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Utilizing Deep Learning for Aspect-Based Sentiment Analysis in Restaurant Reviews

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Abstract

Consumers rely on social media opinions to make product choices and purchases. With the popularity of web-based platforms like Tripadvisor, consumers express their opinions and feelings about food quality, service, and other aspects affecting restaurants through comments. Hence, analyzing these comments can be valuable for others to choose a restaurant or to improve and develop their products and brands. Sentiment analysis utilizes text mining methods to extract, identify, and study emotions and subjective perceptions. Since consumers can use comments to choose a restaurant, this study seeks to provide sentiment analysis of their reviews on the Tripadvisor website about Iranian restaurants. This study is applied in nature, aiming to analyze and manually label 4000 comments from the Tripadvisor website regarding restaurants in ten tourist cities across Iran. It uses a standard extended long short-term memory algorithm for sentiment analysis, a deep learning neural network, and Python text mining packages for modeling. The results indicate that the F-Measure for all aspects exceeds 80%, indicating sufficient efficiency and accuracy of the aspect-based sentiment analysis model for restaurant reviews. The most significant features for customers of Iranian restaurants are the food and the atmosphere. This study represents one of the initial efforts to analyze comments posted on the Tripadvisor website concerning Iranian restaurants. Business owners in the tourism industry, especially restaurant owners, can use the proposed model to automatically and quickly analyze customer feedback, improve performance, and gain a competitive edge. The proposed model can also assist users of online platforms in analyzing the opinions of others, enabling them to make informed decisions more efficiently.

Keywords: Deep learning, Text Mining, Sentiment Analysis, Neural Network.

Introduction

Studies show that the total number of social media users in 2023 has reached 4.8 billion (Nyst, 2023). It is important to note that 150 million users are new users who joined various social media between April 2022 and April 2023 (Nyst, 2023).

Thanks to social media, people have access to the opinions of their friends and even strangers worldwide regarding the services or products they have used (Zhang et al., 2011). These opinions, published in communication channels and social networks, influence many customers' decisions like users' purchase decisions or purchase intentions (Noroozi et al., 2023), and help company managers maintain quality, product development, and brand (Zhang et al., 2011). The users' opinions and feelings hidden in their comments are a suitable source that helps business owners for more informed decision-making (Karimi et al., 2024).

In recent years, communication channels and online platforms such as Yelp, TripAdvisor, and Airbnb have allowed individuals to publish experiences (Vu et al., 2017). Meanwhile, Tripadvisor is one of these sources of information and is the world's largest travel website, widely used to publish comments about hotels, restaurants, and tourist attractions (Khorsand et al., 2020). Although people use various sources such as advertisements in magazines and television and suggestions from friends to find an appropriate restaurant, as mentioned before, the development of technology and the use of social networks to express opinions influence the decisions of many people on the web (Jia, 2018; Schouten & Frasincar, 2016).

Since online comments are anonymous and voluntary, social pressure to express opinions is reduced, and real feelings are expressed. Furthermore, opinions are usually expressed immediately after the experience, making comments more accurate, but the questionnaire uses memory that may not contain real feelings and beliefs (Yan et al., 2015). By exploring users' content, restaurant owners can achieve many vital points to improve quality effectively and inexpensively (Jia, 2018). Generally speaking, text mining is to find a hidden pattern among the big data that determines people’s attitudes and feelings towards a particular subject that is hidden in opinions. Therefore, opinion mining is about extracting and analyzing people’s opinions, and sentiment analysis is a technique that extracts and collects those emotions in sentences (Divyashree & Majumdar, 2017).

The sentences in each comment contain aspects that form the subject of that comment, including the specific concepts of each restaurant. Aspect-Based Sentiment Analysis (ABSA) calculates the opinion meaning of each entity and its aspects that are mentioned explicitly or implicitly in the text (Zuheros et al., 2021).

Studies show that in recent years there has been a growth in the tourism industry’s sentiment analysis. The co-occurrence map of "sentiment analysis" and "tourism" keywords, which have been extracted from Scopus, discloses that the combination of sentiment analysis and tourism is a new trend in recent years (Fig 1). Fig 1 presents the result of the VOSviwer analysis.

