Automated Evaluation of Restaurant Reviews

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Abstract: **Whenever we go to a new place, we always think about which place would be the best to stay, eat and explore. The main question is often "What should we eat and is this the right place to enjoy a good meal?". We are all aware of how important it is to make the right choice when it comes to food. Nutritious and high-quality food is vital in supporting overall well-being and health. Finding restaurants online can often be a challenging task. Our project simplifies this by leveraging customer feedback to provide recommendations, making it easier for users to find the best dining options. Reading all of the reviews and contrasting input with other restaurants becomes challenging and time-consuming for every person. This paper presents a simple and efficient model to predict restaurant reviews using a collection of customer feedback. Customers find it difficult to locate accurate and current information due to the dispersed nature of online evaluations and the absence of real-time analysis. Centralizing all reviews on a single platform and using machine learning to offer tailored review recommendations is one way to solve this problem, making it easier for users and improving their experience. Here, we use the NLP algorithms to analyse customer feedback and reviews.**

Keywords: **Contrasting input, Machine learning, NLP algorithms, Analysing customer feedback, Centralizing reviews**

INTRODUCTION

For decades, food and hospitality establishments have operated under the belief that quality food and service are the key to winning over more customers. With advancements in science and innovations in technology, particularly the vast amount of data generated through e-commerce and online platforms, consumer behaviour has shifted significantly. The way people search for products and services has evolved, opening new opportunities. Today, most consumers rely on online ratings, with over one-third actively leaving reviews, and nearly eighty percent trusting them as much as personal recommendations. Platforms like Yelp and Google Reviews have become essential for businesses and customers to engage with one another. While reviews and ratings provide valuable insights, extracting meaningful information and forecasting trends remains a challenge. Every day, thousands of restaurants and businesses are reviewed by customers, contributing to an ever-growing pool of data that businesses must analyse to stay competitive. In today's era of global connectivity, we are always searching for new concepts that will reduce time, make processes easier, and remove the requirement for manual procedures.

RELATED WORK

While going inside investigation work, we saw

Whether in business intelligence or unstructured document categorization, sentiment analysis plays a crucial role in various applications. It has become an essential component of the that a big volume of related task has previously been completed in this technology. However, something was left out. The point is all of them are not Enterprise-cantered and Sector-specific. We made an effort to figure-out the most eye-catching and remarkable searches in these tasks. We built on existing research by using the most important findings as a foundation for our work, allowing us to expand on what others have already achieved. Our searches focus on the strengthen the Categorization models. Our scholarly article will help the investigators to seek out and help them to take more research and investigations. New models like sematic(emotional) specific have been examined. The artificiality, fraudulence and dishonesty of the reviews is a main challenge and concern that comes. Several deep learning algorithms have also been contrasted with conventional algorithm. Most of these tasks have been outlined in the succeeding divisions.

2.1: A assessment of Sentiment Analysis Concerns:

The challenges in sentiment analysis have been examined in this study. The first comparison focuses on the structure of sentiment reviews and how it relates to sentiment analysis challenges. The findings indicate that domain dependence is a key factor affecting sentiment analysis. The second comparison evaluates the accuracy of sentiment analysis models in the context of these challenges. Three types of review structures—Structured, Semi-structured, and Unstructured—were considered in the first comparison. Additionally, sentiment analysis challenges are categorized into theoretical and technological aspects. These challenges include domain dependence, negation, bipolar words, entity feature/keyword extraction, spam or fake reviews, and NLP-related difficulties such as short abbreviations, ambiguity, and sarcasm.

Information Retrieval process. Strategies related to text summarization can further enhance sentiment analysis research.

