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# Implicit aspect based sentiment analysis for restaurant review using LDA topic modeling and ensemble approach

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## Abstract
***Technological advancements in e-commerce and Web 2.0 have revolutionized how customers express their opinions about services and features through reviews on various websites. This trend is particularly prominent in the travel industry, where online sources offer valuable insights into the food and accommodations of destinations. However, the abundance of reviews available online presents a challenge for travelers in filtering relevant information. To tackle this issue, aspect-based sentiment analysis (ABSA) was proposed as a technique for extracting opinions based on specific features. Topic modeling and sentiment analysis are two significant techniques employed to assist in this analysis. Topic modeling involves identifying thematic relationships among documents, while sentiment analysis aims to determine the expressed opinions in the text. This study utilized one of the leading travel websites, Tripadvisor, to gather customer reviews of different restaurants. These reviews were then subjected to aspect-based sentiment analysis using latent Dirichlet allocation (LDA) and ensemble bagging support vector machine (EBSVM) classifier techniques. The objective is to identify the most relevant aspect within the restaurant domain and enhance sentiment analysis performance. To address class imbalances in the datasets, the synthetic minority over-sampling technique (SMOTE) was implemented. The performance of LDA was evaluated using the coherence score, which indicates the quality of topics generated for restaurant reviews. The effectiveness of the EBSVM classifier was measured using metrics such as accuracy, precision, recall, and F1 score. The proposed model achieved an accuracy of 96.1%, surpassing other techniques. Overall, this study demonstrates the effectiveness of aspect-based sentiment analysis in extracting relevant opinions from a large volume of reviews. It also highlights the potential of machine learning techniques in enhancing sentiment analysis performance. The suggested approach outperforms other techniques discussed in the existing literature, contributing to an overall improvement in sentiment analysis.***

## Keywords
***LDA, Topic modeling, ABSA, EBSVM, SMOTE.***

## 1.Introduction
The internet is a global web that links millions of people, and therefore, it has become the hub of modern-day social life [1]. It is widely appreciated for providing an open platform where individuals can connect and express their opinions on anything and everything in their environment. However, it can be difficult for an individual to trawl through each online resource. Therefore, approaches for evaluating this collection of documents are essential.

As a result, techniques like feature (aspect) extraction and sentiment analysis play a crucial role in leading individuals, businesses, and organizations in the right direction. This work seeks to provide insight into features concerning the desired domain.

Sentiment analysis is the act of examining whether a piece of writing (e.g. tweets or reviews about books, movies, restaurants etc.) is negative, positive, or neutral in its tone. It's also known as sentiment mining and involves analyzing opinions, assessments, feelings or attitudes about topics, people or organizations [2]. For example: "I love the garlic noodles at your restaurant" could be classified as a

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positive statement. Companies can use sentiment analysis to discover patterns in customer preferences and recommendations for new products and services based on that data. Natural language processing (NLP) and artificial intelligence (AI) applications are also able to quickly gather website reviews to gain insight into how consumers view a particular product or services [3]. This can help companies understand their customers better and inform strategic decisions in terms of product offerings and pricing. People believe in each other's opinions; when choosing where to eat or stay, customers don't base their decisions just on personal experience but also trust what they read in reviews. It can be disheartening to receive unfavorable reviews, but it's important to remember that even good reviews may contain some negative feedback and that this can reflect accurately on our products.

Aspect extraction is a process that could assist in finding the hidden aspects relating to the corpus. It will extract the main contents of a new article or unearth the pondered areas from a set of user reviews. Identifying and extracting implicit aspects and features from a given text is one of the primary obstacles in aspect-based sentiment analysis (ABSA) [4]. Topic modelling is a methodology for discovering and understanding the aspects contained in unlabeled text documents. In this method, documents are sorted into similar classes based on the aspects they include. Topic modelling, treats words as documents; the documents are collections of distinct topics, each representing a probability distribution of words [5]. Latent Dirichlet allocation (LDA) is a probabilistic approach widely used in topic modelling [6, 7]. The underlying assumption of the LDA model is that documents are composed of various topics, with each topic being a cluster of words [8]. It creates a list of topics with the desired number of words based on their probability distributions. This method assists in identifying the similarity, if any, between documents by analysing the probability distribution of the topics in these documents.

Sentiment analysis is a text-mining technique that investigates people's thoughts, perceptions, and sentiments towards products, entities, and subjects [9]. In this study, customer reviews of restaurants are used as the dataset. This work develops a model based on the LDA to extract implicit and explicit features and proposes an ensemble machine-learning technique known as ensemble bagging support vector machine (EBSVM) for opinion mining. An ensemble strategy fuses various base classifiers to form a new classifier that is more reliable than its components. The study analyses feature-specific opinions. The ensemble model has been adapted to enhance feature-based opinion mining substantially. *Figure 1* shows an architectural diagram for predictive positive and negative sentiment analysis

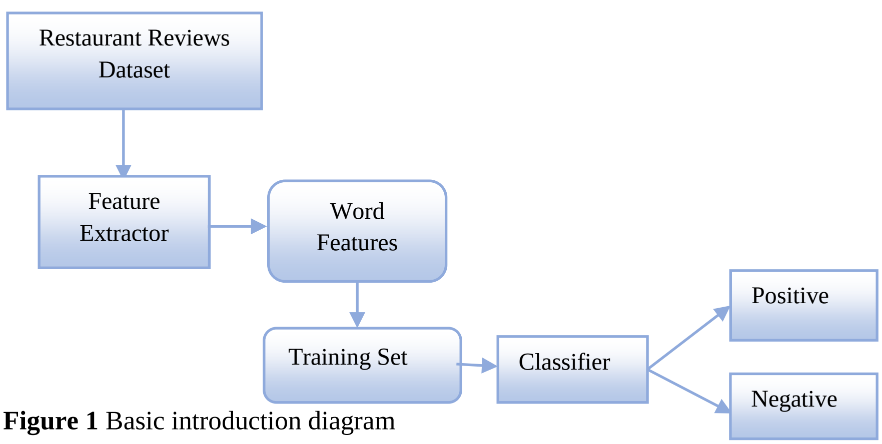


**Figure 1** Basic introduction diagram

## 1.1Motivation for the research

Reviewing data opens up new ways for users and businesses to make strategic decisions to improve their businesses. These platforms receive tonnes of hits and comments every second, making it difficult for decision-makers to make immediate strategic decisions. Many researchers have investigated NLP subtasks. The rapid growth of social media and e-commerce portals has seen significant advances in sentiment analysis and its variations. Many organisations and companies use these tasks to improve their business based on user preferences. When most users describe a product, they may have many opinions about its features. Sentence-level sentiment analysis is needed to classify such reviews correctly. It can be operated using the principles of feature-based sentiment analysis [10].

