[1]Sripriya Arunachalam
[2]R. Sangeethapriya
[3]J. Akilandeswari
[4]B.Dhiyanesh
[5]V. Ruckmani
[6]S. Prakasam

Fuzzy Logic In The Digital Travel Era: Enhancing Tourist Experience Through Comprehensive Hotel Reviews And Sentiment Analysis

Journal of Electrical Systems

Abstract: - In today's society, social media is becoming a more and more important part of our everyday lives as it continues to evolve. Lot of of users assess and tourist rate attractions daily, and hotels play a significant part in travel. Following reviews can be implicated to fuzzy logic, which will be beneficial for resolving the fame of tourist attractions and hotel reviews. Tourists can choose their accommodation and travel destinations with ease based on the outcome of the fuzzy control system. In this research, fuzzy logic has been used to implement sentiment analysis. To provide precise pass on relating to a few aspects chosen by the end user, the system uses attributes including food quality, service, locations, and ratings. This method enables customers to assess a certain hotel service's quality using a variety of factors. Additionally, a user can compare various hotels in depth. To accomplish this, a membership task that specifies how a smooth value maps to the term on a scale of 0 to 1 is used in the proposed system of fuzzy logic. It essentially outlines "how good" something is and how to produce complex behaviour from a condensed, understandable set of professional guidelines before passing these variables to a fuzzy control system. Using a set of rules, a fuzzy control system connects fuzzy variables. These laws are merely mappings that explain the relationships between one or more fuzzy variables. After specifying the inputs and obtaining the priority of the alternatives, the control system is finally simulated. As food preferences, service quality, and user-specific amounts vary, the system is scaled for each individual user. As a result, the system offers more accurate outcomes and increased classification method accuracy for the supplied review data set. Future research will use the Trapezoidal Fuzzy Number (TpFNs) as an evaluation tool to reflect clearly the variation of an element from 0 to 1 in order to increase the model's accuracy.

Keywords: Social media trends, Sentiment analysis, Comparative analysis, User-specific scaling, Fuzzy logic, Trapezoidal Fuzzy Number, Classification method

I. Introduction

Social networking is currently expanding quickly. On daily basis, millions of individuals assess and review tourist destinations on travel websites. It is possible to use fuzzy logic to analyse these reviews. An accurate study of the reviews might reveal a popularity trend for tourism destinations. An overview of the results obtained from the sentiment analysis will help tourists choose their tour destination and plan.

Reviews on hotels and other tourist attractions are quite important. When hotels accurately manage their internet booking sites, prospective guests will feel at ease and book their hotels without thinking twice. Categorizing ratings to glean insights is currently a key element for the hotel industry. Reviews reveal the opinions of past guests regarding the services provided by a hotel. While it's important to consider negative ratings, positive reviews can also be used to highlight a hotel's performance.

Sentiment analysis provides several benefits to the hotel industry, such as understanding customer sentiment towards a property and avoiding a negative reputation in the market. With so many reviews available on various websites, doing your own research is no longer your responsibility for success in the hotel industry. You need an automated system that is accurate, reliable, fast, efficient, and capable of delivering superior results to support business decisions. As a result, we need clever techniques to locate the information we're looking for. There aren't many clever and ideal methods that effectively address this searching issue in the realm of trip adviser and hotel evaluations.

[1] *Corresponding author: Assistant Professor, Department of Computer Science and Application, Faculty of Science and Humanities ,SRMIST Vadapalani City Campus, Chennai, Tamil Nadu, India.
[2*]Assistant Professor, Information Technology, Sona College of Technology, Salem, Tamil Nadu, India.
[3]Professor, Information Technology, Sona College of Technology, Salem, Tamil Nadu, India.
[4] Associate Professor, Computer Science and Engineering, Dr. N.G.P. Institute of Technology, Coimbatore, Tamil Nadu, India.
[5]Research Scholar, Computer Science and Applications, Sri Chandrasekarendra Saraswathi Viswa Maha Vidyalaya University, Kanchipuram, Tamil Nadu, India.
[6]Associate Professor, Computer Science and Applications, Sri Chandrasekarendra Saraswathi Viswa Maha Vidyalaya University, Enathur, Kanchipuram, Tamil Nadu, India.
priyaarun02@gmail.com[1], sangeethapriya.r@sonatech.ac.in[2,*], akilandeswari@sonatech.ac.in[3], dhiyanu87@gmail.com[4], rukkhue@gmail.com[5], SP@kanchiuniv.ac.in[6]
Correspondence Mail: sangeethapriya.r@sonatech.ac.in

Fuzzy logic is now the most cutting-edge algorithm for certain computer vision applications. There are difficulties like a vast and varied collection of input parameters. Fuzzy logic is the answer to our issue. We then define the fuzzy link between the input and output variables using a fuzzy triangle number. In this study, we transform the hotel review and tourist destination problem into a fuzzy domain and offer an ideal resolution using fuzzy logic. Food, quality, service, hotel room cleanliness, the staff at a tourist destination, or the service at a restaurant, are the main factors in hotel reviews and tourist destinations. The ardour of hotel classification controls on the degree of food, environment, quality, outdoor seating etc. that is calculated based on the ratio of overall rating of hotel.

