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UNCOVERING CONSUMER SENTIMENTS AND DINING PREFERENCES: A LEGAL AND ETHICAL CONSIDERATION TO MACHINE LEARNING-BASED SENTIMENT ANALYSIS OF ONLINE RESTAURANT REVIEWS

[1]Mohammad Nazmul Alam, [2]Kulwinder Kaur, [3]Md. Shahin Kabir, [4]Naznin Huda Susmi, [5]Sohrab Hussain

[1]Assistant Professor, [2]Assistant Professor, [3]Assistant Professor, [4]Student, [5]Assistant Professor

[1]Department of Computer Applications, [2]Department of Computer Applications, [3]Department of Law, [4]Department of CSE, [5]Department of CSE

[1]Guru Kashi University, Bathinda, Punjab, India, [2]Guru Kashi University, Bathinda, Punjab, India, [3]Raffles University, Rajasthan, India, [4]East Delta University, Chittagong, Bangladesh, [5]East Delta University, Chittagong, Bangladesh

Abstract: The prevalence of people sharing their opinions on social media, Twitter, and restaurant review websites has led to sentiment analysis becoming a popular research topic in natural language processing. Sentiment analysis involves extracting useful information from text data and categorizing it into different labels based on sentiment. This paper discusses the development of supervised machine learning techniques for classifying consumers' words used in their restaurant experiences. The dataset was collected while keeping legal and ethical issues in mind and was preprocessed to prepare it for classification. Supervised machine learning classifiers were then applied to the prepared dataset to build an automated system that classifies text sentiment based on sentence polarity (positive or negative). The paper presents a successful machine learning approach for predicting sentiment (positive or negative) in consumers' restaurant experiences, achieving better accuracy using the Support Vector Machine classifier among other classifiers.

Index Terms: **Machine Learning, Legal, Ethical, Restaurant Review, Support Vector Machine, Decision Trees.**

I. INTRODUCTION

Sentiment analysis involves mining opinions from text data, predicting polarity, and extracting information from it. With the increasing popularity of social media, sentiment analysis has become an area of interest in natural language processing. Consumers express their opinions on various topics, such as movies, books, food, etc., through comments on social media [1]. This helps companies understand consumers' behavior and preferences. However, collecting and analyzing data from the web and consumers' opinions requires careful consideration of legal and ethical issues, such as data privacy, consent, bias, transparency, and legal compliance. To conduct sentiment analysis based on online review data, we have taken measures to protect personally identifiable information and avoid biases. We use consent to collect data directly from users and maintain transparency in our analysis.

We also comply with legal regulations on data privacy, consumer protection, and intellectual property rights. In this study, we focus on sentiment analysis of consumers' dining experiences at restaurants using machine learning algorithms.