### 1.2Contribution of the research

This research introduces methods for extracting pertinent aspect-based opinions from extensive online restaurant reviews using implicit ABSA techniques. These techniques are particularly useful for handling unstructured data and facilitating the analysis of customer feedback. The primary objective is to enhance the accuracy of sentiment analysis by employing an ensemble machine learning classifier (EBSVM). To accomplish this objective, the research employs appropriate preprocessing techniques to prepare the datasets for analysis. Additionally, a topic modeling method is utilized to identify the significant aspects within the restaurant domain. Lastly, an ensemble machine learning technique is applied to improve the efficiency of opinion mining. The focus of this investigation is to propose a model that can enhance the efficiency and effectiveness of ABSA. By utilizing implicit ABSA techniques, employing suitable preprocessing techniques, applying topic modeling, and leveraging an ensemble machine learning classifier, the research strives to achieve this goal.

This section aims to provide an overview of the paper. Section 2 presents a review of the research conducted by different scholars in the field. Section 3 describes the architecture of the methodology implemented in this study. Section 4 offers a comprehensive discussion of the results obtained. Discussion has been explored in Section 5. The final section presents the conclusions drawn from the study and suggests potential future research directions.

## 2.Literature review

Ozyurt and Akcayol [11] proposed a sentence segment LDA approach to extract product features and perform sentiment analysis based on these features. The dataset used in this study consisted of smartphone reviews in the Turkish language. This method proved to be effective in identifying the key aspects of the product. Latif et al. [12] conducted an analysis of several topic modeling techniques on a dataset of 0.8 million Urdu tweets. The techniques evaluated included latent semantic analysis, probabilistic latent semantic analysis, LDA, and non-negative matrix factorization (NMF). To gather the tweets, the Twitter application programming interface (API) was utilized, and various hashtags were used as search queries to ensure a diverse dataset. Additionally, the tweet text underwent preprocessing, and three variations of the collected dataset were created as a subsequent step. Numerous features were extracted to represent the documents using different n-gram techniques. The analysis revealed that NMF outperformed strategies using term frequency-inverse document frequency (TF-IDF) feature vectors in the context of Urdu Twitter texts. On the other hand, LDA proved to be superior to the other techniques by effectively merging short texts into larger pseudo documents.

An innovative approach was proposed by Pratama et al. [13] in ABSA of hotel reviews that uses LDA topic modelling to extract latent issues and support vector machines (SVM) to classify aspect sentiment. The researchers proposed five aspects of hotel reviews in this study: food, service, location, comfort, and cleanliness. Three categorization techniques expand the similarity score range from aspect categorization 1 (AC1) to AC3. The accuracy score obtained as a result is 0.94. Researchers have also extracted and analyzed tweets against the backdrop of COVID-19 in the tourism and healthcare sectors worldwide and performed sentiment analysis package in a study by Mishra et al. [14]. The LDA topic modelling technique was applied to identify the hidden pattern and identify similarities between terms between clusters. The concluding step was to predict and categorize the opinions of customers using a cutting-edge deep learning long short term model-recurrent neural network (LSTM RNN) classification model. This model supports the system's ability to monitor citizens' opinions shared via social media websites like Twitter.

The ability of deep learning models to classify sentiment accurately from social media data has been examined by Alsayat [15], particularly the data regarding the coronavirus pandemic. A tailored deep learning model, incorporating advanced word embedding and a LSTM network, is being suggested to improve performance. Experiments conducted on datasets from Twitter, Amazon, and Yelp determined that the proposed models exhibit greater classification accuracy than others. Abdullah et al. [16] suggested a novel approach to feature-based opinion mining in restaurant reviews that considers both explicit and implicit aspects. This specific approach combines three techniques: grammatical rules, a hybrid approach, and senti circle. Aspect and opinion developed with the support of The WordNet and TF-IDF. The results emphasized the approach's accuracy, precision, recall, and F1 score performance. The ABSA by AlGhamdi et al. [17] combines seeded aspect LDA (SA-LDA), SentiWordNet, and the hybrid approach. The work identified and extracted all potential aspects from the textual data. The removed aspects were mapped to their opinions using a topic model and lexicon classification. A sentiment analysis model can be developed using an ensemble learning classifier known as stacking to determine the sentiment orientation of extracted aspects. The approach suggested is capable of accommodating applications that span across multiple domains.

Gangadharan and Gupta [18] proposed an agriculture named entity recognition method (AERTM) using topic modeling techniques. They developed an ensemble model that combines the AERTM algorithm with the agriculture vocabulary (AGROVOC). The terms and phrases in their work were tagged using LDA and AGROVOC, allowing for the creation of a knowledge base specific to agriculture. In a separate study, Banjar et al. [19] introduced an aspect-based sentiment analysis for polarity estimation of customer reviews (ABSA-PER) to analyze customer reviews and determine their polarity. This method involves data preprocessing, calculating aspect co-occurrences, and estimating polarity. The ABSA-PER model demonstrated superior accuracy compared to baseline methods, achieving 85.7% accuracy for aspect extraction and 86.5% accuracy for polarity estimation.

Kishan [20] proposed a two-layer heterogeneous ensemble learning (TLHEL) model to address fault prediction issues. This model employed diverse classifiers to detect different faults and utilized the stacking technique to handle minor errors. Furthermore, outlier removal and data balancing techniques were implemented to optimize the fault prediction model. In another study, Wang et al. [21] investigated the challenges posed by imbalanced datasets. The paper discussed five methods for classifying such datasets: data sampling, algorithm-level classification, feature-level classification, cost functions, and deep learning. It also introduced a new sampling method based on the synthetic minority oversampling technique (SMOTE), SVMs, and k-nearest neighbors (KNN). Additionally, the analysis included evaluation criteria for classifiers and addressed the current problems and solutions for unbalanced datasets.

