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Restaurant Review Classification and Analysis

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Abstract- **Restaurants nowadays prefer taking online orders. It not only helps in getting effective customer feedback but also useful for managing orders easily. We are moving towards an automated and digital world. Having a significant online presence is necessary for any restaurant to be successful and prosperous. Getting customer feedback and analyzing them in an effective manner makes the difference. This study analyses the restaurant reviews and presents useful information that the ratings do not consider or overlook. Combined research is done using two different datasets of restaurant reviews in this paper. Machine learning algorithms like Naïve Bayes and Logistic regression is used for first classifying the reviews in proper aspects then performing sentiment analysis on them. Summarization is done using gensim and results are displayed using effective visualization techniques. Future work is also discussed so that an efficient analysis system can be developed utilizing the potential of reviews.**

Keywords- Support Vector Machine (SVM), Naive Bayes classifier, Sentiment Analysis, Topic Modelling, aspect classification.

1.Problem Introduction

For years food and hospitality businesses are running on the assumption that good food and service is the way to attract more customers. But the advent of science and technology, more importantly, the data created by the use of online platforms has pointed towards new findings and opened new doors: Most consumers nowadays rate a product online, over 1/3rd of them write reviews and nearly 88% of the people trust online reviews. Review Services like Yelp, Google Reviews, etc. provide customers and businesses a way to interact with one another. Reviews and Ratings are useful sources of information but significant problems exist in extracting relevant information and predicting the future through analysis and correlation of the existing data. Each day thousands of restaurants and businesses are reviewed by the customers.

The main objective of the work proposed in this paper is to enhance the user experience by analyzing the reviews of restaurants and categorize them in some aspects so that a user can easily know about the restaurant. Restaurants are not able to utilize reviews for their businesses. We want to use the aspects that are important in the food and service industry so that we can analyze the sentiment of text reviews and help them to improve their businesses. This research paperwork

can be applied to many other industries related to food and hospitality.

2. Related Previous Work

When diving into this research work, we found that a large amount of relevant work has already been done in this field but what was missing was the fact that most of them were not industry oriented. We tried to incorporate the most noticeable findings in these works as our base so we could build upon the work already done. Most of the work focuses on improving the models for classification.

This research paper will help the researchers to learn and help them to take further implementations and improvements. New methods like semantic orientation have also been discussed. The Fakeness of the reviews is a common problem that arises. Some deep learning techniques have also been compared with classical techniques. Some of these works have been summarized in the subsequent sections.

2.1. A survey of Sentiment Analysis Challenges

The consequences of challenges in the area of sentiment analysis [1] has been discussed. Sentiment review structure is compared with sentiment analysis challenges in the first distinction. The effect of this distinction shows that domain-dependence [2] is an important part of sentiment challenges. The second comparison deals with the accuracy of sentiment analysis models based on the challenges. Structured [3], Semi-structured [4], and Unstructured [5] are three types of review structures that were used for the first comparison. Theoretical and technological are the two types of sentiment analysis challenges. The challenges include Domain dependence, negation [6], bipolar words [7], entity feature/ keyword extraction [8], spam, or fake review[9], NLP overheads like (short abbreviations, ambiguity, emotions, sarcasm). Parts-of-speech (POS) tagging [10] gives highly accurate results for the theoretical types of challenges. The phrases and expressions of n-gram [11] give it an edge over all other techniques used for a technical set of challenges. The results explained the effectiveness of sentiment analysis challenges for improving the accuracy of the model [12].

2.2. Aspect based Sentiment Oriented Summarization of Hotel Reviews

Due to the unstable size of review dimensions and customer produced content, different text analytic approaches like opinion mining [13], sentiment analysis, topic modeling [14], aspect classification, play a significant role in analyzing the content. Topic Modelling can find diverse topics in a corpus of text because of its statistical nature. For every aspect type, there is a certain opinion linked to it and the Sentiment analysis method can effectively bring out these emotions. Whether it is a business intelligence problem or a case of unstructured document categorization sentiment analysis is useful for most of the cases. It has emerged as the most important aspect of the Information Retrieval process. The strategies regarding text summarization [15] can boost sentiment analysis research. The opinion mining of the hotel reviews is done using SentiWord[16] library. The reviews were summarized on different aspects and sentiment analysis was performed. [17]

2.3. Assessing the Helpfulness of Online Hotel Reviews

A review can be considered useful for decision making purposes only when it is thoughtful and insightful. The indicators representing the importance of reviews are different for diverse research areas due to ease of access. In the case of travel and hospitality websites, the reviews containing maximum votes are considered to be more informative and useful for consumers. It can be helpful in optimizing the cost of the search

for most of the consumers by using feature engineering.[18].