The information in this essay is listed as following. A review of the research on trip advisor sentiment analysis is provided in Section II. Section III provides a description of the sentiment analysis process as well as its visualisation and performance evaluation. In Section IV and V, the experiment's results are displayed using rule viewer and surface view. In Section VI covers the conclusion and the future research paper's topic.

II. RELATED WORK

In this paper, various text analytics methods have been investigated and contrasted [1]. This study uses lexical, rule-based, and machine learning-based sentiment analysis techniques. The machine learning approach has a detailed discussion of SVM (Support Vector Machine), NB (Naive Bayes), TFIDF Vectorization, and Count Vectorization feature extraction sentiment analysis. The advantages and disadvantages of various sentiment analysis techniques have been carefully compared. Numerous comparative measures, such as performance, effectiveness, and accuracy, have shown that the TFIDF Vectorization+ RF method produces the best outcomes. As described in [2], a topic-based system for SA of hotel reviews has been implemented. They used "text mining" and "Text analysis" technology. Its main goal is to organise and process hotel guest reviews. Customers can use this approach to gain a sense of the level of service that various hotels provide. Additionally, hotel managers would use the built application to get statistics and summaries regarding the feedback of their customers. The system also gives users the option to compare several hotels using predefined criteria, and it displays the results graphically using histograms. One might compare this to a general or focused report. The latter is accomplished by filtering opinions in accordance with a particular characteristic or aspect (price, location, cleaning, etc.)

A translation API is also used by the built system to analyse opinions from different languages. The use of the "topic tree" has enhanced the functionality of such a system above other ways, according to research study.

Sentiment analysis, as described in [3] article, extracts feature and identifies sentiment from a document, a sentence, or an aspect. Text preparation also involves a number of processes. The author used several classification techniques like SVM and decision trees, as well as polarity detection and aspect selection. It was discovered that aspect-based sentiment analysis worked better than other methods. Author [4] has used pre-trained CNN models like Inception BN and VGG, averaged all image attributes for a specific industry, and trained an SVM classifier to forecast how the industry would change. In order to provide the model a better regional grasp of various objects in photos, they employed a faster rCNN technique. They received the highest F1 score for label prediction (0.82).

The author of this work [5] has investigated and contrasted a number of sentiment analysis techniques. Different levels of sentiments include document, sentence, and aspect levels. These levels have been extended, and a hybrid solution is offered by combining lexicon-based and machine learning techniques to generate the best results. It does the analysis in stages. The first stage involves utilising specified terms from the lexical dictionary to search for the polarity of the words. The second stage involves using the results from the previous stage to train the machine learning algorithm. According to studies, a hybrid method that combines supervised and uncontrolled elements is suggested to boost performance.

In this study [6], the author used a range of features, including adjectives, the top 2633 unigrams, bigrams, unigrams+bigrams, and unigrams+position, to do sentiment analysis on a dataset of movie reviews. Additionally, the accuracy of other classification techniques, such as maximum entropy, naive bayes, and SVM, was compared. Studies show that SVM offers the best accuracy, while naive bayes offers the worst accuracy.

There are a number of techniques for mining views, including trend-based, aspect-based, and block of text techniques, as discussed in [7]. The work proposes aspect-based opinion mining, in which attributes of tourist locations are gleaned from visitor reviews and then categorised into favourable and unfavourable attitudes with the appropriate aspects. They employed WordNet and POStagger for aspect extraction and opinion trend extraction. They classified the tweets into categories depending on that: good, negative, and neutral. The efficiency of system can be getting better by using ML.

In order to identify online travel products like a typical tourist review, restaurant, and weather,) suggested in [8] a vocabulary linked two-channel CNN-LSTM with an online tourism review dataset for sentiment classification. This uses a parallel two-channel CNN-LSTM layer and sentiment padding. According to the author, CNN may overcome two significant problems by employing this technique. 1. a sentence having a changeable length sequence 2. A highly developed trained model. The authors come to the conclusion that CNN-LSTM with Lexicon integration produced the best results for the dataset used in the tourism review. Future studies could make use of huge and unbalanced data sets to enhance model performance or speed up training.

Deep learning models were utilised in [9] to comprehend the information worth of online hotel reviews. The input information is derived from 32,582 and 4810 reviews as well as user-provided photos on Yelp and Trip Advisor. The author contends that by fusing user-provided photographs with revised prose, this method improved the quality of hotel evaluations. The outcome from the deep learning model is then contrasted with the model for machine learning. The best outcome, or 79 percent accuracy, has been reached, the report finds. The author suggests using an attention-based neural network in future research to better comprehend each neuron.

DL and visual analytics were utilised to examine reviews of hotel and comments [10]. The input data are gathered from 1088 hotels in London based on a trip planner. Also crawled were 113,685 reviews from vacation planning websites. The employment of pre-trained word embedding gloves the effectiveness of the model is compared to more established techniques like naive base, SVM, and KNN. The suggested model for the 3CNN trial results increased by 10.12%, 17.18%, and 13.5%, respectively.