II. RELATED RESEARCH

In this section, we have reviewed various research papers related to restaurant reviews, which have implemented different methodologies and techniques. While the focus of the papers is on restaurant reviews, they differ in their approaches. Our primary focus is on sentiment analysis using machine learning algorithms. Over the past few years, numerous studies have been conducted on this topic, and while the research differs, most studies have emphasized the importance of customer satisfaction for a restaurant's success. If customers are not satisfied, it can negatively impact the restaurant's results. Our review of these papers has identified the strengths and weaknesses of each study related to this research topic. We have taken 26 research papers related to this topic and after analyzing all papers we have got the following observation. The best accuracy of 90% was achieved using the Random Forest classification method on a limited dataset collected from social media platforms. However, for better performance, deep learning, and neural networks are preferred [1]. A Naïve Bayes data mining approach was used to analyze genuine consumer datasets, but the research was limited due to the small dataset size [2]. The proposed method used Twitter data to optimize the quality of food and find the best product using electronic devices. However, it was inflexible and had lower accuracy [3]. A dictionary-based approach using the VADER lexicon technique was used to enhance overall performance, but the sentiment score could have been more accurate [4]. Logistic regression was used for effective accuracy and cybersecurity data prediction, but using more features may improve its performance [5]. The algorithm used for qualifying the best result in data mining was good, but its accuracy was not satisfactory [6]. The system using different algorithms achieved high accuracy and the best prediction results. It also extracted the attributes of expressions beyond just identifying opinions [7]. Although Naïve Bayes calculates future probability predictions from data, its accuracy was not significant [8]. The Bag-of-Words (BOW) feature method achieved a good accuracy rate of 73.34%, but using more classifiers may improve its performance [9]. The paper describes a pipeline approach but does not provide information about classifier accuracy rates [10]. The dataset used was not sufficient, although the results showed that consumers' sentiments in five attributes could significantly explain differences in star ratings [11]. The proposed restaurant review classification system achieved 80.48% accuracy using the random forest algorithm. However, using more datasets and classifiers could improve its performance [12]. A restaurant recommender system was proposed based on semantic similarity evaluation, but it lacked the best accuracy required [13]. The main approach used was hyperparameter tuning to decipher sentiment tendencies, but more data and a better algorithm than SVM may be necessary for better accuracy [14]. The authors found that logistic regression outperformed other methods in terms of accuracy for sentiment classification [15]. The proposed CLB scenario and IANFIS methods performed well for sentiment analysis and future prediction of online products, but keyword processing may fail to provide the complete context of an entire piece [16]. Although the proposed method was successful and effective, the accuracy of the used algorithm was not satisfactory [17]. Various techniques were used to find the best performance and exact results of classifiers, but the results were not satisfactory [18]. The collected data was not sufficient to find accurate results for online education [19]. The safety of customer and seller details was maintained, but the research was time-consuming [20]. Various classifiers were used, such as decision trees, Naïve Bayes, random forest, and neural networks like LSTM and GRU, making the research time-consuming [21]. The service had a significant effect on reviews, and negative reviews could have a detrimental impact on business [22]. The precision, recall, accuracy, and error rates were found for people who gave positive or negative reviews of a restaurant. The error rate was 275, which was not satisfactory [23]. Sentiment analysis was conducted on 1000 reviews in Bangla, achieving an accuracy rate of 805, but using more classifiers or optimization may improve the result [24]. The experimental results were evaluated using the f1 score, accuracy, ROC curve, etc. However, using multiple classifiers made the research time-consuming and did not achieve the expected results [25]. The system was designed for optimized performance using data, but working with big data posed a significant challenge [26].

III. METHODOLOGY

The methodology is required for further work. We will get the outcome that we are looking for by using the methodology. For the research, we have gathered almost 1000 pieces of data on consumer feedback on a restaurant. Sentiment analysis of customer product reviews is the approach. The dataset used for our research purpose is from online review data. The procedure we have followed is bellowed.

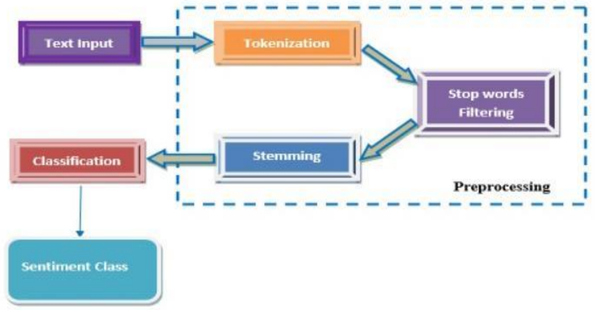

Fig.1. Working procedure of Sentiment analysis

A. Data Set

First of all, we need a dataset as our model completely works on data. We collected our data from “Kaggle” a website where we can get customer feedback on the restaurant.

There are two parts to our dataset.

1) A “Review” containing customer dining experience on a restaurant as a review

2) “Sentiment” denotes one of two possible results, where 0 indicates negative reviews and 1 indicates positive reviews

B. Data Preprocessing

For future work like classification, we need to preprocess the data. By preprocessing data we prepare the data for future work and data get ready for the model by preprocessing the data.