Desuky and Hussain [22] developed various techniques to tackle the unbalanced dataset problem, as such datasets exhibit incorrectly classified results with a bias towards the majority class. They introduced a modified hybrid strategy using simulated annealing to select an optimal set of main class records and classification techniques such as SVMs, KNN, and decision tree (DT) for assessing efficiency. The efficiency of the technique was conducted by testing on 51 real datasets, and it outperformed contemporary techniques in 14 datasets and performed better in the rest of the dataset. In their study, Naim [23] introduced a novel approach called priority sentence part weight assignment (PSPWA), which employs supervised learning algorithms and convolutional neural network (CNN) to perform aspect term extraction on the cricket and restaurant datasets. According to the findings, despite the imbalance of the datasets, CNN exhibited superior performance compared to other learning algorithms, with F1 scores of 0.59 and 0.67 achieved for the cricket and restaurant datasets, respectively.

Arseniev-Koehler et al. [24] proposed discourse atom topic modelling (DATM) to recognize topics in a dataset and represent documents as topic sequences. The method mentioned above combines topic modelling and word embedding, utilizing a group of vectors to create a concise depiction of an embedding space. The authors demonstrated the method's effectiveness through the analysis of the national violent death reporting system, identifying 225 latent topics in the narratives and uncovering gender biases in reporting. By assessing guest reviews, potential areas for enhancement can be identified in hotel services using this method, which provides a versatile and widely applicable way to model topics in textual data. However, processing large amounts of review data often leads to errors in feature classification and opinion analysis based on aspects. To address this issue, Sunardi and Harjo [25] used TF-IDF and LDA to improve accuracy results and BERT embedding and semantic similarity for AC. The evaluation resulted in the precision, recall, and f-1 measure of 0.86, 0.92, and 0.89 for aspect extraction and 0.96, 0.98, and 0.97 for ABSA.

In their work [26], Wen and Zhao proposed an opinion-mining technique for imbalanced textual comments that integrates deep learning and class-imbalanced learning methodologies within the bidirectional long-short term memory (BiLSTM) framework. The suggested approach involves utilizing adaptive synthetic sampling to address minority class samples in cases of low imbalance while employing the CNN-BiLSTM model to build a sigmoid for sentiment classification. In situations of high inequality, the majority class samples are sampled repeatedly, and multiple rounds of adaptive synthetic sampling for the equalization of minority class samples are performed. Each group of training data is learned using BiLSTM, and ensemble learning is used to generate the final opinion classification performance. Sethi [27] proposes a hybrid ensemble method (HEM) for sentiment analysis to provide more flexible and accurate solutions. This method employs a compound blend of unigram, bigram, trigram and PCA as a dimension reduction strategy. The findings imply that data imbalances can have an impact on the use of SVMs in real-time applications. Compared to many other methods, the revised bagging process is efficient and effective. The study is focused on binary classification, and future research can assess the impact of various domain and regional characteristics as well as extend sentiment analysis to multi-class emotion categorization systems.

D'Aniello et al. [28] research provides techniques for ABSA called the knowledge management and information systems (KnowMIS-ABSA) model. A case study evaluation is carried out to demonstrate the benefits of the Know MIS-ABSA model using product reviews. Cyril et al. [29] proposed a sentiment analysis model that utilizes a clustering technique called k means clustering, which measures Euclidean distance using different aspects. The tweets are then classified using SVM, which measures the support value based on the measures above. The model achieved a 92.48% accuracy and 92.05% sentiment score, which was better than the existing models.

Mujahid et al. [30] conducted an analysis of people's sentiments towards e-learning using a Twitter dataset and employing machine learning and deep learning techniques. The study utilized TextBlob, VADER, and SentiWordNet to analyze the polarity and subjectivity scores of the tweets' text, and different machine learning approaches were employed for opinion mining. The random forest and SVM classifier, using Bag-of-Words (BoW) features, achieved an impressive accuracy of 0.95. The performance was evaluated for the outputs obtained from TextBlob, VADER, and SentiWordNet, as well as the classification outcomes from both machine learning and deep learning models. Additionally, topic modeling was employed to identify the key topics related to e-learning concerns. In a different study, Tao and Zhou [31] focused more on the administrative and economic aspects rather than the consumer perspective. Their research examined the predictors of business closures by analyzing online consumer reviews and validating predictive models specifically for the restaurant industry, which experiences high closure rates.

Obiedat et al. [32] discussed how online media, particularly through social media platforms, have increasingly become prominent in food and beverage events. As a result, customer reviews of these establishments have seen a significant rise. These reviews serve as crucial sources of information for both customers and decision-makers in the food and beverage industry. Sattar et al. [33] highlighted that advancements in communication technology have facilitated valuable connections among individuals in different regions. In response, many companies are adopting modern approaches such as sentiment analysis and profile-based sentiment classification to assess user reviews and enhance product quality. Chen et al. [34] pointed out the proliferation of user reviews on restaurant review sites. To assist users in quickly grasping the essence of review information and reducing the amount of text, the authors proposed an approach to automatically generate aspect-based review summaries based on predefined topics and sentiments. This method aids in condensing the review content.

These articles represent various innovative approaches that combine LDA topic modeling with diverse machine learning algorithms for ABSA across various data types, including hotel reviews, student feedback, and customer reviews. From the literature, it is evident that LDA is a prominent algorithm employed for topic detection. Class imbalance poses a challenge to sentiment analysis. However, adopting ensemble techniques can enhance the performance of opinion mining.

## 3.Methods

This work introduces an ABSA model for extracting relevant aspect-based opinions from an extensive collection of online restaurant reviews. The topic modelling technique LDA is used to extract the most important aspects (implicit and explicit) while also suggesting the EBSVM classifier, an ensemble machine learning method, for conducting sentiment analysis. The SMOTE [35] technique is employed in this study to tackle imbalanced datasets. This work consists of three stages. The architectural overview of the model is shown in *Figure 2*.