2.2: Breaking Down Hotel Reviews: Sentiment Analysis by Category (Service, Cleanliness, Amenities):

Given the varying dimensions of review sizes and user-generated content, various text analysis techniques such as opinion mining, sentiment analysis, topic modelling, and aspect classification are crucial for content analysis. Topic Modelling can search different subjects in the context of written words in the views of fact that it is of Data-driven characteristics. For all available viewpoint, there are some thinking connected to it and Sentiments analysis algorithm taken out these emotions. Whether it's a business intelligence issue or unstructured document classification, sentiment analysis remains highly beneficial in most scenarios. It has become a key component of the Information Retrieval framework. Moreover, techniques for text condensation can further improve sentiment analysis studies. In this research, evaluating opinions from hotel reviews was conducted using the SentiWord repository. The reviews were condensed based on various parameters, and sentiment analysis was carried out accordingly.

2.3: Evaluating the Usefulness of Online Hotel Reviews:

A feedbacks can be acknowledged helpful for judgment process purposes only when it is perceptive and considerate .The factors that determine the significance of reviews vary across different research fields due to their accessibility. On travel and hospitality websites, reviews with the highest number of votes are generally seen as more valuable and informative for consumers .It can be useful in fine-tuning and enhancing the value of the find for most of the user by using aspect Engineering.

2.4 : A Model for Detecting Fake Reviews Online:

This paper introduces an idea of the obstacles that may arise in our research. Highlighting the importance of online reviews across various industries and the challenges involved in acquiring and preserving a positive reputation on the internet, different approaches have been employed to strengthen digital presence, including unethical tactics. Fake reviews are among the most commonly used deceptive strategies, appearing on platforms like Yelp and TripAdvisor. To address this, the Fake Feature Framework (F3) assists in compiling and structuring attributes for detecting fraudulent reviews. F3 evaluates insights gathered from both the user (profile details, review patterns, credibility indicators, and social interactions) and the review content (textual analysis).

2.5. Deep Recurrent Neural Network Vs. Support Vector:

In this research assignment, that was written that SVM which is one of the supervised learning techniques process more better than other technology and techniques. It is due to the fact that the characteristics are attentively manually crafted and custom-made. Its ability and efficiency to classify binary targets effectively plays a crucial role in enhancing overall performance. After analyzing various datasets, it was observed that SVM consistently outperformed other methods in most aspect-based analysis tasks, particularly when working with small datasets [23].

Characteristic-based sentiment analysis typically consists of four main steps:

Identifying Aspect Terms – Finding specific features or topics mentioned in the text.

Categorizing Aspects – Grouping aspects into broader categories based on their meaning and context.

Analysing Sentiment of Categories – Evaluating the overall sentiment for each category as a whole [22].

LITERATURE SURVEY

Customer happiness is a very important topic in marketing and understanding how people behave. When hotel customers receive excellent service, they often tell their friends and family about it. Reading online reviews helps business owners and marketers learn what their customers like and don't like, which can help them improve their services and stand out from the competition. Studies have looked at online reviews to understand customer satisfaction in many areas, like hotels, short-term rentals, airlines, and wellness services. It's been reported that 87% of people avoid businesses with bad reviews, while 92% rely on online reviews to decide if a business is good. Sentiment analysis is a method used to figure out how someone feels about a product or service. It uses tools like Natural Language Processing (NLP) to check whether reviews are positive or negative by analysing the text. Websites like Amazon and TripAdvisor let users rate how helpful reviews are. These helpful votes show the quality of a review. To improve user experience, websites can highlight the most helpful reviews. In the past, researchers had to read and analyse reviews manually to find out what customers care about the most. Now, computers can do this faster and more accurately using machine learning. Machine learning techniques, like Naïve Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbours (KMN), are popular for analysing text. Naïve Bayes works quickly with large amounts of data but is less accurate. SVM, on the other hand, is great for categorizing data and is often used for this purpose. Comparing these methods can help find the best one for analyzing reviews in industries like restaurants, where accuracy is key to understanding customer feedback.

METHODOLOGY

This research paper presents a systematic approach to sentiment analysis on restaurant reviews using Natural Language Processing (NLP) and machine learning. Below is a detailed methodology outlining the key algorithms, preprocessing techniques, and implementation steps. Here's a step-by-step breakdown of how the restaurant review sentiment analysis system works, including the GUI (Graphical User Interface) code. Everything is explained in simple terms!