We did the preprocessing in various steps. First, we removed punctuation then removed stop words. After that from the clean text did tokenization and vectorization. As a result, we utilize a data preprocessing activity, and the model’s accuracy and efficiency are also improved. The steps are as follows:

1) Import libraries: We used the libraries pandas, "matplotlib", "nltk", "nltk.corpus", “string”, “stop words”, “Count vectorizer”, Classification report, confusion matrix, acc_score, roc_auc_score, roc_curve, sklearn, and more for our work.

2) Import datasets: After importing it, we named it “food review.”

3) Check Missing Data: There were no missing values. This step isn’t required for our dataset.

4) Encode Categorical Data: There are no category values in our dataset. As a result, we also skipped this step.

5) Split the data set: Split the data set into two different data sets. One is a training data set, and the other is a testing data set. A training data set and a testing data set are created from our main dataset. For the training data set, we selected 70% of the data, and the remaining 30% of the data was selected for the tasting data set. The training set is a subset of the main dataset used to train our different types of Machine Learning and the output is already known. The testing data set contains the remaining data, and it will be used to test our model performance, and the model predicts the outcome using the testing data set.

6) Feature scaling: We set the variables in the same range and on the same scale in feature scaling so that no one variable dominates the others. However, because this step was not required, we skipped it.

C. Feature Extraction and Uses

Here we convert raw data from our main dataset into numerical data or features in different types of filtering those data that can be handled by not changing the original data set. Converting Raw data or, in this case, text to numerical data, we can gain better performance rather than raw data by applying Machine Learning (ML). Importing Data:

TABLE I. IMPORTING EXCEL DATASHEET

Review (–ve=0)& (+ve=1)	**Review**	**Sentiment**
0	Wow... Loved this place.	1
1	Crust not good	0
2	Not tasty and the texture was just nasty	0
3	Stopped by during the late May bank holiday of...	1
…..	…….	……
998	The whole experience was underwhelming, and I .	0
999	Then, as if I hadn't wasted enough of my life.	0

Table I has three columns where one shows the serial number, the second represents a review of customers and the third one is sentiment. Where by the value 0 we can understand the negative review and by the value 1 we can understand the review is positive. Here is the graphical representation of the dataset. It represents the sentiment column of the dataset.

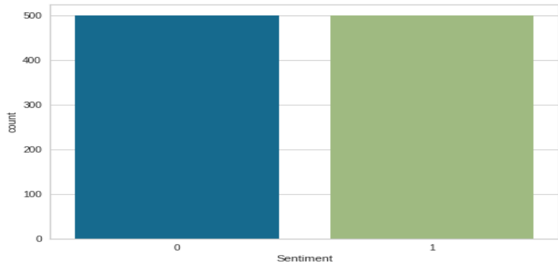

Fig.2. Graphical representation of positive and negative review

In fig.2 in the X axis, there is sentiment input and in the Y axis, there is a count that means serial of review. By this graph, we can say that there is 500 positive review and 500 negative reviews among 1000 review.

Here we can see that service, great, food, place, etc. words are mostly used words in a positive review which have a higher number in frequency.

In a negative review, consumers used service, food, worst, time bad, etc. words frequently. We can see that consumers discussed most of the time about the food and service of a restaurant instead of others. They discussed on food quality and service of restaurants when they were talking about bad reviews and when they were enjoying the dining.

D. Classifiers

For our research, we have picked Logistic Regression, Multinomial Naïve Byes, Support Vector Machines, K- Nearest Neighbor, Decision Tree, Random Forest, and X-G Boost Classifiers to train our model as a machine learning algorithm. After training the method we have found out the F1 scores which take both into precision and recall ratings of the models. Then using a matrix, we found out the accuracy of the model and its comparison between the train and test dataset model. Further, we will show more about all the classifiers we have used.