The phases of the work area

3.1.Data Pre-processing

3.2.Aspect extraction using LDA

3.3.Sentiment analysis using EBSVM classifier

## 3.1 Data Pre-processing

The restaurant review statements extracted from the Tripadvisor website using the web crawler were used as the dataset for this study. During the preprocessing phase, the dataset is prepared for processing through techniques, including tokenization, stop word removal, stemming, part of speech (POS) tagging, and term frequency.

### 3.1.1.Tokenization

The tokenization process breaks down the review sentence into words, phrases, symbols, and other elements.

### 3.1.2.Stop word removal

The objective of this step is to eliminate common words that do not have as much meaning as keywords.

### 3.1.3.Stemming

This technique is applied to determine the root form of a word [36]. During this process, words are reduced to their base or root words.

### 3.1.4.POS tagging

POS tagging involves labelling each word in a given text with a specific marker indicating its grammatical categories, such as a noun, verb, or adjective. This helps to identify nouns or noun phrases in reviews that represent a practical aspect of analyzing [37].

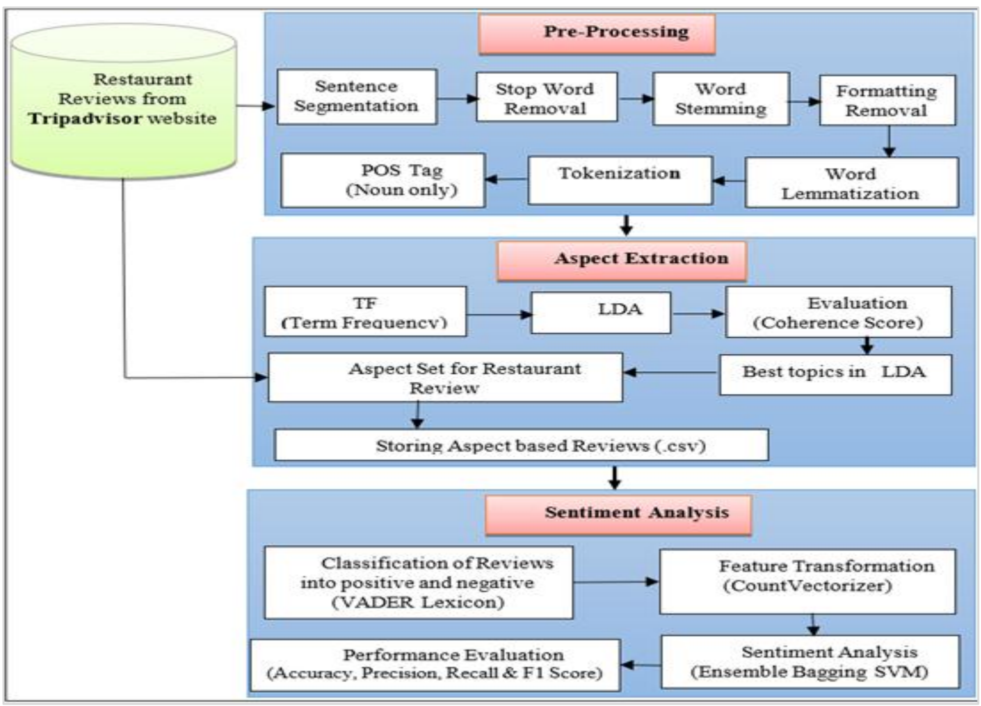


**Figure 2** proposed methodology

## 3.2Aspect extraction using LDA

This phase aims to extract aspects from the restaurant reviews using the Topic modelling methods, LDA. In topic modelling, the latent thematic structure of a large corpus of text documents is automatically discovered [38]. The process of extracting aspects is divided into two parts. In the first step, TF-IDF generates the vector space model. In the second step, LDA identifies the topics related to words found in the review documents.

### 3.2.1. TF

The TF-IDF measures the significance of words in a set of documents by counting their occurrences [39]. Additionally, it evaluates the relevance of keywords and discriminatory information for each word.

### 3.2.2. LDA topic modeling

LDA is a probabilistic model [40] that studies the relationships among topics, terms, and text documents. In the LDA, topics are assigned to the review documents by algorithm 1. The algorithm takes as input a corpus of restaurant reviews and the number of predefined topics (K) and produces K sets of topics, each associated with a cluster of words.

**Algorithm 1**
**Input:** A corpus of restaurant reviews and the number of predefined topics (K).
**Output**: K sets of topics, each associated with a cluster of words.

1. Initialize the algorithm by randomly assigning each word to one of the K topics.
2. For each document D and each word W in the document, calculate:
   a. The percentage of words related to topic T in document D (P (T|D)).
   b. The percentage of words assigned to topic T across all documents that contain words related to W (P (W|T)).
3. Based on the calculated probabilities and the topic assignments of all other words, reassign topic T' to word W with probability P (T) × P (W).

The algorithm starts by randomly assigning each word of the corpus to one of K topics. It then iterates through each document and for each word in the document, calculates the probability of the word belonging to each topic and the probability of the topic being present in the document. To calculate the probability of a word belonging to a topic, the algorithm looks at all other documents that contain the word and calculates the percentage of times the word is assigned to the topic T. Similarly, to calculate the probability of a topic being present in a document, the algorithm looks at all other words in the document and calculates the percentage of times the words belong to the topic T. Finally, based on these calculated probabilities and the current topic assignments of all other words, the algorithm reassigns the topic T' to a word W with a probability computed as the product of P (W|T) and P (T|D), normalized by the sum of this value for all topics. This reassignment is done for all words in the corpus until the algorithm converges to a stable set of topics and topic-word distributions. In summary, the algorithm iteratively updates the word-topic assignments and topic-word distributions until convergence to produce a set of K topics with associated sets of words.

Within each cluster, topic labels are assigned based on terms that appear in the cluster. The words present in each cluster have a coherence score. It is a method of determining the topic's quality. The coherence score is determined by assessing the degree of association between the most frequent words in a given topic. It reflects how closely related the top terms are to one another. The higher the coherence score, the more coherent and interpretable the topic is. The aspect set is created according to the highest coherent score of each topic. Food, service, staff, ambience, and price are the aspects of restaurant reviews. A specific sentence for each aspect is extracted by scanning the review sentence for topic words. The reviews of these five aspects are stored in separate .csv files. Algorithm 2 explains the workflow. The input for this algorithm 2 is a corpus of restaurant reviews, which typically contains many sentences. The goal of this algorithm is to identify the aspects of the restaurant that are being discussed in the reviews, and to group the relevant sentences together based on their aspect.

