information is invaluable for refining existing products, introducing new features, or tailoring services to align with customer preferences. In essence, it facilitates a continuous feedback loop that fosters adaptive and customer-focused decision-making.

In a competitive market, staying ahead requires more than just a quality product; it demands a comprehensive understanding of the market landscape. Review analysis equips businesses with the tools to benchmark their performance against competitors. By studying the strengths and weaknesses highlighted in reviews, companies can strategically position themselves, identify unique selling propositions, and differentiate their offerings in the market.

Review analysis is not merely retrospective; it extends to predictive analytics. By identifying patterns in historical reviews, businesses can anticipate trends and forecast customer preferences. This foresight is invaluable for staying agile in a rapidly evolving market, enabling companies to proactively adapt to changing consumer expectations and emerging industry trends.

In the decision-making hierarchy of modern businesses, data-driven insights hold a paramount position. Review analysis contributes to evidence-based decision-making by providing a rich source of qualitative and quantitative data. Whether it's fine-tuning marketing strategies, optimizing customer service protocols, or refining product development, reviews offer a treasure trove of actionable intelligence.

## **2. INTRODUCTION:**

### **2.1. PROBLEM STATEMENT**

In the realm of culinary entrepreneurship, the decision to open a restaurant is multifaceted, with location playing a pivotal role in determining success. This project aims to leverage advanced data analysis techniques on a cleaned and processed dataset containing restaurant reviews to provide actionable insights for prospective restaurant owners. The focus is on advising whether a given location within the city is conducive to establishing a new restaurant.

### **2.2. MOTIVATION**

The motivation behind undertaking this project stems from the recognition of the challenges faced by aspiring restaurant owners and investors in the highly competitive and dynamic hospitality industry. Establishing a restaurant involves a myriad of decisions, with one of the most critical being the choice of location. This project seeks to empower individuals in the culinary domain with data-driven insights, transforming the traditionally intuition-based decision-making process into a more informed and strategic endeavor.

- ❖ **Enhancing Decision-Making:** The project recognizes the limitations of subjective decision-making in the context of restaurant establishment. By applying advanced analytical techniques to the dataset, it seeks to enhance decision-making processes, offering stakeholders a more comprehensive and objective evaluation of potential locations. In doing so, the project aligns with the broader trend of embracing data-driven strategies in various industries.
- ❖ **Addressing Industry Challenges:** The restaurant industry is constantly evolving, influenced by factors such as changing consumer preferences, economic fluctuations, and global events. This project aims to address the dynamic nature of the industry by providing actionable insights derived from a thorough analysis of restaurant reviews. By understanding current trends and sentiments, entrepreneurs can position themselves strategically in the market.
- ❖ **Facilitating Entrepreneurship:** Encouraging entrepreneurship in the culinary sector is a key motivation. By offering valuable information on popular cuisines, successful restaurant types, and economically viable locations, the project serves as a catalyst for individuals aspiring to enter the restaurant business. This aligns with the broader goal of fostering innovation and diversity in the entrepreneurial landscape.

## **2.3. OBJECTIVE**

- ❖ **Sentiment Analysis:** Conduct sentiment analysis on the reviews to gauge the overall sentiment towards restaurants in different locations. Understand the prevailing sentiments, both positive and negative, to assess the general perception of dining establishments.
- ❖ **Identifying Popular Cuisines and Dishes:** Analyze the dataset to identify the most popular cuisines and dishes among customers. This information can guide menu planning for a new restaurant, ensuring alignment with local preferences.
- ❖ **Comparative Analysis of Ratings:** Compare and contrast the ratings and reviews of existing restaurants in various locations. Determine if there are particular areas with a higher concentration of well-rated establishments, indicating a potentially favorable environment for a new restaurant.
- ❖ **Correlation with Economic Factors:** Explore any correlations between the economic factors of a location and the success of restaurants. Factors such as the average cost for two people, the type of restaurant, and customer reviews could provide insights into the economic viability of opening a new establishment.
- ❖ **Spatial Analysis:** Utilize spatial analysis to map out restaurant distribution across the city. Identify clusters or gaps in restaurant availability, helping to pinpoint areas with untapped market potential.

## **3. DETAILED DESCRIPTION OF THE PROJECT:**

### **3.1. PROPOSED WORK WITH TOOLS AND DATASETS USED**

In this project, Jupyter Notebook served as the primary software for performing data analysis using Python. Employing essential libraries such as scikit-learn (sklearn), matplotlib, seaborn, pandas, and numpy, we executed robust data cleaning procedures. The dataset underwent thorough preprocessing to ensure its readiness for analysis. Leveraging the SVM (Support Vector Machine) machine learning algorithm, we performed insightful analysis on the cleaned data. Visualizations, crafted with matplotlib and seaborn, provided a clear and intuitive representation of key patterns and trends, enhancing the interpretability of the dataset and contributing to the overall efficacy of the project.