In this paper [11],the author K. Gaihre and P. Shrestha (2022) have used a dataset of hotel reviews and ratings from TripAdvisor for their study. The dataset contains more than 515,000 reviews of hotels in different parts of the world. The authors have then used various DL methodologies such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based models such as BERT and GPT-2 for predicting the hotel ratings. They have compared the performance of these models based on metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Pearson's correlation coefficient.

The results of the study show that the Transformer-based models such as BERT and GPT-2 outperform the other models in terms of prediction accuracy. Also, look over the prominent of different features in predicting the hotel ratings and found that features such as the sentiment of the review and the number of positive and negative words have a remarkable consectary on the prediction precision.

Anoop Kumar and Ravi Kumar Jatoth (2022) suggested an online [12] review explores the use of machine learning techniques to classify hotels based on online reviews. The authors collected a dataset of hotel reviews from various online [14-16]sources and used different feature selection and extraction techniques to preprocess the data. They then compared the performance of six classification algorithms, including Decision Tree, Random Forest, Naive Bayes, Support Vector Machine, k-Nearest Neighbors, and Artificial Neural Networks, using variety evaluation metrics such as accuracy, precision, recall, and F1-score. The outcome visible that the RF methodology surpassed the previous classifiers with an mean value of 85.48%.

Memory) for comparative analysis of hotel reviews, and compares its performance with classical ML protocols. The study uses a dataset of hotel reviews scraped from TripAdvisor, consisting of over 20,000 reviews from 10 different hotels in Las Vegas.

In this study [13] LSTM-based model is trained on the review data and is able to predict the rating given by a user to a particular hotel, as well as provide a sentiment analysis of the review. The authors compare the performance of their model with four classical ML techniques, including Naive Bayes, SVM, Random Forest, and Logistic Regression.

The outcome show that the LSTM-based model surpassed all four classical ML techniques in both rating prediction and sentiment analysis. The authors also conduct an analysis of the errors made by the models, and find that the LSTM-based model is better able to handle negations and complex sentence structures.

III. METHODOLOGY

The prime goal of this project is to create a fuzzy process that uses different input variables as queries and generates an output value by assigning a value score or precedence level to each parameter. A higher score indicates a better preferred parameter for a certain search query.

3.1 Dataset

The study makes use of review information from several travel websites. Data in CSV format has been gathered from Kaggle including review text and ratings that go with it. We determined the sentiment, whether it was positive, negative, or neutral, from the rating. A grade of greater than 3 is regarded as favourable. If the number is fewer than three, it is seen as negative, and if it is greater than three, it is regarded as neutral. The following six factors have been taken into consideration as input variables: service, environment, food, and budget, location, and user reviews. Three membership levels have been specified for each input variable.

3.2 Proposed System

In this section, we have detailed about the hotel place classification. The proposed system consists of three phases i. Define fuzzy sets ii. Determine the membership function and fuzzy rules iii. Perform defuzzification.

Define the fuzzy sets: The first step is to define the fuzzy sets for the input variables (i.e., hotel amenities, services, and facilities) and the output variable (i.e., hotel classification). These fuzzy sets can be defined using linguistic terms such as poor, average, good, and excellent.

Determine the membership functions: Once the fuzzy sets are confined, the next step is to resolve the membership function for each fuzzy set. Membership functions assign degrees of membership to each linguistic term based on input variables. These membership functions can be defined using triangular or trapezoidal membership functions.

Develop the fuzzy rules: After the membership functions are defined, the next step is to develop the fuzzy rules. The relationship between input and output variables are define by fuzzy rules. For example, "if the hotel amenities are good and the hotel services are excellent, then the hotel classification is excellent".

Perform fuzzy inference: After the fuzzy rules are developed, the next step is to perform fuzzy inference to determine the degree of membership of each fuzzy set. This is done by applying the membership functions and fuzzy rules to the input variables.

Perform defuzzification: The next step is to perform defuzzification to obtain a crisp output value. This can be done using the weighted average method, which calculates the centroid of the output fuzzy set based on its degree of membership.

Determine hotel classification: The final step is to determine the hotel classification based on the defuzzified output value. This can be done using a threshold value, where if the output value is below a certain threshold, the hotel is classified as poor or average, and if the output value is above the threshold, the hotel is classified as good or excellent.

In fuzzy logic, instead of using crisp values (0 or 1) to represent membership in a particular category, membership is represented by a degree of membership, which can range from 0 to 1. This allows for more nuanced and flexible categorization.

3.2.1 Weighted Average Method

Models for making decisions typically use subjectively determined weights for criteria and ambiguous probability for world states. As a result, the models are more accurate if the criteria's weights and world state probabilities are described using the fuzzy sets theory's tools.