2.4. A framework for Fake Review Detection in Online

This paper paves an idea of the challenges that we could face in our research. Specifying the significance of online feedback for different types of industries and the amount of difficulty attached in procuring and maintaining a favorable honor on the Internet, diverse methods have been used to enhance digital existence, including unethical practices. Fake reviews are one of the most preferred unethical methods which exist on sites such as Yelp or TripAdvisor. In response to that Fake Feature Framework (F3), helps to assemble and constitute features for fake reviews choice. F3 estimates knowledge obtained from both the user (personal profile, reviewing activity, trusting information, and social interactions) and review elements (review text).[19]

2.5. Sentiment Analysis of Hotel Reviews

It is observed that Semantic orientation can also be used as a sentiment analysis model to classify reviews as 0 or 1 representing negative and positive respectively. It is possible to classify a review on the foundation of the average semantic orientation of phases in the review which comprises adverbs and adjectives. It is expected that there will be an efficient value when we merge semantic orientation [20] with sentiments. The review is recommended only if the mean is positive and otherwise not it is recommended. The Naive Bayes model generally performs better than SVM [21].

2.6. Deep Recurrent Neural Network Vs. Support Vector

In this paper, it was discussed that SVM which is one of the supervised learning techniques performs better than other approaches and models. It is because of the fact that the features are carefully hand-crafted to train the SVM model. Its effectiveness in the classification of binary targets is also an important trait to support this performance. After analysis of different datasets, it is observed that SVM performed better in almost all of the aspect analysis problems [23] consisting of small datasets.

Generally, aspect-based sentiment analysis is divided into 4 main parts:

1. Extraction of aspect-terms
2. Recognition of polarity aspect-terms
3. Recognition of aspect-category
4. Recognition of polarity of aspect-category [22]

3. FOLLOWING TWO DATASETS ARE USED FOR REVIEW ANALYSIS

3.1 SemEval-2014 Task-4 Dataset

For aspect classification, the dataset is taken from SemEval-2014 Task-4. Our dataset consists of over 3 thousand English sentences from different restaurant reviews. The dataset format is in XML consisting of reviews with their aspects and polarity. Terms also mentioned in the dataset on which the aspects are based. There is more than one aspect related to some of the reviews [24].

3.2 Zomato Bangalore Restaurant Dataset

Zomato Bangalore restaurant dataset uploaded in 2019. The data was scraped from Zomato for educational purposes only. Dataset consists of 17 columns with 51717 unique URLs and 8792 Unique restaurants. Some of the fields in location and phone are missing. We ignore the column Phone no. The review list columns contain reviews of restaurants for a specific restaurant. The

analysis of the restaurants and sentiment classification is done using this dataset [25].