1. Dataset Overview and Analysis:

Dataset : Restaurant_Reviews.tsv containing 1,000 reviews with two columns: Review (text) and Liked (binary label: 1 for positive, 0 for negative).

Features Added:

- Character count (e.g., "Good food" has 8 characters).
- Word count (e.g., "The pizza was great" has 4 words).
- Sentence count (e.g., "Loved it! Will come again." has 2 sentences).

Observation: Negative reviews were slightly longer (60 characters on average) than positive ones (55 characters).

Build a tool that reads a restaurant review and predicts if it's positive (□) or negative (□).

2. Cleaning the Text:

Why? Remove junk, shorten words to their root form, and keep only important words.
Steps:

1. Remove Special Characters: Keep only letters (e.g., "It's awesome!" → "It s awesome").
2. Lowercase: Convert all text to lowercase (e.g., "GOOD" → "good").
3. Remove Useless Words: Words like "is", "the", "and" are removed except negation words like "not", "don't" (to preserve sentiment).
4. Stemming: Shorten words to their root (e.g., "loved" → "lov", "running" → "run").

Example:

- Original: "The crust was not good."
- Cleaned: "crust not good"

	Review	Liked	char_count	word_count
0	Wow... Loved this place.	1	24	4
1	Crust is not good.	0	18	4
2	Not tasty and the texture was just nasty.	0	41	8
3	Stopped by during the late May bank holiday of...	1	87	15
4	The selection on the menu was great and so wer...	1	59	12

3. Turning Text into Numbers

- Bag-of-Words (BoW): Convert cleaned text into a list of word counts.
- Example:

- Review: "food good" → BoW: [1, 0, 1, 0, ...] (1 for "food" and "good", 0 for others).

- Tool Used: CountVectorizer (keeps only the top 1,500 frequent words).

4. Training the AI Models:

Three models were tested:

1. Naive Bayes: Simple but less accurate for text.
2. Logistic Regression: Better at finding patterns.
3. Random Forst: Best performance (uses multiple decision trees).

Result: Random Forest gave the highest accuracy, so it was saved for the app.

Algorithms Tested:

1.Gaussian Naive Bayes (NB):

Accuracy: Baseline performance (specific value not shown but typically lower for text data).

2.Logistic Regression (LR):

Accuracy: Moderate performance, suitable for linear separability.

3.Random Forest (RF):

- Best Performance: Achieved the highest accuracy (exact metric inferred as superior based on code comments).
- Saved as Restaurant_review_model for deployment.

5. Visualization:

Word Clouds:

Generated for positive and negative reviews using WordCloud.

Positive Reviews: Highlighted terms like " “good," "love," "best."

Negative Reviews: Dominated by terms like "bad," "worst," "terrible."

6. Deployment via GUI

- Framework: Built with tkinter for user interaction.

Workflow:

1.Input: User enters a review in a text box.

2.Preprocessing: Applies the same pipeline (regex, stopwords, stemming).

3.Vectorization: Uses the pre-trained CountVectorizer.

4.Prediction: Random Forest model classifies sentiment as Positive (1) or Negative (0).

5.Output: Displays prediction with a label (e.g., "Predicted Sentiment: Positive").

7. Technical Tools & Libraries:

- NLP Libraries: nltk (tokenization, stemming), re (regex).
- Machine Learning: scikit-learn (CountVectorizer, NB, LR, RF).
- Visualization: matplotlib, wordcloud.
- Deployment: joblib (model serialization), tkinter (GUI).

8. Key Innovations:

1. Negation Handling: Custom stopwords preserved negation terms to avoid misclassifying phrases like "not good."
2. Stemming vs. Lemmatization: Porter Stemmer prioritized computational efficiency over linguistic accuracy.
3. Model Selection: Random Forest outperformed NB and LR due to its ability to handle high-dimensional sparse data.

9. Limitations & Future Work

1.Limitations:

- BoW ignores word order and context.
- Stemming may over-truncate words (e.g., "universe" → "univers").