A fuzzy weighted average c of fuzzy numbers c1, c2, . . . , cn with non-negative fuzzy weights ∝1, ∝2, . . . , ∝n is defined in [2] as a fuzzification according to the extension principle (1) of the operation $\sum_{i=1}^{n} \propto i\ ci / \sum_{i=1}^{n} \propto i$,$\propto i > 0, i = 1,2,3 \ldots n, \sum_{i=1}^{n} \propto i \neq 0,$

The membership function U(u) is given by,

$$U(u) = \max\{\min\{U1(u1), U2(u2) \ldots\ldots U3(u3), \propto 1(\propto 1), \propto 2(\propto 2) \ldots\ldots \propto n(\propto n) \tag{1}$$

$$\frac{\propto 1\ c1 + \propto 2\ c2 + \propto 3\ c3 \ldots\ldots\ldots\ldots \propto n\ cn}{\propto 1 + \propto 2 + \propto 3 \ldots\ldots\ldots\ldots \propto n} \tag{2}$$

3.22 Decision-level fusion is integrated into the fuzzy rule system.

Fuzzy models create fuzzy rules for input-output data by using an effective methodology.

If Y is C and Z is D, then z = f (C, D),

Z is the smooth function in the concomitant, C, and D are the fuzzy sets in the predecessor, and Y and Z are the input variables. This procedure is carried out in three stages: fuzziness of the input variables, rule assessment (inference), and defuzzification.

3.2.3Fuzzification

The three scalar parameters j, i, and g, where i identifies the peak and j and g identify the base of the triangle, determine the membership of each linguistic term T in the triangular fuzzy space. s: h [0,1] is the definition of a Membership Function (MF), in every element of h is changed to a range between 0 and 1. This notion is applicable to a fuzzily defined set S on the discourse universe X. Equation provides the formula for the triangle function using j, i, and g as the three parameters (3).

$$\mu s(x) = \begin{cases} 0, h \leq j \\ 0, h \geq k \\ (g-h)/(g-i), e < h \leq k \\ (h-j)/(i-j), j < h \leq g \end{cases} \tag{3}$$

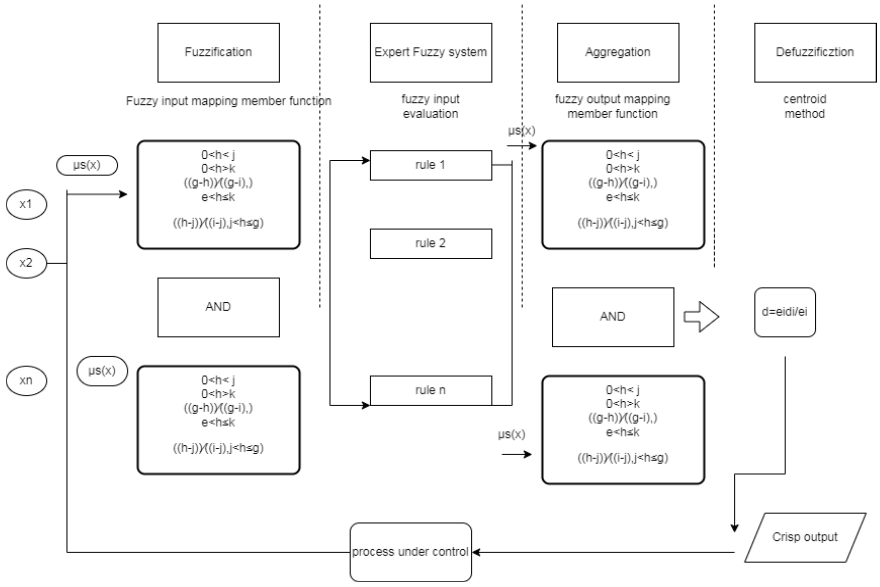

Fig 1: Proposed Hotel place classification parameter switching system

This MF's graphic representation is shown in Fig. (1-3), and its parameter values are h=0.125, i=0.4, and j=10. Three input fuzzy sets are built using this MF: Low (L), High (H), and Medium (M). The values range from 0 to 10, with 0 being the least number. In eq, the midpoint is determined (3). The triangle fuzzy MF for the fuzzy sets Low, High, and medium is created with the following parameters: Low: "min, min, mid," and High: "mid, max, max.”

3.2.4 Formulation of Rules

The guidelines have been developed under the presumption that a high tip would be given for excellent food and/or service. In the situation where one of the food or service belief scores is less and the hetero is soaring, the lower food average score forecasts a flip, and the greater food average score suggests retaining the forecasted emotion. Retaining the projected sensation's polarity entails not flipping the projected feeling, while doing so requires shifting it from positive to negative or vice versa. Next, the formulation of the proposed fuzzy rule-based system is discussed.