IV. EXPERIMENT RESULTS AND DISCUSSION

A. Classification Report

Now that we know the basics of a classification report let us look at the reports of our models.

TABLE II. LOGISTIC REGRESSION CLASSIFICATION REPORT

Review(–ve=0)& (+ve=1)	**Precision**	**Recall**	**F1 score**
0	0.75	0.76	0.75
1	0.76	0.76	0.76

This is the classification report of the Logistic Regression. By 0 value of the row means a negative review & 1 means a positive review of consumers. Predicting a positive value is 0.76 and 0.76 of the precision and recall. Counting precision, and recall we get the result of an f1 score is 0.75. The founded values of precision, and recall for predicting the negative value are 0.75 and 0.76. By measuring these values we find the value of the f1 score is 0.75. If we look at both f1 scores of logistic regression we can see that the positive review is slightly higher than the negative review.

TABLE III. KNN CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.66	0.74	0.70
1	0.722	0.64	0.68

This is the classification report of the K-nearest neighbor. By 0 value of the row means a negative review & 1 means a positive review of consumers. Here the precision of a positive review is 0.722 and a negative review is 0.66 and the precision for a positive review is higher here. The recall for a positive review is 0.64 and the negative value is 0.74, so it is shown here that the recall for a negative review is higher than for a positive one. Using precision-recall we can find the f1 score for a negative review is 0.70 and the f1 score for a positive review is 0.68. Here f1 score for a positive review is less than a negative review.

TABLE IV. DECISION TREES CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.72	0.76	0.74
1	0.75	0.71	0.73

This is the classification report of Decision Trees Classification. By 0 value of the row means a negative review & by 1 it means a positive review of consumers. For precision positive review is 0.75 and the negative review is 0.72 and the precision for the positive review is slightly higher than the precision for the negative review. Recall for a positive review is 0.71 and recall for a negative review is 0.76, so recall for a negative review is higher than the positive review of consumers. Calculating both precisions and recall we get the value of the f1 score for a negative review is 0.74 and the f1 for a positive review is 0.73, Positive review of consumers is higher here.

TABLE V. MULTINOMIAL NAÏVE BAYES CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.72	0.76	0.74
1	0.75	0.71	0.73

This is the classification report of Multinomial Naïve Byes. By 0 value of the row means the negative review & by 1 it means a positive review of consumers. The precision for a negative review is 0.72 and the precision for a positive review is 0.75 which is slightly higher than the positive review. Recall for a negative review is 0.76 and recall for a positive review is 0.71. Here recall for negative reviews is higher than the recall for a positive review. Calculating precision and recall we find the value of the fi score for a negative review is 0.74 and the f1 score for a positive review is .73.

TABLE VI. SVM CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.76	0.76	0.76
1	0.76	0.76	0.77

This is the classification report of SVM. By 0 value of the row means a negative review & 1 means a positive review of consumers. The precision for a negative review is 0.76 and the precision for a positive review is 0.76 which is similar to the positive review. Recall for a negative review is 0.76 and recall for a positive review is 0.76. Here recall for a negative review is similar to the recall for a positive review. Calculating precision and recall we find the value of the f1 score for a negative review is 0.76 and the f1 score for a positive review is 0.77.

TABLE VII. RANDOM FOREST CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.73	0.82	0.77
1	0.80	0.71	0.75

This is the classification report of Random Forest Classification. The precision for a negative review is 0.73 and the precision for a positive review is 0.80 which is higher than the positive review. Recall for a negative review is 0.82 and recall for a positive review is 0.71. Here recall for negative reviews is higher than the recall for positive reviews. Calculating precision and recall we find the value of the f1 score for a negative review is 0.77 and the f1 score for a positive review is 0.75.