**Algorithm 2:**
**Input:** Restaurant review corpus.
**Output:** Aspect-based reviews.

```
1.  Preprocess the review sentence
        data1 ← Symbols_Removal
        Data2 ← Tokenization (data1)
        data3 ← Stop_Word_Removal (data2)
        Data4 ← Stemming (data3)
        data5 ← POS_Tagging (data4)
2.  Extract the Aspect using LDA (algorithm 1).
3.  For each "Topic", do
        Mapping topic-aspects
    End
4.  For each "aspect", do
        Read the review sentence
        If the sentence contains "Topic words", then
          Write the sentence in the aspect file.
        Else
          Skip the sentence
        End
    End
```

The algorithm 2 starts by preprocessing the review sentences, which involves removing symbols and punctuation, tokenizing, removing stop words, stemming, and tagging each word with its POS. The next step utilizes the LDA algorithm to identify the different aspects discussed in the restaurant reviews. This step produces K sets of topics, each associated with a cluster of words. Finally, for each aspect, the algorithm reads through the review sentences and checks whether each sentence contains any words that are related to that aspect (based on the topic-aspect mapping). If a sentence contains relevant words, they are added to the file for that aspect. Otherwise, the sentence is skipped. The output of this algorithm is a set of files, one for each aspect, that contain the sentences from the reviews that relate to that aspect. These aspect-based reviews can be useful for analysing the strengths and weaknesses of the restaurant in different areas, and for identifying patterns in customer feedback.

## 3.3Sentiment analysis using EBSVM classifier

Consumers and businesses can benefit from sentiment analysis, which extracts information about opinions from reviews. In this study, an aspect-based review sentence is classified as positive or negative according to the Lexicon-based approach. SMOTE is applied to address the class imbalance problem in the datasets. This study presents a novel approach to enhancing the classification accuracy of sentiment analysis, which introduces an ensemble classifier known as EBSVM for opinion mining. This phase is divided into three sections.

3.3.1.Classification based on lexicons
3.3.2.Balancing the dataset with SMOTE
3.3.3.Transformation of features using CountVectorizer
3.3.4.Sentiment analysis based on the EBSVM classifier

### 3.3.1.Classification based on lexicons

Lexicon-based classification divides the aspect-based review into positive and negative based on the number of words that appear in the two opposing lexicons. In lexicon-based analysis, the polarity of words and phrases in a text must strictly influence the text's semantic orientation [41]. The SentimentIntensityAnalyzer from nltk.vader_lexicon is used in this research to classify the sentiment, and the polarity scores () function is used to determine the polarity score for each sentence. The polarity-based review sentences are stored in separate .csv files.

### 3.3.2.Balancing the dataset with SMOTE

The class imbalance challenges the sentiment analysis as the data are precisely based on the dataset that is being collected. Learning directly from an imbalanced dataset can yield suboptimal outcomes due to the limited information provided by a few minority class instances. Therefore, to conduct an error-free analysis, the dataset must be balanced. SMOTE is used as the oversampling method to generate synthetic samples based on feature-space similarities between existing minority classes [42, 43].

### 3.3.3.Transformation of features using CountVectorizer

The CountVectorizer converts the input text into a vector by counting the frequency of each word's occurrence in the text [44]. The Scikit-learn library in Python provides this tool. The CountVectorizer converts input texts into matrices of token counts. This work uses 'sklearn.model_selection - train_test_split' for separating the training and testing data. Among the data collected, 80% of the corpora are used for training, while the other 20% are chosen randomly for testing.

### 3.3.4.Sentiment analysis using the proposed EBSVM classifier

The ensemble approach improves the predictive model's performance by combining multiple classifiers. Bagging, also known as bootstrap aggregation, is an ensemble approach for improving prediction accuracy [45]. This method combines the results of the same algorithm on the training set using adaptive or random techniques. This work proposes a bagging SVM Classifier to improve the classification performance. A multiple SVM is created from each sub-sample of training data (10 sub-samples, each containing 100 samples), and then each SVM result are combined to get the best prediction.

# 4. Results

## 4.1Dataset

Online reviews have become one of the most critical factors when selecting a restaurant. As one of the world's leading travel website, Tripadvisor [46] offers information and reviews of restaurants, hotels, and attractions around the globe. Consumers can use restaurant reviews to get information about how other people have experienced a restaurant, which can be helpful to them while making a decision. This analysis relied on the restaurant review dataset. Customer feedback from Indian restaurants in four distinct metropolitan areas was collected with web crawlers. This work extracted 46,660 reviews, shown in *Table 1*.

**Table 1** Dataset description

| Metropolitan Cities | Popular Restaurants | Reviews |
|---|---|---|
| **Delhi** | Restaurant 1 | 3335 |
| | Restaurant 2 | 2630 |
| | Restaurant 3 | 3560 |
| | Restaurant 4 | 3335 |
| **Kolkata** | Restaurant 1 | 2620 |

| Metropolitan Cities | Popular Restaurants | Reviews |
|---|---|---|
| | Restaurant 2 | 2820 |
| | Restaurant 3 | 2360 |
| | Restaurant 4 | 3362 |
| **Chennai** | Restaurant 1 | 2531 |
| | Restaurant 2 | 2561 |
| | Restaurant 3 | 2751 |
| | Restaurant 4 | 3301 |
| **Mumbai** | Restaurant 1 | 2880 |
| | Restaurant 2 | 3240 |
| | Restaurant 3 | 2700 |
| | Restaurant 4 | 2674 |
| **Total number of Reviews** | | **46660** |

## 4.2Performance metrics

The probabilistic model LDA is implemented using the Gensim package. The coherence score [47] metric evaluates a model's efficacy. The pair-wise similarity score of frequently occurring words within a topic is calculated here. The objective of computing pair-wise word similarity scores is to identify the words most closely associated with each other in terms of meaning. The topic coherence score is calculated by selecting the top N frequently occurring words in each topic. In this study, N is assigned as 9. Then, aggregate the pair-wise scores to obtain each topic's coherence score. The term frequency is calculated using Equation 1.