**Software Requirement:**

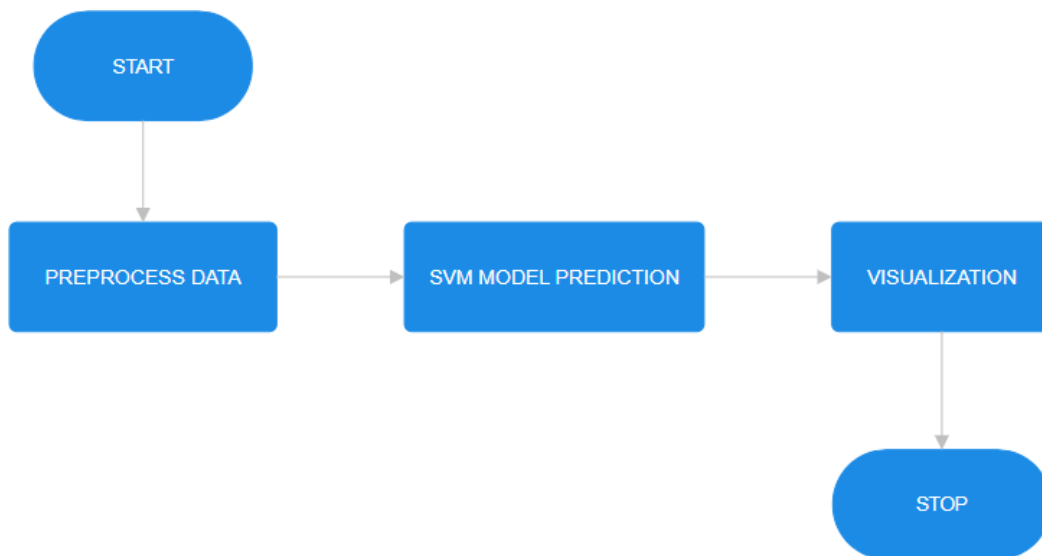
- ❖ Anaconda environment
- ❖ Jupyter Notebook

**Language Used:**

- ❖ Python

**Dataset Used:**

<https://www.kaggle.com/datasets/himanshupoddar/zomato-bangalore-restaurants>

**3.2. WORKFLOW DIAGRAM****4. IMPLEMENTATION:****4.1. PROGRAM CODE**

```
#!/usr/bin/env python
# coding: utf-8
# In[270]:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, roc_curve
plt.style.use('dark_background')
```

```
# In[271]:

df=pd.read_csv('zomato.csv')
df.head()

# In[272]:

df.shape

# In[273]:

df.columns

# In[274]:

df=df.drop(['url','address','phone','menu_item','dish_liked','reviews_list'],axis=1)
df.head()

# In[275]:

df.info()

# In[276]:

df.drop_duplicates(inplace=True)
df.shape

# In[277]:

df['rate'].unique()

# In[278]:

def handlerate(value):
    if(value=='NEW' or value=='-'):
        return np.nan
    else:
        value=str(value).split('/')
        value=value[0]
```

```

        return float(value)

df['rate']=df['rate'].apply(handlerate)
df['rate'].head()

# In[279]:

df.rate.isnull().sum()

# In[280]:

df['rate'].fillna(df['rate'].mean(),inplace=True)
df['rate'].isnull().sum()

# In[281]:

df.info()

# In[282]:

df.dropna(inplace=True)
df.head()

# In[283]:

df.rename(columns={'approx_cost(for two
people)':'cost2plates','listed_in(type)':'type'},inplace=True)
df.head()

# In[284]:

df['location'].unique()

# In[285]:

df['listed_in(city)'].unique()

# In[286]:

df = df.drop(['listed_in(city)'], axis=1)
df.columns

```



```

# In[287]:

df['cost2plates'].unique()

# In[288]:

def handlecomma(value):
    value=str(value)
    if ',' in value:
        value=value.replace(',','')
        return float(value)
    else:
        return float(value)

df['cost2plates']=df['cost2plates'].apply(handlecomma)
df['cost2plates'].unique()

# In[289]:

df.head()

# In[290]:

df['rest_type'].value_counts()

# In[291]:

rest_types=df['rest_type'].value_counts()
rest_types

# In[292]:

rest_types_lessthan1000=rest_types[rest_types<1000]
rest_types_lessthan1000

# In[293]:

def handle_rest_type(value):
    if(value in rest_types_lessthan1000):
        return 'others'
    else:
        return value