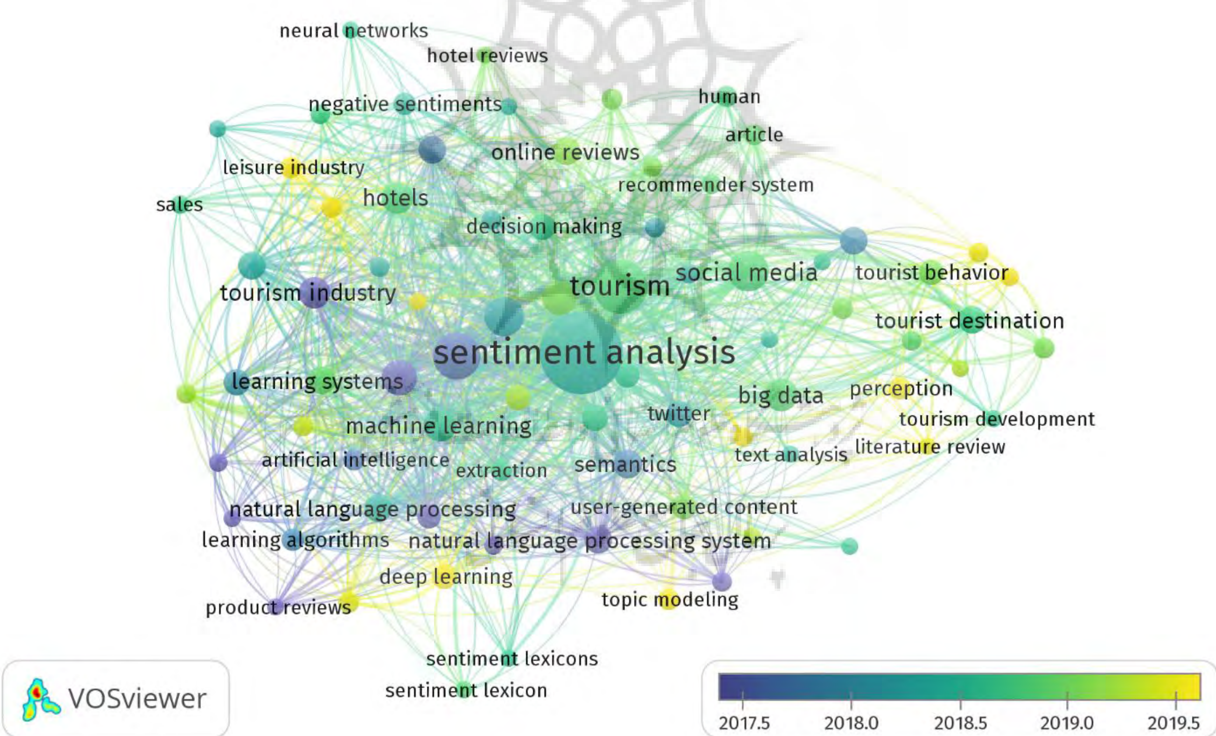

Figure 1. The keywords co-occurrence of "sentiment analysis" and "tourism"

Nowadays, eating in restaurants is growing in Iranian society due to several reasons, such as increasing women's employment rate and lifestyle changes. It provides a good market for the restaurant industry and makes competition to attract new and keep existing customers more challenging (Haghighi et al., 2012).

Because people visit restaurants several times a year, the restaurant is no longer a place to eat but also a part of the entertainment and interactions of the community. It is also an industry with a high volume of transactions in the country. For this reason, it is necessary to pay special attention to this part of society, improve the quality, and reduce the shortcomings according to the customers' wishes. Previously, collecting data and comments was challenging, but now customers reflect their needs and opinions on social networks and websites, which constitutes a considerable amount of raw data. Preparing this raw data and turning it into usable information is the main challenge now in retrieving people's opinions.

The text of the published comments and the documentation of these websites are unstructured. With the help of sentiment analysis and text mining tools, unstructured texts become comprehensible information, concepts, and patterns. The extracted information is an excellent opportunity for restaurant owners to identify opinions about their restaurant and competitors. Therefore, due to the mentioned importance of the restaurant industry in Iran, paying attention to users' opinions is considered the most important thing for the success of a restaurant. The large volume of comments on websites like Tripadvisor provides more accurate analysis and results to obtain users' opinions.

For this reason, in this study, we have analyzed the sentiment of customers of Iranian restaurants in the cities of Tehran, Isfahan, Shiraz, Yazd, Kerman, Kish, Qeshm, Mashhad, Tabriz, and Kashan. According to our research, such a study has not been done in Iran, and restaurant owners can benefit from its results. We propose and develop a deep learning-based model, an appropriate tool for opinion mining, to investigate users' opinions about Iranian restaurants based on their comments on the Tripadviser.com website.

In the second section, we will review similar studies, and later in the third section, we will discuss our methodology. The fourth section consists of the evaluation criteria, and finally, this study will be discussed and concluded in section five.