TF= (No. of Occurrences of a Word in Document)/ (No. of Words in all Documents) (1)

Equation 2 is the formula for calculating the pair-wise similarity score, and Equation 3 is for calculating the coherence score of each topic.

$(wi,wj)$ =log$(wi,wj)/p(wi)p(wj)$ (2)

Coherence = $\sum_{i<j} (wi,)$ (3)

In a random document, the probability of observing the word 'wi' is represented by p(wi), while the probability of observing the word 'wj' is represented by p(wj). The probability of both 'wi' and 'wj' co-occurring in a random document is represented by p(wi,wj).

The confusion matrix [48] shown in *Table 2* is used to evaluate the efficacy of the EBSVM model. To analyze the model's efficiency, accuracy, recall, precision, and F1 score are utilized. The accuracy of a classifier refers to its ability to correctly predict the label of newly discovered data or previously unknown data. Equation 4 is the formula for accuracy. The precision aims at measuring the number of relevant data items selected. Equation 5 is used to calculate the precision. Recall measures how accurate the model is at detecting positive samples. Equation 6 is the formula for recall. The F1 score is computed using Equation 7. The F1 score is used to measure performance by taking precision and recall into account [49].

**Table 2** Confusion matrix

| | | Positive | Negative |
|---|---|---|---|
| **Actual Conditions** | **Positive** | True positive (TP) | False negative (FN) |
| | **Negative** | False positive (FP) | True negative (TN) |

$Accuracy=TP+TN/TP+TN+FP+FN$ (4)

$Precision=TP/TP+FP$ (5)

$Recall=TP/TP+FN$ (6)

$F1\ score=2\times precision*recall/precision+recall$ (7)

The study analyzes the performance of two techniques, LDA for topic modelling and an EBSVM classifier for sentiment analysis.

## 4.3Aspect extraction model (LDA)

The proposed LDA topic model was developed using the Google Co-laboratory in Python. Its mean coherence score evaluates the model. *Table 3* shows the coherence score for k topics, where the k values range from 1 to 20. The coherence score of this model ranges from 0.17 to 0.47; the highest score is 0.47.

**Table 3** The coherence score Of 'K' topics

| **Topics (K=20)** | **Mean coherence score** |
|---|---|
| 01 | 0.17 |
| 02 | 0.21 |
| 03 | 0.25 |
| 04 | 0.25 |
| 05 | 0.37 |
| 06 | 0.33 |
| 07 | 0.37 |
| 08 | 0.41 |
| 09 | 0.42 |
| 10 | 0.44 |
| 11 | 0.46 |
| 12 | 0.46 |
| 13 | 0.45 |
| 14 | 0.46 |
| 15 | 0.47 |
| 16 | 0.44 |
| 17 | 0.37 |
| 18 | 0.34 |
| 19 | 0.32 |
| 20 | 0.35 |

The LDA generates a collection of topics and a list of words. After the clustering process, the label for each cluster is based on the terms present in that cluster. Topics 11, 12, 13, 14, and 15 are chosen based on their highest coherence scores to create a fine-tuned aspect set. Through LDA topic modelling, aspects regarding food, service, staff, ambience, and price are extracted from the dataset. *Table 4* shows the aspect set extracted based on the highest coherence scores.

The algorithm scans the review dataset to find a match with topic words to extract aspect-specific reviews. Reviews of each aspect are saved in separate .csv files. *Figure 3* shows the extracted reviews related to the food aspect.

**Table 4** The aspect with the highest coherence score extracted using the LDA topics model

| **Topic#11 Service** | **Topic#12 Staff** | **Topic#13 Food** | **Topic#14 Ambience** | **Topic#15 Price** |
|---|---|---|---|---|
| Service | Staff | Food | Ambience | Price |
| Good | Good | Service | Cuisine | Value |
| Care | Polite | Meal | Atmosphere | Recommendation |
| Guest | Breakfast | Lunch | Quality | Plenty |
| Offer | Helpful | Taste | Thing | money |
| Thank | Variety | Ambiance | Tea | cost |
| Hope | Friendly | Idlis | Family | High |
| Prompt | Family | Variety | Variety | Reservation |
| View | Kolkata | Sizzler | Awesome | Reception |

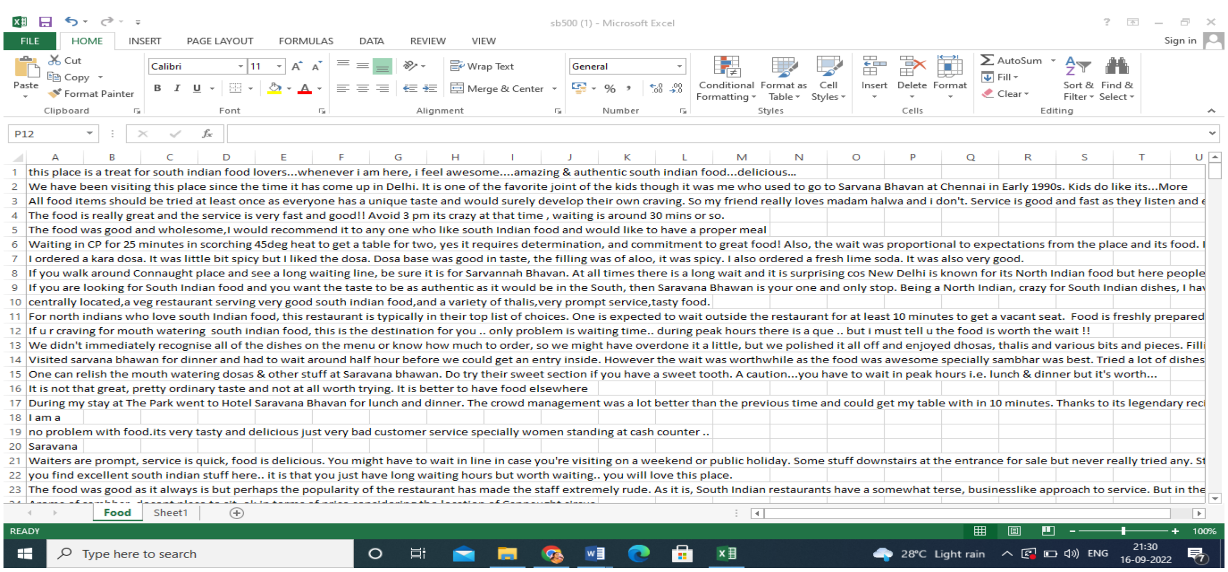


**Figure 3** Extracted reviews related to the aspect –food

### 4.4Sentiment analysis

*Table 5* shows the class distribution of reviews for each aspect. Each positive and negative review aspect is classified according to a Lexicon-based classification. Since the dataset is imbalanced, the SMOTE is used to balance the dataset. *Figures 4* show class distribution before and after applying SMOTE.