```

```
df['rest_type']=df['rest_type'].apply(handle_rest_type)
df['rest_type'].value_counts()
```

```
# In[294]:
```

```
df.head()
```

```
# In[295]:
```

```
df['location'].value_counts()
```

```
# In[296]:
```

```
location=df['location'].value_counts()
location_lessthan300=location[location<300]
```

```
def handle_location(value):
    if(value in location_lessthan300):
        return 'others'
    else:
        return value
```

```
df['location']=df['location'].apply(handle_location)
df['location'].value_counts()
```

```
# In[297]:
```

```
df.head()
```

```
# In[298]:
```

```
df['cuisines'].value_counts()
```

```
# In[299]:
```

```
cuisines=df['cuisines'].value_counts()
cuisines_lessthan100=cuisines[cuisines<100]
```

```
def handle_cuisines(value):
    if(value in cuisines_lessthan100):
        return 'others'
    else:
        return value
```

```

df['cuisines']=df['cuisines'].apply(handle_cuisines)
df['cuisines'].value_counts()

# In[300]:

df.head()

# In[301]:

vectorizer = CountVectorizer()
X = vectorizer.fit_transform(df['cuisines'])

y = df['rate'] > 4

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

svm = SVC()
svm.fit(X_train, y_train)

y_pred = svm.predict(X_test)

accuracy_score(y_test, y_pred)

# In[302]:

df['type'].value_counts()

# In[303]:

location_counts = df['location'].value_counts()

plt.figure(figsize=(16,10))
sns.barplot(x=location_counts.index, y=location_counts.values)
plt.xticks(rotation=90)
plt.show()

# In[304]:

df['online_order']

# In[305]:

online_orders = df['online_order'].value_counts()
online_orders.plot(kind='bar',color=['blue', 'magenta'])

```

```

plt.title("Online Order Distribution")
plt.xlabel("Ordered Online?")
plt.ylabel("Count")
plt.show()

# In[306]:

book = df['book_table'].value_counts()

plt.figure(figsize=(6,6))
sns.barplot(x=book.index, y=book.values)
plt.xticks(rotation=90)
plt.show()

# In[307]:

plt.figure(figsize=(6,6))
sns.boxplot(x='online_order',y='rate',data=df)

# In[308]:

plt.figure(figsize=(6,6))
sns.boxplot(x='book_table',y='rate',data=df)

# In[309]:

df1=df.groupby(['location','online_order'])['name'].count()
df1.to_csv('location_online.csv')
df1=pd.read_csv('location_online.csv')
df1=pd.pivot_table(df1,values=None,index=['location'],columns=['online_order']
,fill_value=0,aggfunc=np.sum)
df1

# In[310]:

df1.plot(kind='bar',figsize=(15,8))

# # Book Table vs Location

# In[311]:

df2=df.groupby(['location','book_table'])['name'].count()
df2.to_csv('location_booktable.csv')
df2=pd.read_csv('location_booktable.csv')

```

```

df2=pd.pivot_table(df2,values=None,index=['location'],columns=['book_table'],fill_value=0,aggfunc=np.sum)
df2

# In[312]:

df2.plot(kind='bar',figsize=(15,8))

# # Type of Restaurant vs Rate

# In[313]:

plt.figure(figsize=(14,8))
sns.boxplot(x='type',y='rate',data=df,palette='inferno')

# # Type of Restaurant vs Location

# In[314]:

df3=df.groupby(['location','type'])['name'].count()
df3.to_csv('location_type.csv')
df3=pd.read_csv('location_type.csv')
df3=pd.pivot_table(df3,values=None,index=['location'],columns=['type'],fill_value=0,aggfunc=np.sum)
df3

# In[315]:

df3.plot(kind='bar',figsize=(36,8))

# # No. of votes vs Location

# In[316]:

df4=df[['location','votes']]
df4.drop_duplicates()
df5=df4.groupby(['location'])['votes'].sum()
df5=df5.to_frame()
df5=df5.sort_values('votes',ascending=False)
df5.head()

# In[317]:

plt.figure(figsize=(15,8))
sns.barplot(x=df5.index,y=df5['votes'])

```

```
plt.xticks(rotation=90)

# In[318]:

df6=df[['cuisines','votes']]
df6.drop_duplicates()
df7=df6.groupby(['cuisines'])['votes'].sum()
df7=df7.to_frame()
df7=df7.sort_values('votes',ascending=False)
df7.head()

# In[319]:

df7=df7.iloc[1:,:]
df7.head()

# In[320]:

plt.figure(figsize=(15,8))
sns.barplot(x=df7.index,y=df7['votes'])
plt.xticks(rotation=90)
```

## 4.2. RESULT ANALYSIS

From figure 1, we can see that BTM location in the city has most number of restaurants whereas St. Marks Road has the least. One should open a restaurant in an area with less number of restaurants like Old Airport Road.