Literature Review

The theoretical background of the research

Businesses are increasingly becoming aware of the importance of customer feedback. Given the growth of digital platforms to reflect people's feedback, paying attention to them is critical to developing business in a competitive world in various industries. Hence, various data mining studies utilized different methods and approaches in tourism, particularly in restaurants. There are several process models for implementing data mining, one of the most common of which is Crisp, which includes steps in business understanding, data understanding, data preparation, modeling, evaluation, and deployment (Shafique & Qaiser, 2014). This study uses the Crisp's methodology. Businesses today have found that text mining and sentiment analysis provide them with valuable opportunities and information, and restaurants are no exception (Mäntylä et al., 2018). Sentiment analysis is a multi-step process involving data retrieval that requires data source identification, data extraction and selection, data preprocessing, feature extraction, topic detection, and text mining (Alaei et al., 2017) and focuses primarily on the analysis of subjective sentences polarity. However, subjective sentences do not explicitly include explicit opinions (Singh et al., 2020). Sentiment analysis and opinion analysis terms are not precisely equivalent but are often used interchangeably in research papers (Yue et al., 2019) and are two related fields that use natural language processing techniques to extract subjective information (García-Pablos et al., 2016).

Sentiment analysis has two main approaches: machine learning-based approach and lexicon-based approach. Lexican-based approaches further divided into dictionary-based or corpus-based, while machine learning-based approaches can be partitioned into supervised learning, semi-supervised learning, and unsupervised learning approaches (Kulesza et al., 2014; Tyagi & Sharma, 2017). Supervised learning includes standard statistical classification of many labeled items (Yue et al., 2018).

Sometimes users tag through a specific category (for example, hotel) or ranking (scoring) on the websites while submitting a comment. Finally, through this labeled data, a classification model is created to detect the polarity of new data (Alaei et al., 2017).

However, the lexical method does not require any labeled examples; it is therefore considered an unsupervised approach. In this method, words are divided into two classes, positive and negative, and if the sum of the number of positive terms is more, it will be considered a positive document (Tan et al., 2008). Machine learning has deep learning subsets in which different neural network methods are combined to classify patterns. Multiple layers are usually used to learn complex data representations, and higher-level features and correctly classify or measure data properties (Agarwal et al., 2020).

Today, different types of deep learning models are used for sentiment analysis, such as deep neural networks, recurrent neural networks, and convolutional neural networks. In Recurrent Neural Networks (RNN), the connections between neurons form a directional cycle, which creates feedback loops. The primary function of this network is to process sequential information based on internal memory taken by guided cycles. Unlike traditional neural networks, the RNN can remember the previous information calculation and reuse it using the next element in the input sequence (Dang et al., 2020). Extended long short-term memory networks (LSTM) are one of the types of recurrent neural networks. The structure of LSTM networks is similar to RNNs, but only there is a kind of memory unit instead of any hidden self-connected unit. Although RNNs are designed to deal with variable sequences, they have limitations. RNNs do not learn long-term dependencies, but the LSTM network uses memory to solve this problem (Roshanfekr et al., 2017).

Empirical background of the research

Sentiment Analysis

With the aim of opinion mining in tourism using unsupervised learning, Dami and Sotoudeh developed a framework for extracting opinions on hotels from the Iran booking website (Dami & Mohammadi, 2017). Abbasi et al. (2019) utilized sentiment analysis to understand the implicit and explicit preferences of users, They used these preferences to develop an accurate recommender system (Abbasi et al., 2019). Li and Yang (2017) collected comments in Chinese about hotels from Tripadvisor. Using the lexical approach, they performed sentiment analysis. They then compared this model with logistic regression and support vector machine, and with the confusion matrix, they found that the supervised approach improves the performance of each model (Li & Yang, 2017). Kharadi and Patel (2017) also used the support vector machine to analyze users' opinions about restaurants and reached acceptable accuracy (Kharadi & Patel, 2017). Zheng et al. (2011) concluded with comments from Openrice users that machine learning techniques work well in categorizing comments in Cantonese. The Naive Bayes performed better than the support vector machine, and as the feature size increases, their accuracy maximizes before over-fitting the categories (Zhang et al., 2011).

Aspect-Based Sentiment Analysis

In machine learning for restaurant reviews, we can refer to the Sahar et al. (2019) study, which has performed aspect-based sentiment analysis using Tripadvisor comments. The Naive Bayes was based on a bag of words and one for nouns; the second approach better-recognized sentiments (Sahar et al., 2019). Using a support vector machine, Yu et al. (2017) distinguished positive and negative comments and their intensity and found that service was more important than food taste (Yu et al., 2017). Park et al. (2016) Analysed tweets about Asian restaurants. Most positive tweets were about food quality, and negative tweets were about service quality or food culture (Park et al., 2016). In another study, with a support vector machine, AdaBoost, and Stochastic gradient descent, the Aspect Category Detection, opinion target expression, and polarity classification on restaurant comments were performed reasonably (Guha et al., 2015).