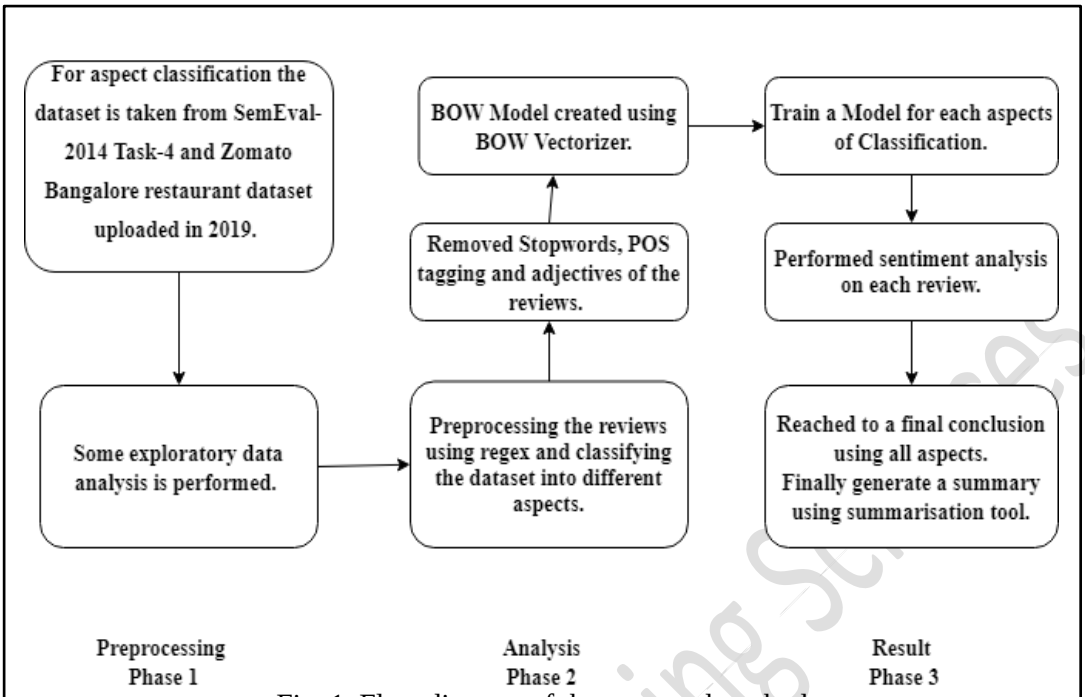

Fig. 1. Flow diagram of the proposed method

4. Proposed Methodology

Explanation of three phases as shown in Fig. 1 is mentioned below:

Phase 1: This phase deals with the collection of the right dataset for classification and sentiment analysis. The dataset for aspect classification has been collected from the SemEval-2014 competition which contains the reviews and the labels associated with the aspects. The labeled dataset for sentiment analysis is taken from Kaggle which has been extracted from Zomato using zomato API.

Phase 2: This phase deals with the aspect classification and preprocessing part for sentiment analysis. It includes stopwords removal, POS tagging, lemmatization, stemming, etc. Feature generation is performed using TF-IDF (Term Frequency) it normalizes the document term matrix. It is the product of TF and IDF. Finally, the dataset is prepared into vectors using the BOW vectorizer for sentiment prediction.

Phase 3: It is the final phase where we are going to do the sentiment prediction on the preprocessed data obtained from phase 2. The sentiments are predicted for each aspect and analyzed. The analyzed results and sentiments are to be displayed using front-end technology. During the whole process, we keep on updating the review database.

5. Exploratory Data Analysis

We create a dataset for aspect classification using Restaurant_Train.xml file. The XML file is converted to the data frame for aspect classification using pandas. We have taken a Zomato review and performed the analysis. We have shown some graphs and charts for a better understanding of the dataset.

It is observed that BTM city has the greatest number of restaurants and New Bel Road has a small number of restaurants but if we combine all blocks of Koramangala then it exceeds BTM (as shown in fig. 2). It gives an idea about the restaurants in a particular city. If we look into this data and order restaurants received from these cities and compare them then we get an idea of improvement. Such information helps in targeting specific areas. For the restaurant

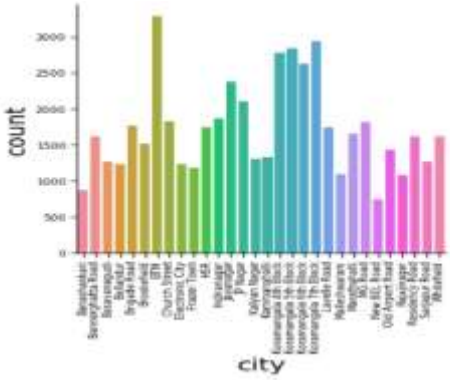

Fig. 2. A number of restaurants in each city.

owners or if someone wants to open a new branch of a restaurant.