From figure 4, we can see that the restaurants that offer online ordering have higher ratings as compared to the ones that don't.

From figure 5, we can see that the restaurants that offer table booking have higher ratings as compared to the ones that don't.

From figure 6, we can conclude that opening a restaurant in areas where there are less restaurants offering online order will prove beneficial.

From figure 7, we can conclude that opening a restaurant in areas where there are less restaurants offering table booking will prove beneficial.

From figure 8, we can see that 'Drinks & nightlife' and 'Pubs and bars' have the highest average ratings.

From figure 9, we can see that, for example, opening 'Drinks & nightlife' type restaurant in 'Commercial Street' would prove beneficial as there are not such restaurants in that location.

From figure 11, we can see that North Indian, Chinese and South Indian cuisine restaurants have the most votes. Restaurants serving these cuisines can benefit a lot.

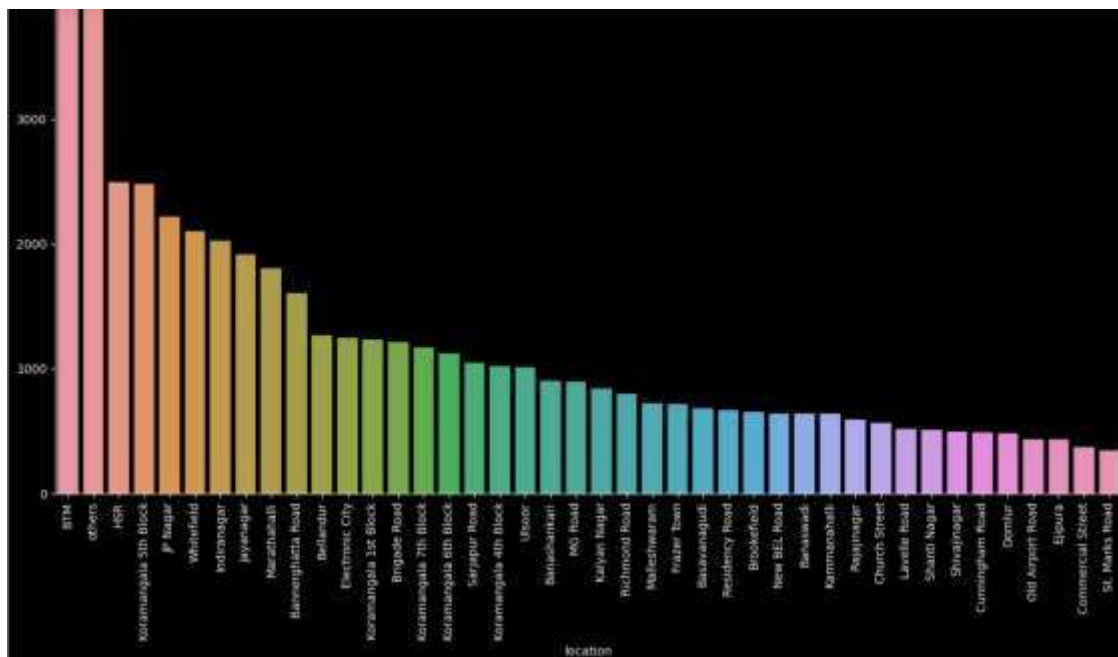


Fig 1. Number of restaurants in a location

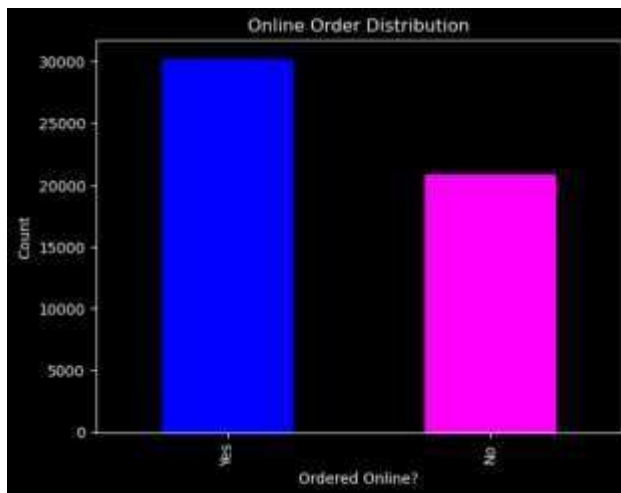


Fig 2. Number of restaurants offering online order