Deep learning in aspect-based Sentiment Analysis

Among the studies that conducted aspect-based sentiment analysis through deep learning is the Nguyen study. He proposed a standard sentiment analysis model on two restaurant and laptop datasets to extract aspects and classify polarity (Nguyen & Shirai, 2018). Ruder et al. (2016) applied LSTM to datasets in five domains (restaurants, hotels, laptops, phones, cameras) and eight languages using the aspect-based method and deep learning algorithm. They concluded that the algorithm that considers a review's structure and the context of a sentence for its predictions could give competitive results only by relying on sentence information (Ruder et al., 2016). In a study with a multiple attention network algorithm, the level of aspects and overall sentiments were extracted from the text of the restaurant and hotel review using the level of aspects and overall customer ranking, which had high accuracy (Qiang et al., 2020).

Among other methods based on attention and combining them with LSTM are Ma et al. (2018) research in which a two-step model including target and sentence encoding was presented. Attention to the level of the target learns to participate in the sentiment part of a target phrase and create a more accurate representation of the target while paying attention to the level of the sentence seeks evidence for the purpose and aspect throughout the sentence (Ma et al., 2018). Or in another example, Wang's study (2016) using restaurant reviews showed that the attention mechanism could focus on different parts of a sentence when other aspects are considered input. Also, the polarity of the sentence is related to the desired aspect (Wang et al., 2016). Maw and Khine (2019) proposed a bi-directional extended short-term memory network for restaurants and hotels in Myanmar but could not correctly classify the aspect with context words (Maw & Khine, 2019).

In another study with Arabic language reviews, a Conditional random field classification was performed to extract the aspect opinion target expressions. The aspect-based LSTM was used to classify the polarity of sentiments, in which opinion target expression aspects are considered accurate expressions to identify the polarity of emotions. This algorithm improved accuracy and performance (Al-Smadi et al., 2019).

Al-Samadi et al. (2018) conducted another study in Arabic by using a hotel dataset in Arabic for aspect-based sentiment analysis. This algorithm identifies aspects, extracts aspect opinion target expression, and identifies the polarity of aspects using the support vector machine and the RNN. The support vector machine performed better, but the neural network operated faster (Al-Smadi et al., 2018). Liu and Shen (2020) assume that a sentence consists of multiple emotional clues and that each emotional clue consists of several words. On the English and Chinese datasets, they used a gated alternate neural network to analyze aspect-based sentiments. This algorithm is derived from a combination of recurrent and convolutional networks (Liu & Shen, 2020).

According to our research, we couldn't find any similar study that has performed aspect-based sentiment analysis on Iranian restaurants. Furthermore, manual data labeling distinguishes this study from many previous studies.

Methodology

This study follows steps of the Crisp's methodology. This methodology includes business understanding, data understanding, data preparation, modeling, evaluation, and deployment (Shafique & Qaiser, 2014). The Fig 2 shows the steps of this study. First, while getting acquainted with the goals of restaurants, their success criteria, and the industry's factors and terms, we also learned about the Tripadvisor website's type of activity, goals, and position. Since the tourism potential and high number of restaurants in 10 tourist cities of Iran led to a high number of comments on the Tripadvisor website, researchers selected these for comment extraction. Then, in the data understanding stage, reviews from ten cities of Tehran, Isfahan, Shiraz, Yazd, Kerman, Kish, Qeshm, Mashhad, Tabriz, and Kashan were collected from the Tripadvisor website. The extracted data needed preprocessing and preparation to enter the model. Data preparation represents all activities to build the final data set for modeling purposes. This step is crucial for all the expected results and, in many cases, has different repetitions (Kamalpour et al., 2017). To prepare the data, we went through the following steps:

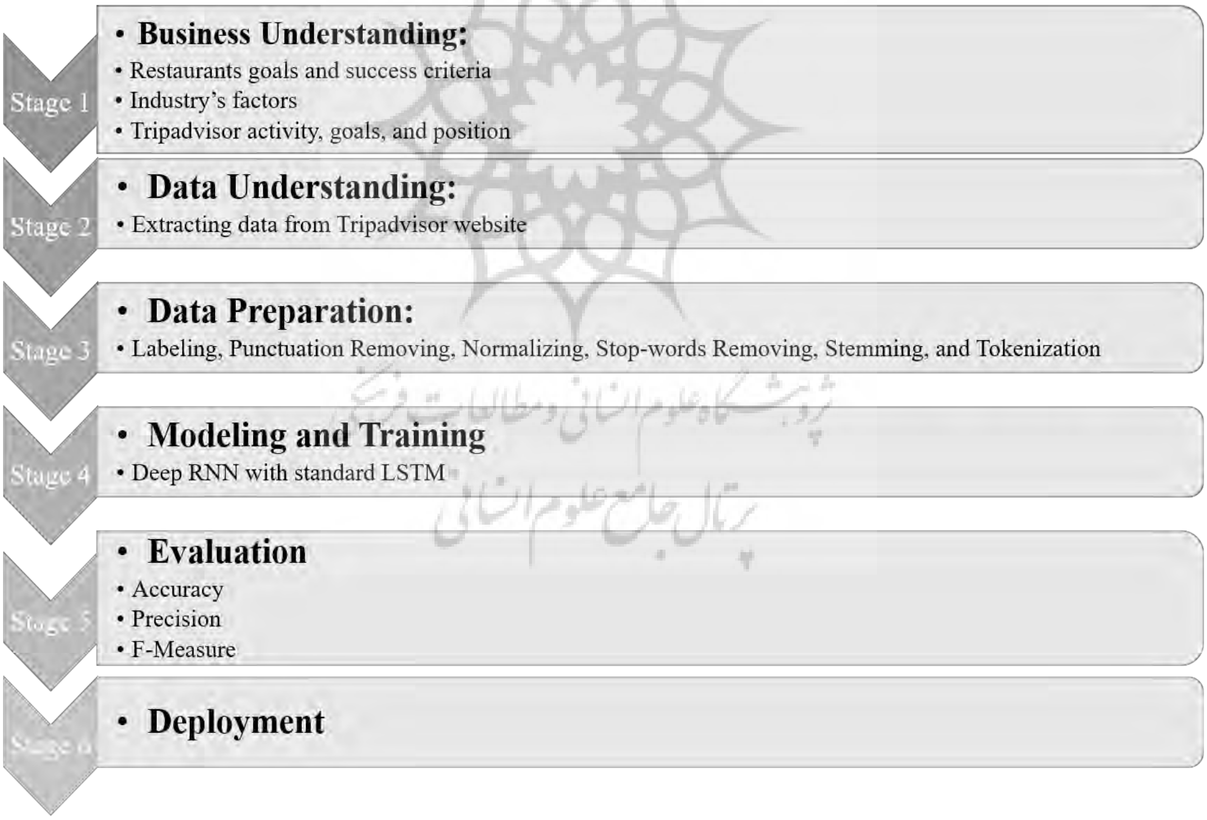

Figure 2 Methodology steps

Labeling: In supervised learning, the model learns from sample data labeled based on some of the target concepts. Hence, an algorithm learns to predict new data labels (Kulesza et al., 2014). TripAdvisor's website defines four dimensions for each restaurant: food, service, value, and atmosphere. Each aspect of these four dimensions was labeled with the following four numbers. A total of 4,000 comments were labeled.

- -2 indicates not being related or not mentioning the aspect.
- -1 means the user's negative opinion about the aspect.
- 1 shows positive user feedback on the aspect.
- 0 indicates the user's neutral opinion on the aspect.

It should be noted that due to the very small and insufficient number of neutral comments for the model to learn, the zero label was removed.

Punctuation Removal: To prepare the text for analysis, it is necessary to remove punctuations, such as [, \.!? @ / # $ *; + "And numbers.

Normalization: To normalize English texts, we changed all the letters to lowercase forms to be integrated for analysis.

Stop-words Removal: To make the model more efficient, repetitive words that do not add knowledge to the text, such as "you", "a", "it", "I", "the" and "of" were removed at this stage.

Stemming: This process converts each word of a sentence into its root form and eliminates the various adjectives of each word. Stemming and etymology reduce noise and improve data retrieval accuracy (Agarwal et al., 2020).

Tokenization: The division of content by division based on distinct distances and symbols and the formation of a package of words is called tokenization (Kharadi & Patel, 2017). Also, this step prepares the data to enter the model. Table 1 shows an instance of the preparation steps:

Table 1. Data Preparation Example

Data Preparation	Sentence Changes
Initial Text	A good and economical place to taste Persian cuisine, but English is out of service here!!
Punctuation Removal	A good and economical place to taste Persian cuisine, but English is out of service here
Normalization	a good and economical place to taste Persian cuisine, but English is out of service here
Stop-words Removal	good economical place to taste Persian cuisine English service here
Stemming	good economy place taste Persian cuisine English service here
Tokenization	[good], [economy], [place], [taste], [persian], [cuisine], [english], [service], [here]

After the preparation step, the comments entered the modeling step. Among the classification methods, deep learning in research has achieved acceptable results, and this type of modeling adopts a multilayer approach to the hidden layers of the neural network (Dang et al., 2020).