TABLE VIII. XGBOOST TREES CLASSIFICATION REPORT

Review(ve=0)& (+ve=1)	Precision	Recall	F1 score
0	0.67	0.92	0.77
1	0.88	0.56	0.68

This is the classification report of XG-Boost Classification. The precision for a negative review is 0.67 and the precision for a positive review is 0.88 which is slightly higher than a positive review. Recall for a negative review is 0.92 and recall for a positive review is 0.56. Here recall for negative reviews is higher than the recall for a positive review. Calculating precision and recall we find the value of the fi score for a negative review is 0.77 and the f1 score for a positive review is 0.68.

B) Confusion Matrix

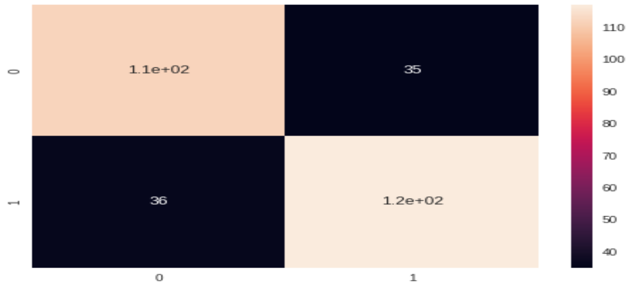

Fig 3. Support Vector Machine Confusion Matrix

This is the confusion matrix for Support Vector Classification. Here the rows are the True classes and false classes and the columns are the predicted classes where 0 is the negative classification and 1 is the positive classification. We can see the True Positive samples are 116 and false positives are 36. Similarly, the True negative samples are 35 and the false negatives are 117.

C. ROC Curve

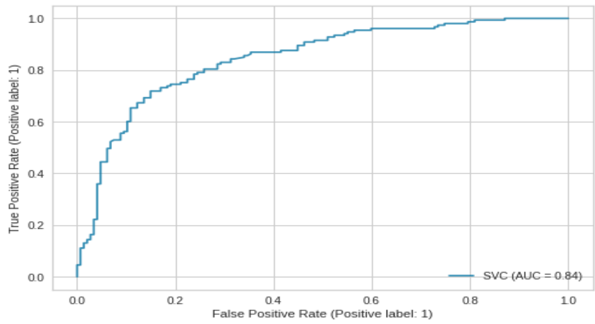

Fig.4. Support Vector Classifier ROC curve

Fig. 4. Shows the ROC curve of support vector classification. Specificity means a false positive rate is indicated by the X-axis on the other hand sensitivity true positive rate is indicated by the Y-axis. The AUC value for this is 0.84. This ROC curve of the Support Vector Classification Model shows that the model sensitivity gradually increases by the value of the specificity

D. Test Accuracy of Machine Learning

Fig.5. Test Accuracy comparison in Machine Learning Algorithm

In fig.5. We can see that Logistic Regression's accuracy score is 7.567 which is not a bad accuracy, For Multinomial Naïve Byes we have got an accuracy rate of 7.433 which is more similar to Logistic Regression. For K Nearest Neighbor, we have got the result 6.90 which is the lowest value we have got by our models, for the Support Vector Machine we have got the highest value which is 7.633 it reflecting that the SVM classifier gives the best performance among others. Then by Random Forest, we get the value of accuracy is 7.6 which is similar to SVM. For XGBOOST we get a score of accuracy is 7.33

V. Conclusion

Social media has become an integral part of people's lives, and it has expanded its reach beyond social circles. It has become a go-to platform for various activities, including choosing a restaurant to dine with friends and family. With numerous restaurants to choose from, people rely on online reviews to make their decisions. To help others with their choices, we collected online review data of restaurants from consumers and used classification algorithms to find the best accuracy. We tested various machine learning algorithms and found that the Support Vector Machine classifier provided the highest accuracy [27]. We further improved the accuracy of SVM by applying hyper parameter tuning. In the future, we plan to expand our dataset by adding more reviews and exploring the use of deep learning algorithms for better performance. We also intend to use hyper parameter tuning on other classifier models to improve their accuracy.

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