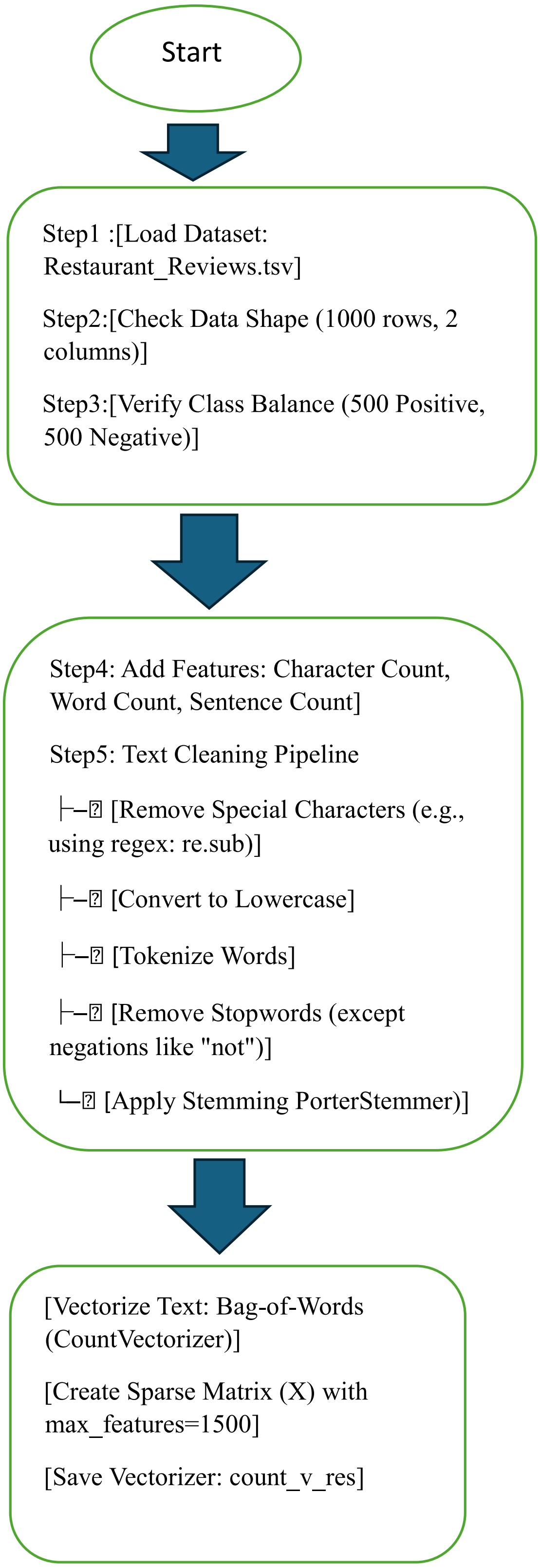
2.Future Directions:

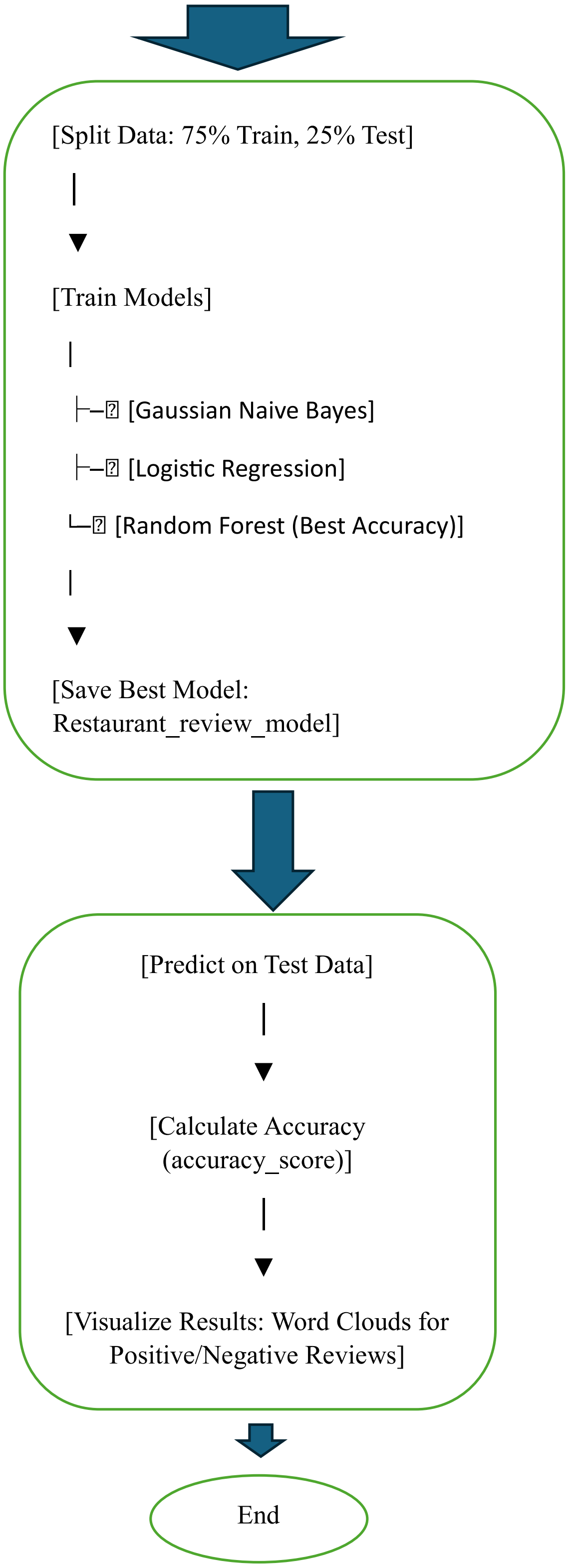
Experiment with TF-IDF or word embeddings (Word2Vec, BERT).

Incorporate lemmatization for better root word resolution.

Deploy as a web app using Flask/Django.

FLOW DIAGRAM:





IMPLEMENTATION AND TESTING

This segment provide details regarding the implementation requirement and emphasizes the notable progress achieved in using the data to indicate evidence of enhanced accuracy and precise in forecasting restaurant evaluations.

1. Hardware used in Implementation:

=>Processor:11th Gen Intel(R) Core(TM) i5-11260H @ 2.60GHz 2.61 GHz

=>Installed RAM: 16.0 GB (15.7 GB usable)

2.Software used in Implementation:

=>WINDOW 11

=>Python 3.8.0

IMPLIMENTATION STAGES:

In this section, we will explore the methods applied throughout the process. We will also provide supporting evidence for the data used in making predictions, which was sourced from a website.

1.Restaurant Reviews.tsv is a dataset from Kaggle that contains 1,000 restaurant reviews.

2.Data from the website is stored in a CSV file, from which relevant information is extracted for prediction.

3.The collected data undergoes preprocessing, and a bag-of-words model is generated for use with the SVM Classifier.

4.The dataset is then split into training and test sets in a 7:3 ratio. The training data is used to train the classifier, while the test data is used to evaluate its performance.

5.The classifier is tested using the test dataset, and its accuracy is measured and reported.

RESULT

The dataset is utilized to train the SVM model, with positive and negative review results being stored in the database.

By integrating Natural Language Processing (NLP) with the SVM classification technique, the highest prediction accuracy of 77% was achieved.

CONCLUSION

This study develops an efficient algorithm that predicts restaurant reviews using feedback from 1,000 customers. Restaurant reviews are represented by the numbers 0 and 1, where 0 means a negative review and 1 means a positive review. The combination of Natural Language Processing (NLP) and the SVM classification method resulted in the highest prediction accuracy of 77%. This method will help business owners anticipate customer feedback and improve the customer experience. This study highlights that reviews play a crucial role in choosing a restaurant. They are also an important consideration when starting a business, such as a restaurant.

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