Unlike traditional neural networks, the RNN uses feedback loops in which the output of each phase is fed to the RNN to affect the outcome of the current stage. This process is repeated for subsequent steps. RNNs have been shown to perform well in sentence-level sentiment analysis and are a robust algorithm for sequential data processing (Al-Smadi et al., 2018). This network is specifically designed for learning data sequences and is mainly used to classify textual data, except that LSTM can learn long-term dependencies.

The model used in this study is a deep RNN of the standard LSTM type, which is implemented with a Keras library by a sequential model. A standard LSTM usually encrypts the sequence in only one direction (Maw & Khine, 2019).

The mathematical representations of neural network cells in LSTM are as follows (Ma et al., 2018):

$$f_i = \sigma(W_f[x_i, h_{i-1}] + b_f)$$

$$\mathbf{I_i = \sigma(W_f[x_i, h_{i-1}] + b_I)}$$

$$\tilde{C}_i = \tanh(W_C[x_i, h_{i-1}] + b_C)$$

$$C_i = f_i * C_{i-1} + I_i * \tilde{C}_i$$

$$O_i = \sigma(W_O[x_i, h_{i-1}] + b_O)$$

$$h_i = O_i * \tanh C_i$$

Component	Description
F_i	Forget Gate
I_i	Input Gate
O_i	Output Gate
W_f, W_i, W_o	Weight Matrix
b_f, b_i	Bias Scalar
C	Cell State
h_i	Hidden Output
σ	Sigmoid Function

After the modeling step, we trained the model and defined the parameters and hyperparameters. In this step, we set aside 20% of the data for the test and applied the remaining 80% for training. Different hyperparameters were selected for each aspect depending on the number of comments in each aspect and trial and error, for example, for the atmosphere aspect as follows:

Table 2. Values of hyperparameters for the atmosphere aspect

hyperparameters	Values
Dropout	%20
Class Weights	1,5,1
Epoch	6
Batch	16
Optimiser	RMSprop
Learning Rate	0/0004
Activation Function in The Hidden Layer	Relu
Activation Function in The Output Layer	Softmax
Loss Function	Categorical Cross Entropy

The next step was to ensure the model's performance by evaluation criteria. From a Crisp methodological point of view, before starting the final application of the model, it is necessary to fully evaluate it in terms of performance, accuracy, and efficiency and review the steps taken for creation to ensure that the model correctly gains business targets. At the end of this stage, a decision must be made about the data mining results' application (Chapman et al., 2000).

Considering the data type and the ultimate goal of the algorithm is influential in choosing the evaluation method. The choice of loss function depends on factors such as the type of desired learning and the activation function. Due to the three-class nature of the model, the categorical cross-entropy function is chosen for the loss function. The following diagrams show that the model training process is done well without over-fitting.

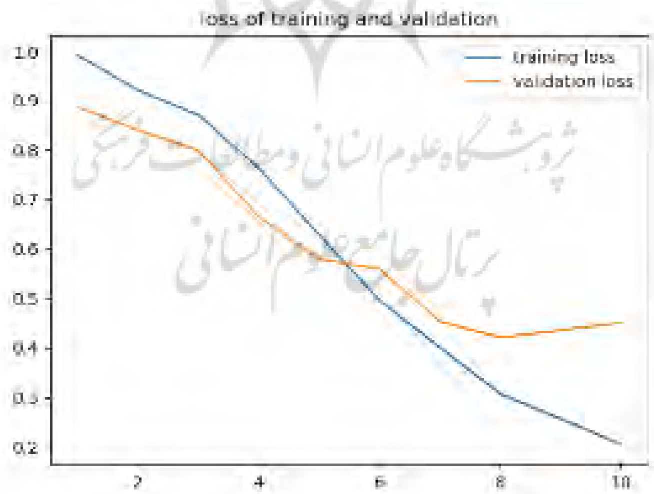

Figure 3. Loss of training and validation

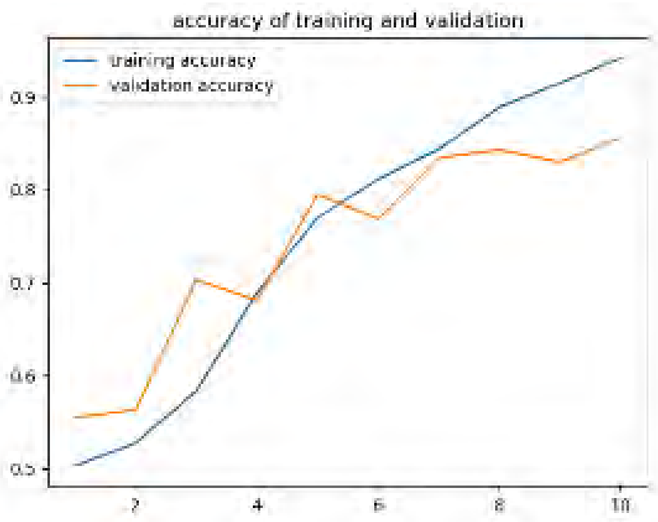

Figure 4. Accuracy of training and validation

There are various algorithms and criteria for evaluation and we used three criteria: accuracy, precision, and F-Measure. In this section, evaluation criteria are introduced and reviewed.