$$\text{Medium} = \frac{min+max}{2} \quad (3)$$

$$TR1 = \text{food\_low} \wedge \text{servive\_low} \quad (4)$$

$$TR2 = \text{food\_high} \wedge \text{sevice\_high} \quad (5)$$

$$TR3 = \text{food\_low} \wedge \text{servie\_high} \quad (6)$$

$$TR4 = \text{food\_high} \wedge \text{service\_low} \quad (7)$$

Table 2 Fuzzy set rules used in this study for hotel classification

Input variables			Output variables
Rule number	parameter	Rule	Changes in output
1	food	MF1	poor
2	food	MF1	average
3	food	MF1	good
4	food	MF1	excellent
5	food	MF1	excellent
6	environment	MF2	excellent
7	environment	MF2	good
8	environment	MF1	good
9	environment	MF2	good
10	quality	MF2	average
11	quality	MF2	average
12	good for kids	MF3	poor
13	good for kids	MF3	poor
14	ambience	MF3	good
15	ambience	MF3	good

16	ambience	MF2	excellent
17	quality	MF2	poor
18	quality	MF1	good
19	outdoor seating	MF1	good
20	outdoor seating	MF1	poor
21	outdoor seating	MF1	good

3.2.5 Defuzzification

Defuzzification is the opposite of fuzzification. It entails switching from unclear formats to attribute values that are vaguely defined. The last column in Table 2 demonstrates that each rule in a fuzzy model has a separate output, hence the final output is derived using a weighted average. The defuzzified output, d, is derived using equation (8), where ei denotes the firing strength of every rule as determined by equations (4–8) and di is the related emotion output determined from Table 2 for each rule.

$$d = \frac{\sum e_{i} d_{i}}{e_i} \tag{8}$$

The review is then finally classified into the low, high, or medium class as shown in eq by looking at the defuzzified output range (9).

$$\text{Output} = \begin{bmatrix} low, 0 < d \ \leq 5 \\ medium, 6 < d \ \leq 15 \\ high, 16 < d \ \leq 25 \end{bmatrix} \tag{9}$$

Our work's main contribution can be summed up as follows as a result of a decision-level synthesis of text classifiers employing a brand-new set of fuzzy rules.

3.2.6 Experimental setup and Implementation

Utilizing fuzzy if-else logic, we establish one variable of output preference in the fuzzy process and infer it from the three input variables. Three functions or levels—low, high, and medium—define the preference.

For illustration, suppose a user selects "excellent" from a list of three possibilities that includes "poor," "average," and "great." The system will display the reviews where the user has left excellent feedback and will presumably rate outside seating as follows:

Good = 0.5, Average = 0.4, and Bad = 0.125

Outdoor seating is scored on a scale of 0 to 10, with awful, average, and wonderful being the possible outcomes. Service quality in the range 5–25 is described by fuzzy sets as follows: terrible is 5%, average is 15%, and superb is 25%.

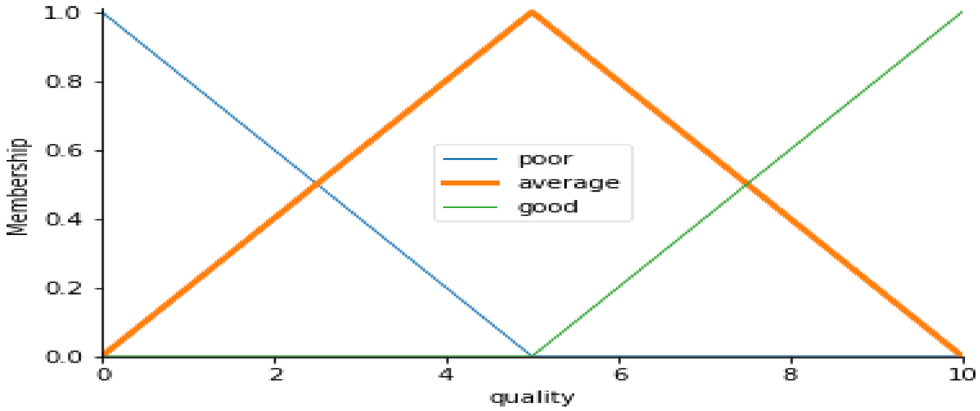

Fig 2: Degree of membership Quality of Service

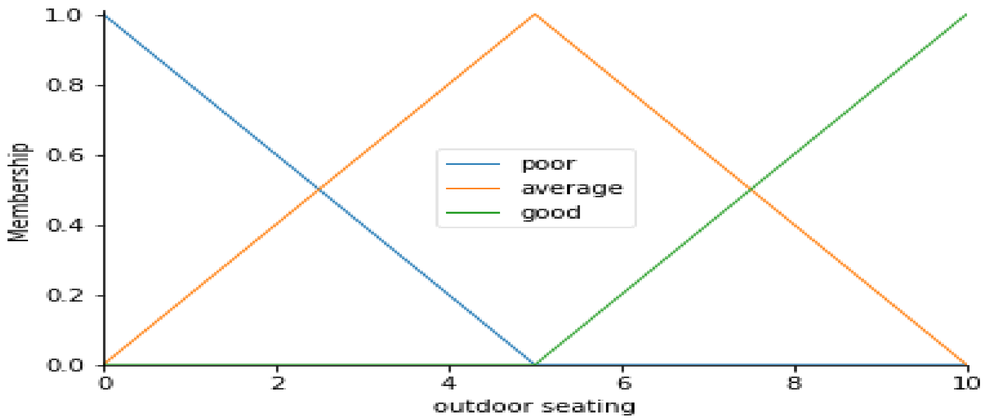

Fig 3: Degree of membership-Outdoor seating

The membership function of a fuzzy set A on a discourse world X is written as A:X [0,1], where each element of X is converted to a range between 0 and 1. This value is also called the attribute value or the attribute value degree of membership. Quantifies the degree to which an element of X is a member of fuzzy set A.