As per the graph (as shown in fig. 3) nearly 58.9% of restaurants are taking online orders while 41.1% don't take online orders. Taking online orders is a necessary parameter to analyze a restaurant because it is very important in times of crises like covid-19 when people don't want to go outside of their houses then they will definitely order food

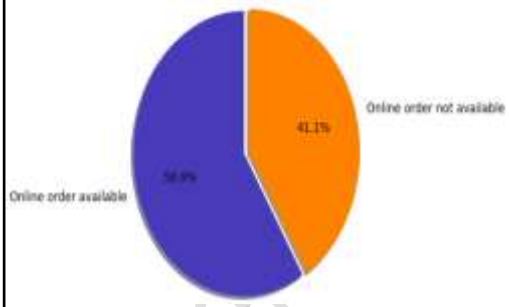

Fig. 3. Pie plot representing total restaurants taking online orders or not.

from the restaurants.

Moreover, people who work in companies find it easier to order online. In such a situation it will be beneficial for restaurants that take online orders (as shown in fig.3). Feedback is one of the most important factors for the restaurant to improve its services when people order online then they will provide feedback for the food quality and service.

BTM and Koramangala are among the restaurants taking the highest number of online orders i.e 2100 and 1750 respectively. It has been observed that the success rate of restaurants increases by taking online orders and feedback from customers.

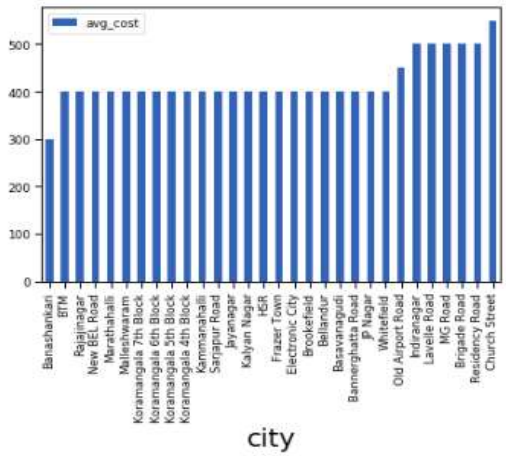

Fig. 4. Bar plot of average cost vs city.

Church Street is expensive and Banashankari is pocket friendly among all restaurants in Bangalore city. Price is evenly distributed around 400 average costs for 2 persons(as shown in fig. 4). It is very much required for the restaurant to keep the average cost at around 500 or less. Most people go to affordable places, so restaurant owners should keep in mind the average cost and a high percentage of discounts.

Biryani is the most sought dish and a good option for a restaurant to have on the menu. Fig. 5 shows the importance of a type of food item in the success of a restaurant. For the owner of the restaurant, it is very much required to have the top dishes on the menu. It is very much clear that in Bangalore people like the biriyani most and it is one of the top

dishes in Bangalore city. Although dishes like Paratha and Masala Dosa are also liked

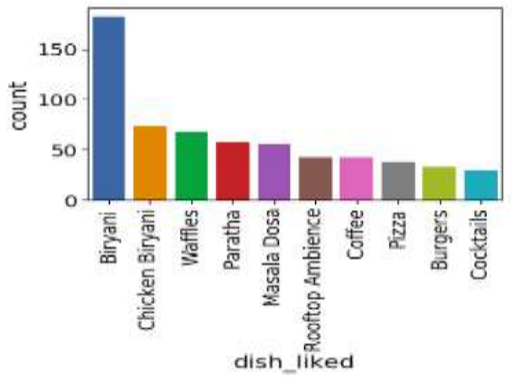

Fig. 5. Top 10 dishes liked by the people of Bangalore.

by people in the morning. From the cleaned obtained dataset, potential features are extracted and converted to a word vector representation. The vectorization techniques are used to convert textual data to a numerical format. Using vectorization, a matrix is

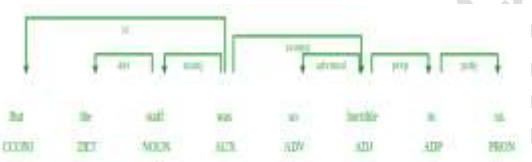

Fig. 6. POS tagging to know the essence of a sentence.

created in which each column represents a review feature and each row represents an individual review.

Here we have done POS tagging to identify the grammatical Parts in a given review like noun, pronoun, verb, adjectives, adverbs, etc (as shown in fig.6). Here speech attached with the different words in the sentence "But the staff was so horrible to us." The PoS tags are very useful for reducing words into their root form. It not only makes it easy to understand but also brings out the sense and relationship between the words of a sentence. Parts of speech are context-dependent, as we can see here the context is about criticizing the staff of the restaurant and giving a negative review. It is used in Language Modelling and chatbots creation.