Accuracy:

Accuracy is a standard evaluation criterion in aspect-based sentiment analysis and is easy to understand. Accuracy shows the ratio of the number of correct classifications to all classes in the samples of all classes. In general, higher accuracy indicates better classification. But this is not always the case. This measure cannot show the classifier's performance in a data set with an unbalanced distribution (Liu & Shen, 2020).

The accuracy calculation equation is as follows:

$$Accuracy = \frac{TrueNegatives+TruePositives}{TruePositives+FalsePositives+TrueNegatives+FalseNegatives} \quad (1)$$

Precision:

In classification, precision is the number of real positives for a class; that is, the number of items that correctly belong to the positive class is divided by the total number of elements belonging to the positive class (Dhurve & Seth, 2015).

$$Precision = \frac{TruePositives}{TruePositives+FalsePositives} \quad (2)$$

F-Measure:

It combines the measure of accuracy and recall. The recall is a correct positive number divided by the total number of components belonging to the positive class. In other words, the positive elements divided by the sum of true positives and false negatives calculate the recall rate (Dhurve & Seth, 2015).

$$F_1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{3}$$

Finally, it should be noted that according to Crisp methodology, the last step of data mining does not end in the evaluation, and the results should be used in future research or businesses.

Results

In this study, it was obtained by sentiment analysis based on the following findings:

We used word cloud as part of data representation before preparing it to build the model. Word clouds provide a better visual representation and help to compare two or more categories. The more repetitions a word is used, the larger the display in the word cloud (Geetha et al., 2017). The most used terms in cities are restaurant, food, good, service, place, and delicious.

Figure 5. Shiraz City word cloud

Figure 6. Isfahan City word cloud

Figure 8. Tehran City word cloud

Figure 7. Mashhad City word cloud

The graphic diagrams below show the percentage of each class in each aspect. Using these charts helps us to understand the data more accurately.