**Table 5** Class distribution of reviews for each aspect

| S. No. | Aspect | No. of reviews | No. of positive reviews | No. of negative reviews |
|---|---|---|---|---|
| 1 | Food | 33247 | 24638 | 1411 |
| 2 | Service | 18107 | 13660 | 668 |
| 3 | Staff | 12285 | 9470 | 285 |
| 4 | Price | 10072 | 7139 | 719 |
| 5 | Ambience | 8110 | 6184 | 203 |

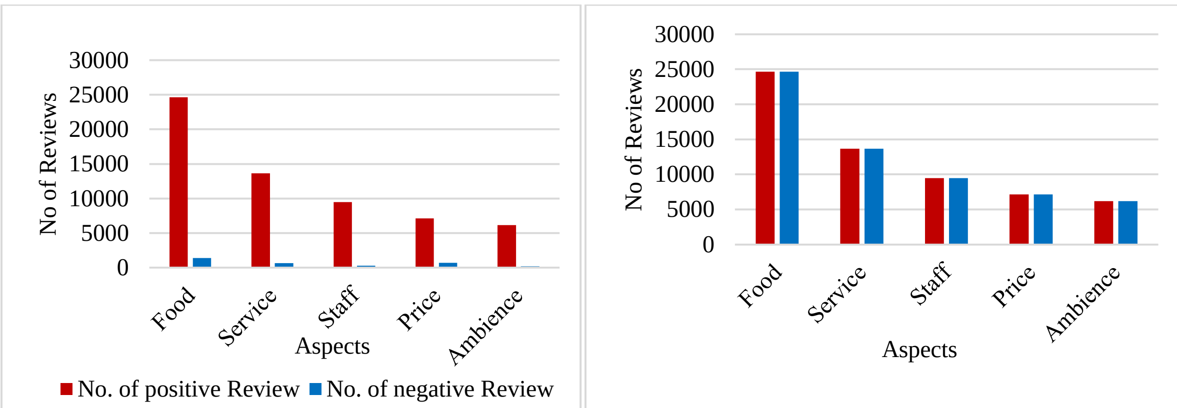


**Figure 4** Class distribution before (a) and after (b) applying SMOTE

The EBSVM classifier's efficacy assessment involves analysing several metrics, including accuracy, precision, recall, and the F1 score. *Table 6* displays each aspect's accuracy, precision, recall, and F1 score for the EBSVM model. Furthermore, comparing the proposed model and existing classification methods in the literature reveals that the former outperforms the latter. *Table 7* compares current articles with the proposed model. This research compares articles that use restaurant reviews as their dataset. The proposed EBSVM classifier has a 96.1% average accuracy (for all five aspects). According to the results, the proposed EBSVM classifier is more accurate than the others.

**Table 6** Results of EBSVM classification

| Aspects | Performance Analysis Metrics | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F1 Score |
| **Food** | 94.4 | 95 | 94 | 94 |
| **Service** | 97.5 | 98 | 97 | 97 |
| **Staff** | 97 | 97 | 96 | 96 |
| **Ambience** | 96.2 | 97 | 96 | 96 |
| **Price** | 95.4 | 96 | 95 | 95 |

**Table 7** Comparative analysis of EBSVM classifier with existing models

| References | Method | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|---|
| [50] | LeBERT | 88.20 | 88.45 | 89.01 | 88.73 |
| [51] | HFV+LSTM | 90.2 | 94.6 | 91.2 | 92.2 |
| [52] | Hybrid-SVM<br>Hybrid-LR | 92.6<br>92.5 | - | - | 91.5<br>90.2 |
| [53] | Stacking,<br>(Base classifiers - | - | 82.7 | 82.7 | 82.7 |

| References | Method | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|---|
| | NB+DT+LR+KNN Meta classifier -SVM) | | | | |
| [54] | HEOLS | - | 85 | 83 | 84 |
| Proposed EBSVM | | **96.1** | **96.6** | **95.6** | **95.6** |

## 5. Discussion

The study explores the effectiveness of ABSA in extracting feature-based opinions from a large volume of online restaurant reviews on Tripadvisor. The data pre-processing phase involves tokenization, stop word removal, stemming, and POS tagging. The proposed model uses the topic modelling technique LDA to extract relevant aspects (implicit and explicit) of the restaurant domain and the EBSVM classifier to conduct sentiment analysis. The study implements SMOTE to overcome the issue of class imbalance in the dataset.

The study uses the coherence score to evaluate the performance of LDA. The topic coherence score is calculated by selecting the top N frequently occurring words in each topic. In this study, N is assigned as 9. This study generates 20 sets of topics and forms cluster of words related to each topic using the LDA algorithm. *Table 3* shows the coherence score for 20 topics. The coherence score of this model varies between 0.17 and 0.47. For the purpose of creating a refined aspect set, topics 11, 12, 13, 14, and 15 are selected based on their highest coherence scores. After the clustering process, labels are assigned to each topic based on the terms formed within cluster. The label assigned to topic 11 is "service", topic 12 is "staff", topic 13 is "food", topic 14 is "ambiance," and topic 15 is "price". Based on the highest coherence, LDA extracted reviews, related to food, service, staff, ambience, and price from the dataset. The aspect set extracted based on the highest coherence scores is presented in *Table 4*.