Finally, we create a word cloud of restaurants Donne Biriyani Mane and Kanti Sweets (as shown in fig. 7). In Donne Biryani Main words like "chicken" and "Biryani" have high frequency whereas in Kanti Sweets words like "Sweet" and "fruitbite" have a high frequency. other common words are "fruit"," good"," place" etc.

The word cloud represented in fig. 8 brings out the illustration of words used in the reviews. A word cloud is generated by counting the number of occurrences of each word in a sentence and then displaying them in an organized manner with the highest count word having the largest font. One can

Fig. 7. Word cloud of Donne Biriyani Mane and Kanti Sweets

clearly understand the restaurant type in this case by just looking at the word clouds.

5. Validation and Model Comparison

Table 1. Classification report of models.

```
Runtime of the model is 0.2713007926940918
Accuracy of MultinomialNB :  0.8662286465177398
Classification Report of MultinomialNB
              precision    recall  f1-score   support

           0       0.26      0.06      0.41        37
           1       0.84      0.69      0.76       353
           2       0.71      0.82      0.76       262
           3       0.42      0.94      0.59        36
           4       0.62      0.80      0.70       113

   micro avg       0.66      0.77      0.71       801
   macro avg       0.57      0.82      0.64       801
weighted avg       0.72      0.77      0.73       801
 samples avg       0.71      0.76      0.72       801
```

```
Runtime of the model is 0.654827356338501
Accurcy -  0.8257555847560988
Classification Report of RandomForest Classifier
              precision    recall  f1-score   support

           0       0.09      0.73      0.16        15
           1       0.81      0.61      0.70       304
           2       0.66      0.70      0.68       284
           3       0.14      0.85      0.24        13
           4       0.57      0.82      0.64        93

   micro avg       0.57      0.67      0.62       789
   macro avg       0.44      0.74      0.48       789
weighted avg       0.70      0.67      0.67       789
 samples avg       0.60      0.67      0.62       789
```

```
Runtime of the model is 2.6811561584472656
Accuracy of SGDClassifier:  0.8588814717477804
Classification Report of SGDClassifier :
              precision    recall  f1-score   support

           0       0.21      0.78      0.33        32
           1       0.84      0.70      0.76       345
           2       0.69      0.79      0.74       265
           3       0.34      0.87      0.49        31
           4       0.62      0.77      0.69       117

   micro avg       0.63      0.75      0.69       790
   macro avg       0.54      0.78      0.60       790
weighted avg       0.71      0.75      0.72       790
 samples avg       0.68      0.75      0.70       790
```

The first column of table 1 contains a classification report of three different classification models used for aspect classification in our paper. The second column contains a vertical bar chart displaying the performance of models on the basis of precision, recall, F1 Score, and time it takes to fit a dataset.

The comparison shows that the MultinomialNB model performs with an accuracy of 86.6%, SGD Classifier performs with an accuracy of 85.8% and Random Forest performs with 82.5%. MultinomialNB classifiers are better than other classifiers in almost every evaluation metric. It takes very

	Model	Fitting time	Scoring time	Accuracy	Precision	Recall	F1_score
0	Logistic Regression	0.485107	0.111021	0.875233	0.872213	0.872268	0.875413
1	Decision Tree	27.858660	0.177371	0.948476	0.948337	0.945541	0.948396
2	Naive Bayes	1.056557	0.591268	0.794225	0.782920	0.801132	0.795648

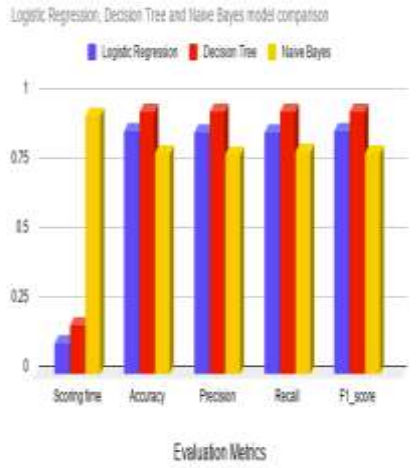

Fig. 8. Comparison between different sentiment analysis models.