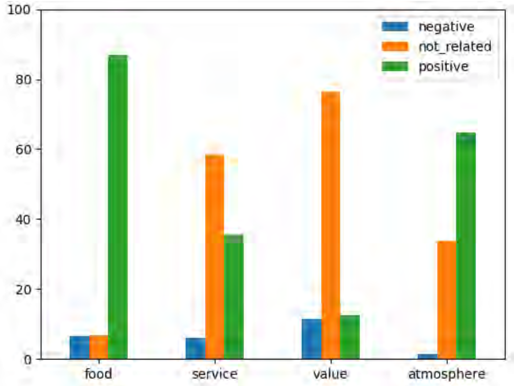

Diagram 1. Shiraz City

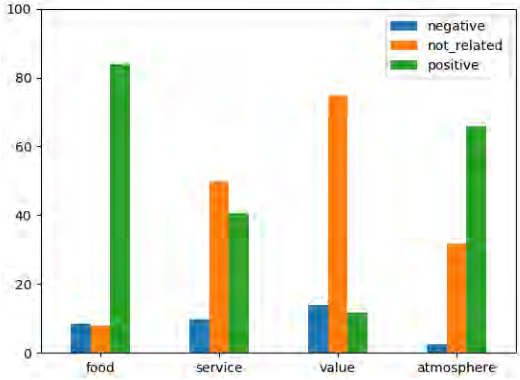

Diagram 1. Isfahan City

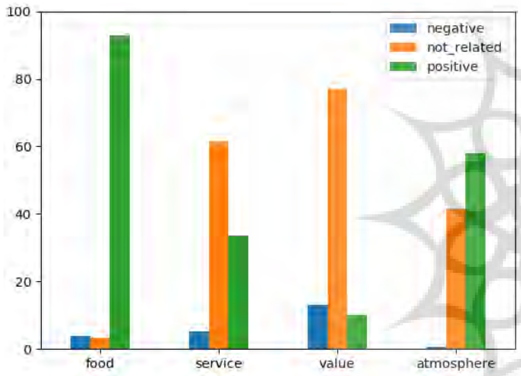

Diagram 3. Tehran City

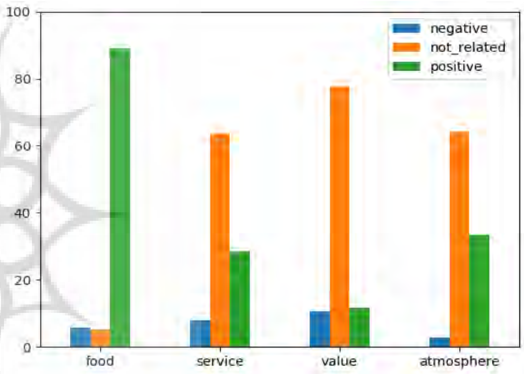

Diagram 4. Mashhad City

According to the charts above, most feedback on the food aspect has been positive. The comments that did not mention the service aspect were more than the other comments, and the percentage of people who had positive comments about the restaurant service was more than the negative comments. Value or price was another aspect not usually addressed in the comments. But among those who have paid attention to it, in Isfahan and Tehran, negative opinions about the price have been more than positive, with a slight difference. In the cities of Shiraz and Mashhad, with a minimal difference, the majority are positive compared to negative reviews. Most of the opinions of Mashhad have not mentioned the aspect of atmosphere. While in other cities, a positive opinion of a restaurant atmosphere is the majority of opinions. The results of the evaluation criteria are as follows:

Table 4. Evaluation Metrics

Measure	Food Aspect	Service Aspect	Value Aspect	Atmosphere Aspect
Accuracy	82.42%	86.71%	87.07%	81.40%
Precision for first class (-2)	48.38%	84.29%	91.66%	80.10%
Precision for second class (-1)	74.19%	87.50%	71.87%	33.33%
Precision for third class (+1)	85.20%	90.67%	75.30%	82.83%
F-Measure	82.42%	86.71%	87.07%	81.40%

The evaluation criteria in the table above show the model's performance separately for each aspect. The accuracy indicates whether the model is adequately trained and predicts the output correctly. In all aspects, this measure has been above 80%, which means the good overall performance of the model. In other words, if we have 100 reviews as an example, it correctly identifies the polarity of the review in each aspect over 80 items. The higher the precision, the smaller the amount of data incorrectly categorized in a particular class. In the first class (-2 label), the precision in terms of food has decreased. The main reason is that in the comments, most people mentioned the aspect of food and very few did not.

For this reason, the accuracy is below 50%. Also, class -1 has low precision in terms of the atmosphere because the number of people dissatisfied with the restaurant's atmosphere was minimal. F-Measure illustrates how a classifier works on classes and the quality of classification. F-Measure above 80% is obtained for all aspects, indicating the model's appropriate classification. As a result, our model has been able to perform aspect-based sentiment analysis on the reviews of Iranian restaurants with acceptable accuracy.

Conclusion

This study shows that the standard long-term, short-term memory neural network method is acceptable for aspect-based sentiment analysis of Iranian restaurants. The algorithm's accuracy was 82.42%, 86.71%, 87.07%, and 81.40% for food, service, value, and atmosphere, respectively. Also, as in previous research, it reminds restaurant owners of the need to pay attention to online feedback and provides practical suggestions to managers. According to the results, food is one of the most frequently used words, and most comments have mentioned it. Therefore, food has been the most important factor mentioned in the comments, and restaurant managers should pay attention to its quality. Also, in most cities, the restaurant's atmosphere has been the second most crucial factor for customers. Therefore, it is essential to consider the factors that improve the atmosphere. Among the cities, Mashhad is the only city that has the largest share of comments that do not significantly refer to the restaurant atmosphere. Paying attention to the opinions published online and analyzing the provided long-term model leads to a competitive advantage. By placing the Tripadvisor logo in the restaurant, managers can encourage customers to leave comment on this website. Many foreign customers of small restaurants had stated in the comments that the restaurant owners had talked to them and considered it a positive point. Restaurant managers can take advantage of this. In the comments of tourists, it was found that using the menu or English-speaking staff is very important. There are also suggestions for future research, such as paying attention to new dimensions and aspects in restaurant research, analyzing and implementing a model with more data and complex deep learning models, or providing a recommending system with the help of these results in research. In this study, the data of Iranian restaurants on Tripadvisor were examined, and the data of other websites and programs can be used for analysis. Also, considering this tourism is an area that includes various industries and activities, the approach presented in other areas of tourism and the research on the existing aspects in them can be used.

Like any other study, we faced limitations. These include reviewing only four aspects of the Tripadvisor site for the restaurant. Some restaurant owners or competitors may have posted fake comments. Also, there were comments in Persian that were not considered in this study. Most importantly, facing data limitations in some classes was critical and led to a reduction in the model's accuracy. Additionally, since the researcher had done the labeling manually, labeling more than 4000 comments was unachievable.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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