Rule: The quality was bad if the food was spoiled or the service is subpar.

Rule 2: Good service equates to average quality.

Rule 3: Outstanding food and/or service indicate that the quality was excellent.

A membership function shows the degree to which a given input belongs to a set, while a defuzzifier turns the latter result into a crisp number. An inference engine generates the fuzzy output using a fuzzy reasoning method. Crisp inputs are transformed into fuzzy values via a fuzzifier.

IV. Results in MATLAB (Rule Viewer)

The method of rule viewer in hotel classification on TripAdvisor using fuzzy logic involves using a set of rules to determine the classification of hotels based on their features and attributes. Fuzzy logic is a mathematical framework that allows for the handling of imprecise or uncertain information. The rule viewer method involves defining a set of rules that describe the various features and attributes of hotels, such as room size, cleanliness, amenities, and customer service. These rules are then mapped to a set of linguistic terms or fuzzy sets, such as "small," "medium," or "large" for room size, "dirty," "clean," or "spotless" for cleanliness, and "poor," "average," or "excellent" for customer service. The fuzzy sets are then used to describe the degree to which a hotel meets each of the rules. For example, a hotel with small rooms might has a value of membership that 0.8 for the set of fuzzy "small," while a hotel with large rooms might have a membership value of 0.2. Using fuzzy logic, the rule viewer method can then combine these membership values to determine an overall classification for the hotel. This is done using a set of fuzzy inference rules, which specify how the membership values for each rule should be combined to determine the overall classification.

Inputs:

Service Quality: bad, good, or good in the range 0-10 using fuzzy sets

Food Quality: vaguely set between 0 and 10, odor and taste

Output: inexpensive, average, generous with obscure sets between 30 percent

–Rules:

If the service is poor or the food is terrible, the tip will be cheaper (5%)

If the service is good, tip is average (15%)

Tip liberally (25%) if the service is excellent or the food is delicious.

Table 3Presents the selected fuzzy rules.

Input variables			Output variables
Rule number	parameter	Change in ratings	Sentiment Output
1	food	good	tip
2	Outdoor seating	average	tip
3	location	excellent	tip
4	service	poor	flip

4.1 Results in MATLAB (Surface View)

Figure 5 shows the surface view. When MF2 decreases, each MF tip has a negative effect. If (the service was bad) or (the food was smelly), then (the tips are low). The chip setting value surface diagram in Figure 6 correlates the chip value with the change in the fuzzy set. If the service value is less than 0.05, the tip value is decreased by 1.5.