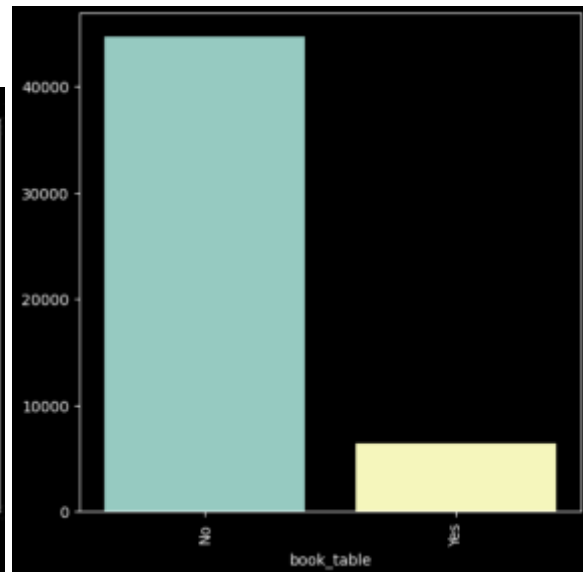


Fig 3. Number of restaurants offering table booking

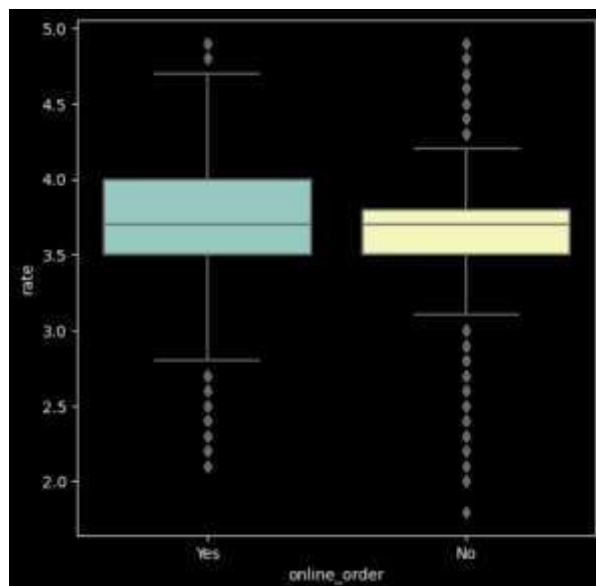


Fig 4. Rating vs Online order

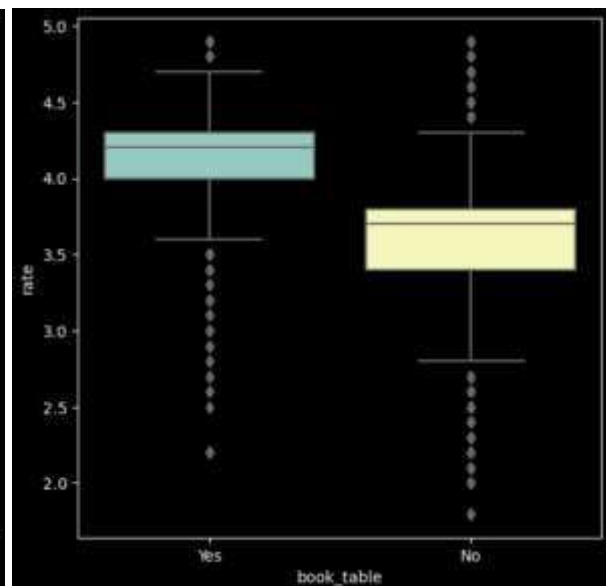


Fig 5. Rating vs Book table



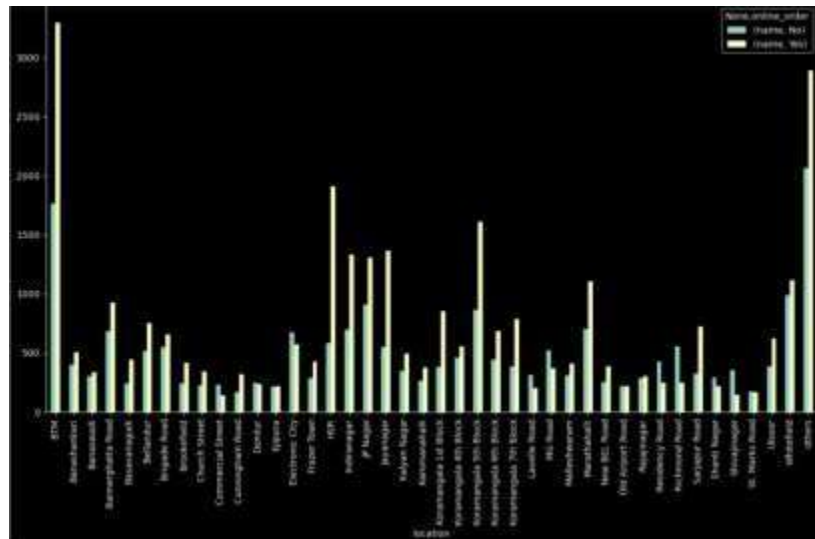


Fig 6. Location vs Online order of restaurants in a location

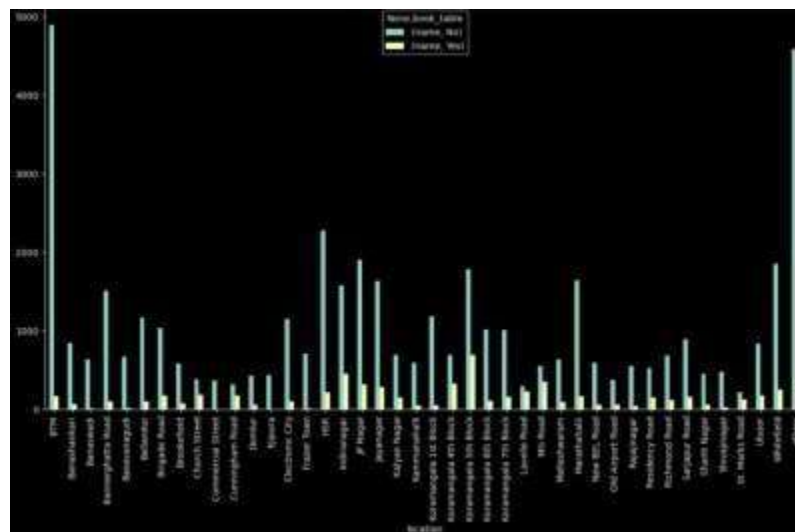


Fig 7. Location vs Book table

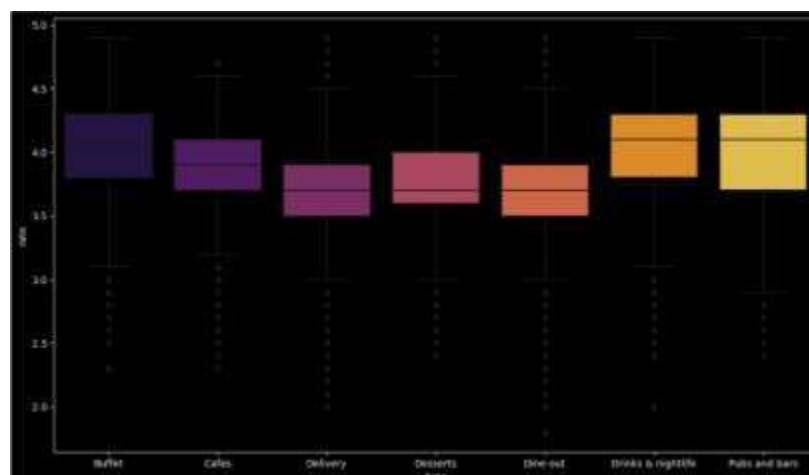


Fig 8. Type of restaurant vs Rate

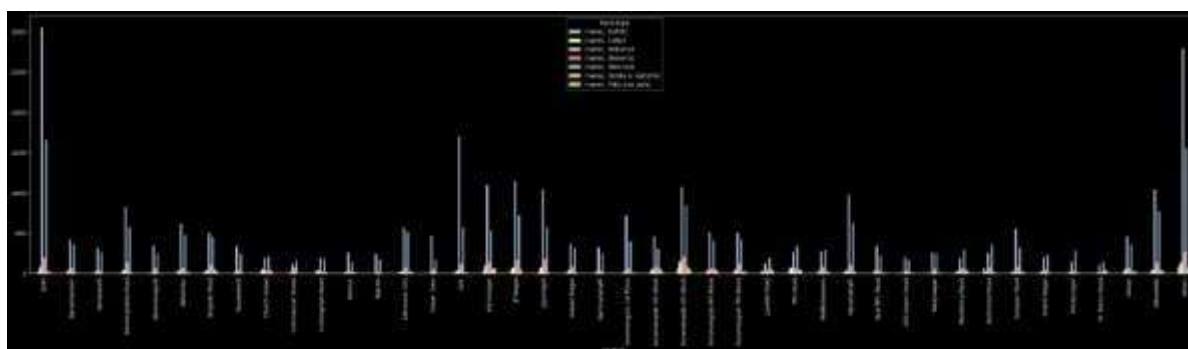


Fig 9. Type of restaurant vs Location

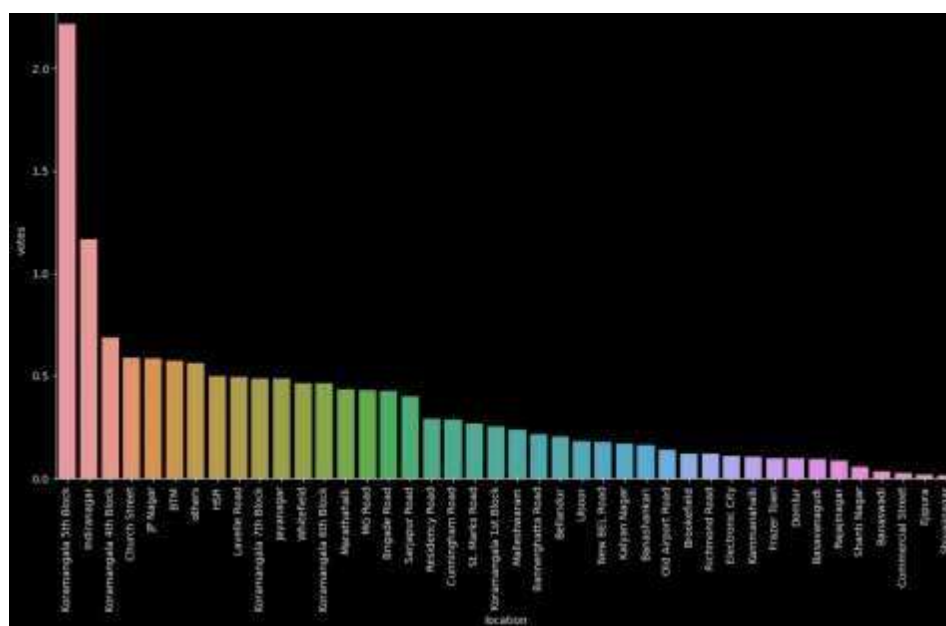


Fig 10. Number of votes vs Location

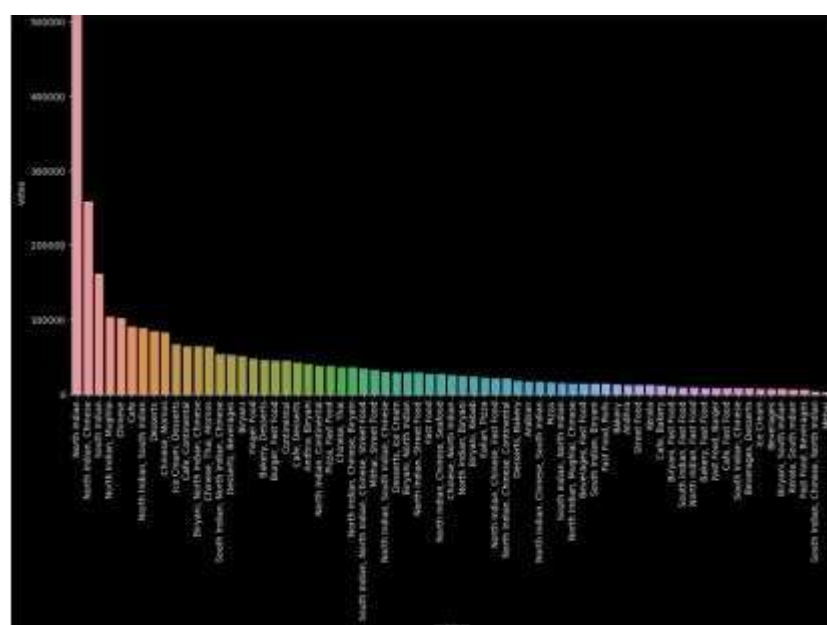


Fig 11. Cuisines vs Votes

Table 1. First few records of the dataset

1	url	address	name	online_order	booked_table	rate	votes	phone	location	rest_type	dish_liked	cuisines	approx_reviews	list_menu_items	listed_in	city
2	https://www.942, 21st Mai	Jaha	Yes	Yes	4.1/5	775	080	Banashankari	Casual Dining	Pasta, Lunch	North India	800	["Rated 4.1"]	Buffet	Banashankari	
3	https://www.2nd Floor, 90	Spice Elepha	Yes	No	4.1/5	787	080 41714	Banashankari	Casual Dining	Momos, Lun	Chinese, No	800	["Rated 4.1"]	Buffet	Banashankari	