In order to store the aspect specific reviews, separate .csv files were created under each five topics. To extract aspect-specific reviews, the algorithm searches for a match word in both the aspect set (as mentioned in *table 4*) as well as review dataset and if a match is found, the resultant aspect specific review is written to corresponding .csv files. A number of 33247 reviews extracted under the topic food, 18107 under the topic service, 12285 on staff, 10072 on price, and 8110 on ambience. As a next step lexicon-based classification is applied to categorize the extracted reviews into positive and negative. *Table 5* shows the class distribution of reviews for each aspect. The dataset is observed to be imbalanced as the number of positive reviews exceeds the negative reviews in a huge proportion. Therefore, SMOTE technique is applied here to balance the dataset. A comparison of class distribution before and after applying SMOTE is shown in *Figure 4*. This work proposes an EBSVM model to improve the performance of opinion mining. The accuracy, precision, recall, and F1 score are used to measure the effectiveness of EBSVM. The proposed model achieves an average of 96.1% on accuracy, 96.6% on precision, 95.6% on recall, and 95.6% on F1 score for all the aspects. The model's accuracy, precision, recall, and F1 score for each aspect are presented in *Table 6*. This work compares the proposed model against five recent studies that used restaurant reviews as their dataset. *Table 7* shows the comparative analysis of the EBSVM classifier with existing models. The comparative analysis indicates that our proposed EBSVM model outperforms other techniques, as it can improve accuracy by 3.6%, precision by 2.1%, recall by 4.4%, and F1 score by 3.4%.

The proposed approach can play a significant role in the travel and hospitality industries, as online reviews play a vital role in attracting customers. By analysing the customer reviews, industries can identify the aspects that need improvement and can take corrective measures to enhance customer satisfaction. Moreover, the model can assist potential customers in making decisions while selecting a restaurant. Additionally, the study demonstrates the potential of machine learning techniques to improve sentiment analysis performance, which is useful for several other industries that rely on customer feedback. Overall, the study demonstrates the effectiveness of ABSA in extracting relevant feature-based opinions from a large volume of reviews and highlights the potential of proposed EBSVM classifier in improving sentiment analysis performance.

### 5.1Limitations

However, there are certain limitations to this study that should be acknowledged. The dataset used only covers a single travel website, which may restrict the generalizability of the proposed model to other domains or languages. Only one feature extraction technique is used in this work. Since this work is completely carried out on the ABSA, other parameters are barely taken into consideration. The evaluation metrics for opinion mining are limited to accuracy, precision, recall, and F1 score. Furthermore, the comparison of the proposed model's performance against other techniques is limited. Therefore, further research is recommended to investigate the generalizability of the findings to other datasets and assess the effectiveness of alternative techniques.

A complete list of abbreviations is shown in *Appendix I.*

## 6. Conclusion and future work

The analysis of digital data to obtain user opinions plays a vital role in today's digital landscape to enhance customer satisfaction. In this context, a model was proposed to analyze customer reviews and generate relevant aspect-based opinions. The model employed an LDA topic model to extract the aspects, and an EBSVM classifier was utilized for opinion mining. Due to the imbalanced nature of the dataset, SMOTE was employed to balance it. The performance of LDA was evaluated using the Coherence Score, which ensures the generation of high-quality topics specifically for restaurant reviews. The aspects related to food, service, staff, ambience, and price were extracted from the dataset using LDA. To assess the performance of the EBSVM classifier, metrics such as classification accuracy, precision, recall, and the F1 score were adopted. The proposed EBSVM classifier achieved an impressive accuracy rate of 96.1%. Moreover, compared to other techniques discussed in the existing literature, the suggested approach demonstrated significant enhancements in overall performance. Future studies will focus on further improving the ensemble classifier to enhance its performance. Additionally, the effectiveness of the proposed approach across different domains will be explored.

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### Conflicts of interest

The authors have no conflicts of interest to declare.

### Author's contribution statement

**Shini George:** Conceptualization, methods, data analysis, draft writing, and result interpretation. **Dr. V. Srividhya:** Supervision, verification and validation of data, final correction, and investigation of challenges.



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## Appendix I

| S. No. | Abbreviation | Description |
|---|---|---|
| 1 | ABSA | Aspect-Based Sentiment Analysis |
| 2 | ABSA-PER | Aspect-Based Sentiment Analysis for Polarity Estimation of Customer Reviews |
| 3 | AC | Aspect Categorization |
| 4 | AERTM | Agriculture Named Entity Recognition method |
| 5 | AGROVOC | Agriculture Vocabulary |
| 6 | AI | Artificial Intelligence |
| 7 | API | Application Programming Interface |
| 8 | BiLSTM | Bidirectional Long-Short Term Memory |
| 9 | BoW | Bag-of-Words |
| 10 | CNN | Convolutional Neural Network |
| 11 | DATE | Discourse atom topic modelling |
| 12 | DT | Decision Tree |
| 13 | EBSVM | Ensemble Bagging Support Vector Machine |
| 14 | HEM | Hybrid Ensemble Method |
| 15 | HEOLS | Hybrid Expanded Opinion Lexicon-SentiCircle |
| 16 | HFV | Hybrid Feature Vector |
| 17 | KNN | K-Nearest Neighbours |
| 18 | KnowMIS | Knowledge Management and Information Systems |
| 19 | LDA | Latent Dirichlet Allocation |
| 20 | LeBERT | lexicon-Enhanced Bert Embedding |
| 21 | LR | Linear Regression |
| 22 | LSTM | Long Short-Term Memory |
| 23 | LSTM-RNN | Long Short Term Model- Recurrent Neural Network |
| 24 | NB | Naive Bayes |
| 25 | NLP | Natural Language Processing |
| 26 | NMF | Non-negative Matrix Factorization |
| 27 | POS | Part of Speech |
| 28 | PSPWA | Priority Sentence Part Weight Assignment |
| 29 | RNN | Recurrent Neural Network |
| 30 | SA-LDA | Seeded Aspect Latent Dirichlet Allocation |
| 31 | SMOTE | Synthetic Minority Over-sampling Technique |
| 32 | SVM | Support Vector Machine |
| 33 | TF-IDF | Term Frequency-Inverse Document Frequency |
| 34 | TLHEL | Two-Layer Heterogeneous Ensemble Learning |