little time (i.e 0.271) while Random Forest takes much (i.e 2.68) to fit and predict the output, that is why it can be used for real-time classification systems. The comparison is done on the basis of performance measure on Restaurant.xml dataset for aspect classification. These models are chosen for

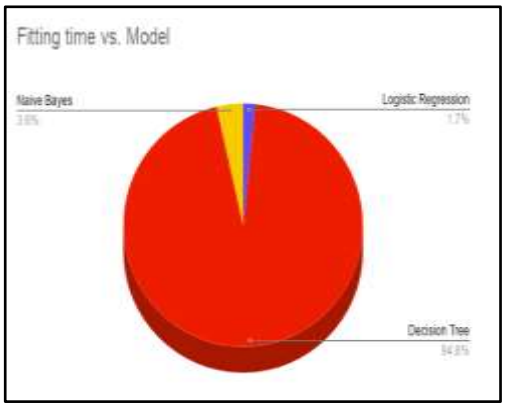

Fig. 9. Fitting time comparison of models

comparison because they perform well on multilabel classification.

In fig. 8 both tabular and graphical representations of different sentiment analysis models are shown. The blue color bars represent the logistic regression model, red represents the decision tree and yellow represents the naive Bayes model. The x-axis has the evaluation metrics and the y-axis contains the values from 0 to 1.

The accuracy, precision, recall, and F1 score of a decision tree is more than logistic regression but Decision trees are nowhere near logistic regression when it comes to the fitting time. The fitting time is the time taken by a model to fit the data and learn from it. At this time the training data is fed to the model with target values.

The scoring time on the other hand is the predicting time. The time model takes to predict the output when a string is given to the trained model. Logistic regression is a better algorithm in terms of both fitting and splitting time so it should be used for real-time applications.

The red portion of the pie chart in fig 9 represents the time taken by a decision tree model to fit the training data, the yellow portion represents the fitting time of Naive Bayes algorithm and the smallest one representing the best fitting time belongs to the logistic regression model. Pie charts are mostly used for percentage distribution so if we measure time to be 100s then logistic regression takes 1.7 seconds to fit the data whereas decision trees take 94 seconds to fit the data. So, a fast algorithm is preferred over a more accurate one for real-time applications.

6. Results

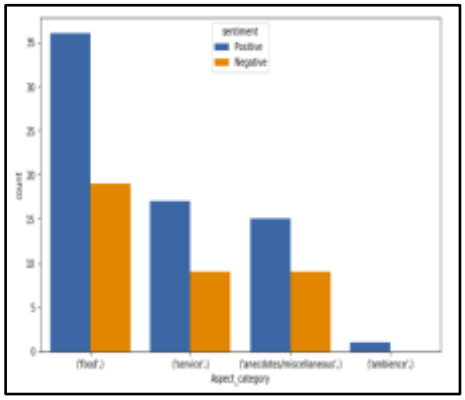

Fig. 10 Result of McDonald's

We can represent our result graphically (as shown in fig.10 and fig. 11) to show positive and negative sentiments for each aspect of a particular restaurant. McDonald's has positive sentiments in almost every aspect (as shown in fig.10). Which shows that it has a good no of positive reviews.

In the food industry, it is very much important for the restaurant to have good quality food. People can compromise on the other aspects but not the quality of food. KFC has a very high value for a food aspect as compared to others which shows that it has a good no of positive reviews. In the food industry, it is very much important for the restaurant to have good quality food. People can compromise on the other aspects but not the quality of food. KFC has a very high value for a food aspect as compared to other aspects (as shown in fig. 11).

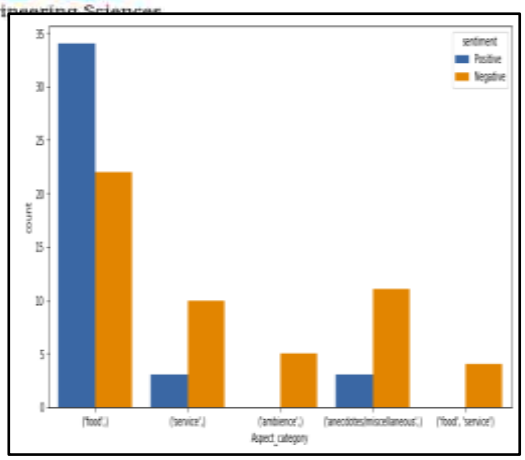

Fig. 11. Result of KFC.