4	https://www.1112, Next to	San Churro	C Yes	No	3.8/5	918	+91 96634	Banashankari	Cafe, Casual	D Churros, Car	Cafe, Mexic	800	["Rated 3.1"]	Buffet	Banashankari	
5	https://www.1st Floor, Ann	Addhuri Udu	No	No	3.7/5	88	+91 96200	Banashankari	Quick Bites	Masala Dosa	South India	300	["Rated 4.1"]	Buffet	Banashankari	
6	https://www.10, 3rd Floor,	Grand Village	No	No	3.8/5	166	+91	Basavanagur	Casual Dining	Panipuri, Gol	North India	600	["Rated 4.1"]	Buffet	Banashankari	
7	https://www.37, 5-1, 4th	Fi Timepass	Dir	Yes	No	3.8/5	286	+91	Basavanagur	Casual Dining	Onion Rings,	North India	600	["Rated 3.1"]	Buffet	Banashankari
8	https://www.19/1, New	Tin Resaswood	In No	No	3.6/5	8	+91	Mysore Road	Casual Dining		North India	800	["Rated 5.1"]	Buffet	Banashankari	
9	https://www.2669, 3rd	Floor Onesta	Yes	Yes	4.6/5	2556	080	Banashankari	Casual Dining	Farmhouse I	Pizza, Cafe,	600	["Rated 5.1"]	Cafes	Banashankari	
10	https://www.1, 30th	Main I Penthouse	C Yes	No	4.0/5	324	+91	Banashankari	Cafe	Pizza, Mock,	Cafe, Italian	700	["Rated 3.0", "Rated 5.1"]		Banashankari	
11	are a bit pric things tend	to service was			Rated 4.1											