This concludes that in the fast-food industry, quality and taste of food is much more important than other aspects. This might not be true for a costly restaurant whereas the service cost increases, people will expect an all-round service as well. Different insights can be drawn for different kinds of businesses.

7. Summarization and Keywords

In summarization, we create a short summary of all the reviews which will help the people or customers to decide which is best for their requirements.

As shown in fig. 12, it contains the text for 'Kabab Ghar' restaurant. The summary and keywords are extracted. The set of keywords for this restaurant are: chicken, food, good taste, ordered biryani, non-veg, order, orders, totally, add double. These results simplify the process of understanding large corpus of reviews. People are very busy nowadays, so presenting them with concise and relevant information can make a big difference in quality and productivity. Gensim tool is used to generate a summary and extract keywords. It is an open-source library for unsupervised topic modeling and natural language processing. It combines the reviews and generates a summary by extracting important sentences and keywords from the reviews (as shown in fig. 12). The algorithm used in it is a TextRank algorithm. It generates a short summary of sentences.

8. Conclusion

After processing a large corpus of reviews, we reach to the conclusion that the MultinomialNB model performs better than other algorithms in almost every evaluation metric. It takes very little time to fit and predict the output, that is why it can be used for real-time classification systems. Although accuracy, precision, recall, and F1

```
text
{'ordered for chicken khabab got some potato mixed with that', 'so tasty I love it', 'OK\nOK', 'gud', 'good food', 'Restorant peoples are i
rresponsible they told me lot of lies  they told food is already delivered but zomato guy is saying they have just given the parcell totall
y mess up with zomato for my first order food is not worth for money ', 'very bad delivery', 'nice but delay in accepting orders', 'One of
the best chicken biryani i ever had The aroma of the biryani  taste of biryani still on my tongue I will order again hope you guys keep the
same taste', 'I have Ordered biryani and kabab it was not good taste very less spicy for bothquality of food not meeting expection and also
mentioned add double masala to biryani but physically I didnt get', 'Sad', 'Its yummy both spicy n tasty I would like to recommend to my fr
iends', 'good', 'too oily', 'Nonveg thali worth the money Butter chicken is so good Fulkas are very smooth Good keep it up and hope you wil
l maintain same qualuty', 'Taste was awsome', 'Worst biryani ever', 'Worst nonveg food had ever in Bangalore Chicken curry and tandoori was
tasteless  From attached photo of chicken gravy you can make out how it will taste Will never order from this restaurant suggesting others
also not to order as well Requesting Zomato to have some way for returning such food', 'ordered full tandoori chicken but they sent less th
an half waste', 'Veg biryani had a piece of chicken in it It is unacceptable', 'Good food'}

summary :
{'I have Ordered biryani and kabab it was not good taste very less spicy for bothquality of food not meeting expection and also mentioned a
dd double masala to biryani but physically I didnt get'}

Keywords :
chicken
food
good taste
ordered biryani
nonveg
order
orders
totally
add double
restorant
```

Fig.12. Summary of Kabab Ghar restaurant.

score of the decision tree is better than other Decision tree fitting time is much higher (as shown in fig. 9). Some other observations taking online orders and table bookings

increases the number of customers. Restaurants should collaborate with delivery sites like Zomato, Swiggy, etc to grow their business. The average cost for a person should not be high. There must be quick bites for the areas where the MNC's are situated, as people don't want to spend more time in restaurants.

9. Future Scope

The work carried out here suggests the usefulness of online reviews in transforming businesses using NLP and text analysis techniques. In the future, a real-time application can be made so that people can use it to analyze the reviews more effectively and grow their businesses. Neural network architectures can be used to make the summarization of text more accurate and readable and to the point.

Summarization of text reviews and the power to get insights from them can open an all-new world into the field of analytics and how we use data in businesses. There is a vast array of techniques that are left to explore which can make this an even more exciting area to study and improve. Not only is there a vast room for future research, but this study can also be performed for various other industries like transportation, hospitality, healthcare as well as education.

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