12	https://www.2870, 21	Mair Smacnago	Yes	No	4.2/5	504	+91	Banashankari	Cafe	Waffles, Past	Cafe, Mexic	550	["Rated 4.1"]	Cafes	Banashankari	
13	https://www.12, 29	Near PE Cal	A/A/A/ Yes	No	4.1/5	402	080	Banashankari	Cafe	Waffles, Past	Cafe	500	["Rated 4.1"]	Cafes	Banashankari	
14	https://www.941, 3rd	FLOOR Cafe	Shuffle	Yes	Yes	4.2/5	150	+91 97421	Banashankari	Cafe	Mocktails, Pi	Cafe, Italian	600	["Rated 1.1"]	Cafes	Banashankari
15	https://www.6th	Block, 3rd	The Coffee	S Yes	Yes	4.2/5	164	+91 97316	Banashankari	Cafe	Coffee, Spag	Cafe, Chint	500	["Rated 1.1"]	Cafes	Banashankari
16	https://www.111, Sapphire	Cal-Eleven	No	No	4.0/5	424	080 49577	Banashankari	Cafe	Sandwich, Or	Cafe, Contie	450	["Rated 2.1"]	Cafes	Banashankari	
17	https://www.1112, Next	to San Churro	C Yes	No	3.8/5	918	+91 96634	Banashankari	Cafe, Casual	D Churros, Car	Cafe, Mexic	800	["Rated 3.1"]	Cafes	Banashankari	
18	https://www.2303, 21st	Cri Cafe	Vivacity	Yes	No	3.8/5	90	080	Banashankari	Cafe	Garlic Bread,	Cafe	650	["Rated 2.1"]	Cafes	Banashankari
19	https://www.241, 4th	Floor Catch	up-ino	Yes	No	3.9/5	133	+91	Banashankari	Cafe	Momos, Mui	Cafe, Fast Fi	800	["Rated 1.1"]	Cafes	Banashankari
20	https://www.405, 24th	Cro Kirthi's	Biryani	Yes	No	3.8/5	244	080	Banashankari	Cafe	Pasta, Gela	Chinese, Cal	700	["Rated 3.1"]	Cafes	Banashankari
21	https://www.5/14, 1	Venka Tibi	Cafe	No	No	3.9/5	91	+91 88847	Banashankari	Cafe	Chinese Mass	Cafe, Italian	300	["Rated 4.1"]	Cafes	Banashankari

## 5. CONCLUSION:

In wrapping up this project, we've journeyed through the world of restaurant reviews and data analysis. By cleaning and processing the data using tools like Jupyter Notebook and powerful Python libraries, we unveiled meaningful insights. From understanding customer sentiments to identifying popular cuisines and using machine learning with SVM, we've equipped aspiring restaurant owners with valuable information. Visualizations added a touch of clarity to our findings. This project isn't just about numbers—it's about helping entrepreneurs make informed decisions when deciding where to open their restaurants. It's a step towards turning dreams of successful culinary ventures into reality.

## 6. REFERENCES:

1. [SmartDraw](https://www.smartdraw.com/flowchart/flowchart-maker.htm). (2023). SmartDraw - Flowchart Maker. Retrieved December 1, 2023, from <https://www.smartdraw.com/flowchart/flowchart-maker.htm>
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