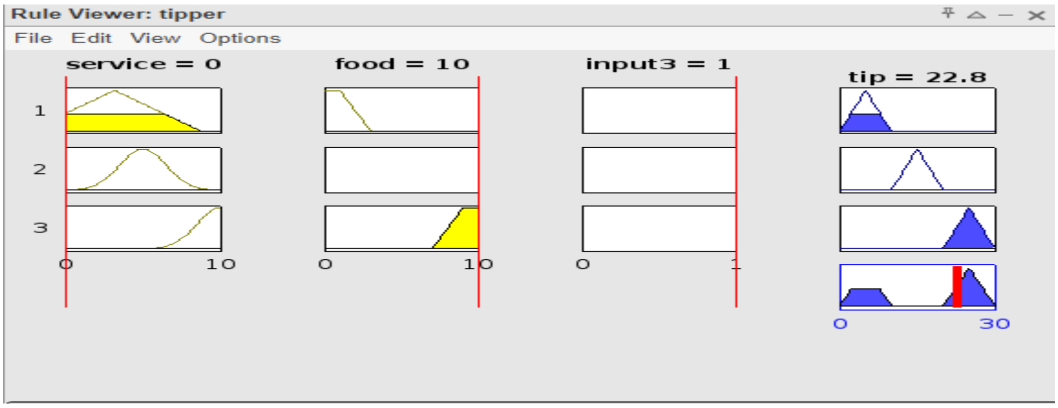

Fig 4:-Rule viewer showing high service value with increase in tip rate

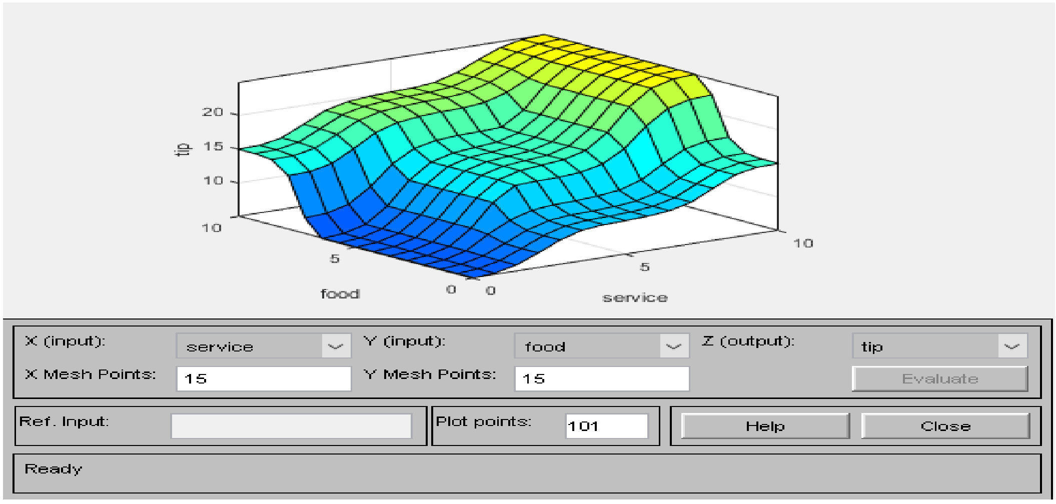

Fig 5: Initiation of the tip rate in surface view

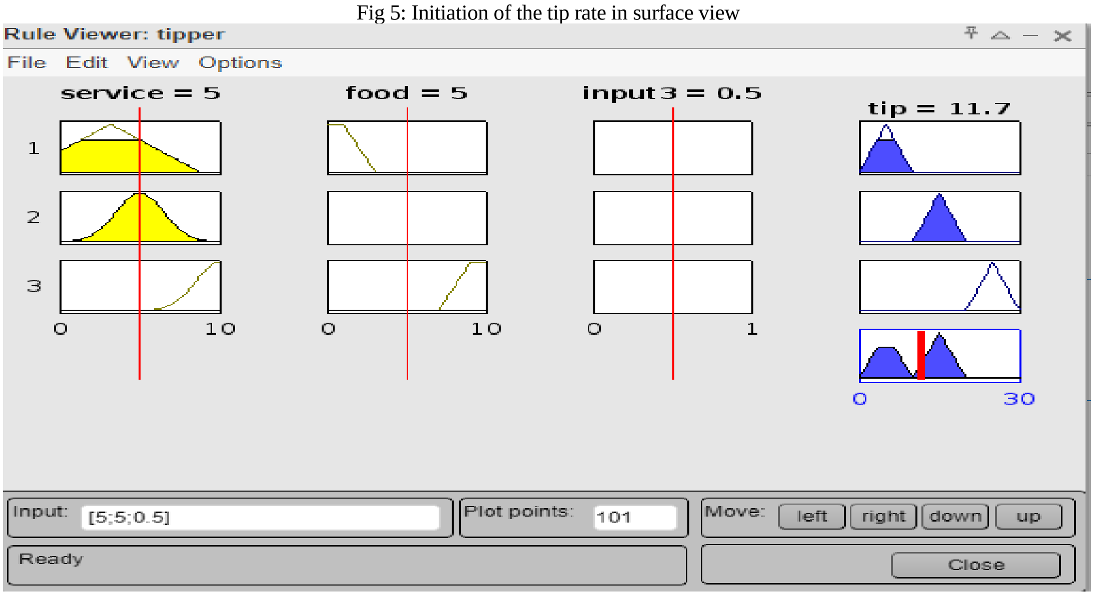

Fig 6: Rule viewer showing high value of quality with increase in tip rate

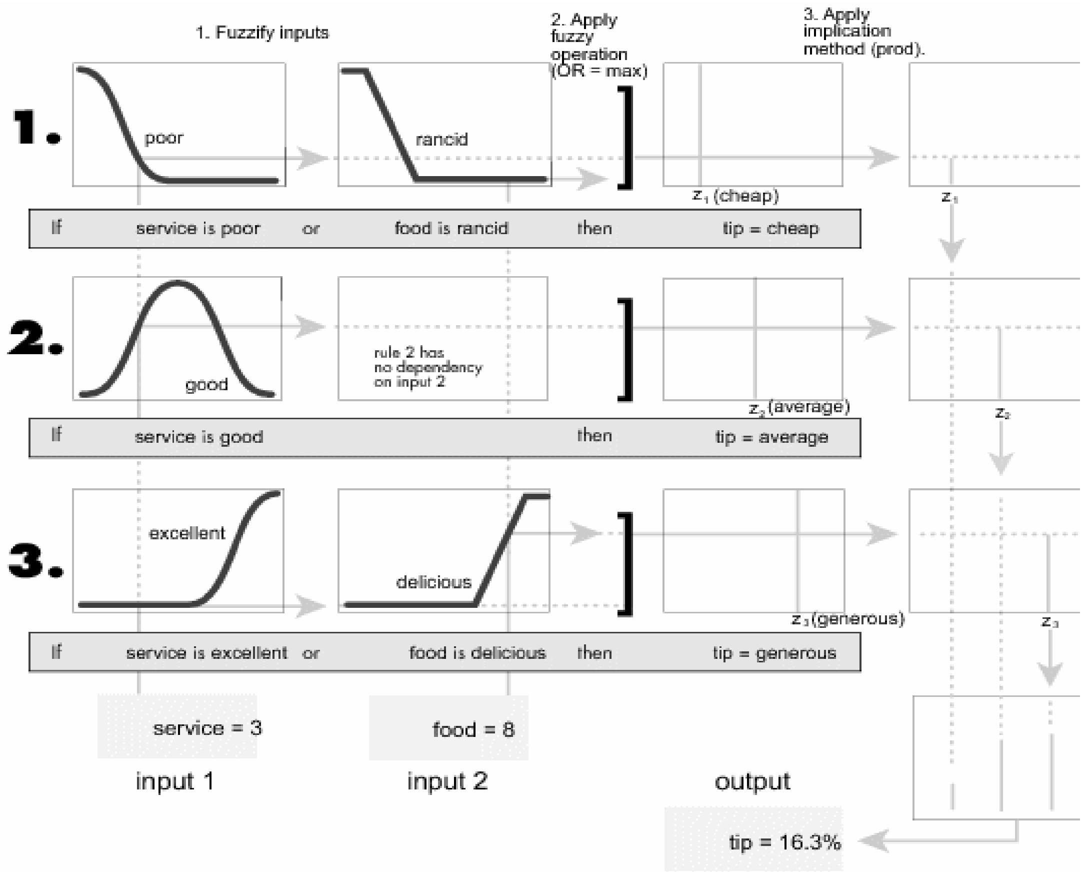

Fig 7:Tip rate definition flow chart

The classification of hotel with review as shown in fig-6. If the service is bad and the food is rotten, the tip is low; if the service is good and the food is good, the tip is high.

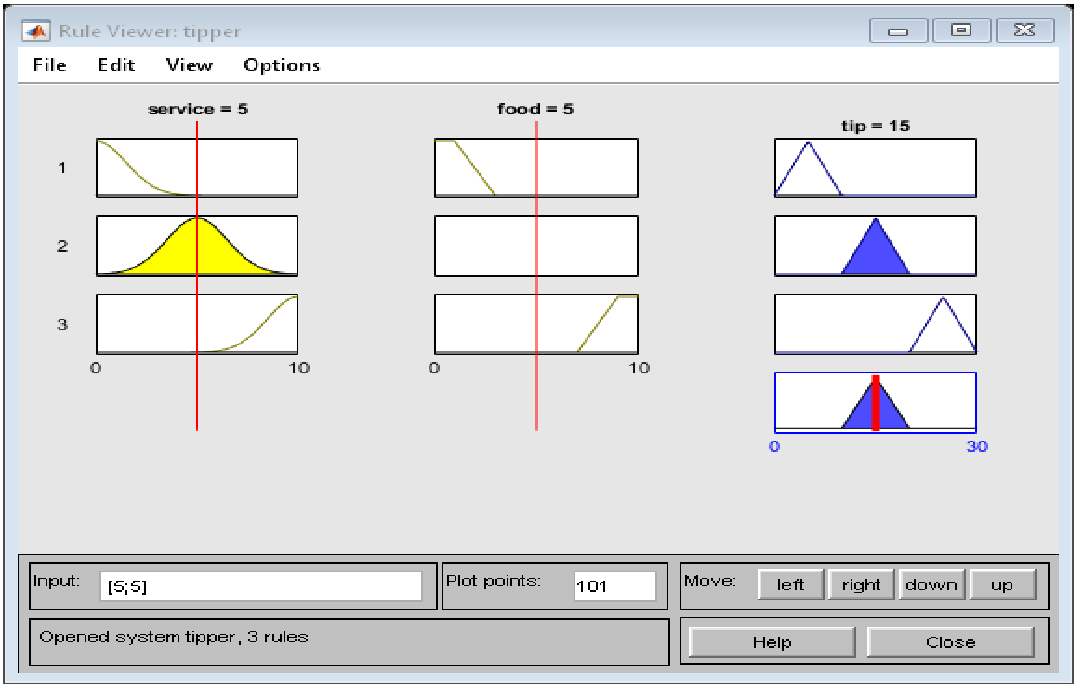

Fig 8: rule viewer showing low sevice with low food rate and decras the tip rate

V. Results and Discussion

Data has been gathered for testing from the Yelp, Kaggle, and travel websites. To keep the computation simple, each preference level is represented for the output curve by a triangular-shaped membership function.

Sample Input

Quality	Good
Evirontment	Amazing
Location	Descent
Service	high
Ambience	Poor

Sample Output

	Review	Review	Preference
Quality	Good	Acceptable	High
Evirontmet	Amazing	Good	High
Location	Descent	Average	Medium
Servie	high	great	high
Ambience	Poor	poor	Low

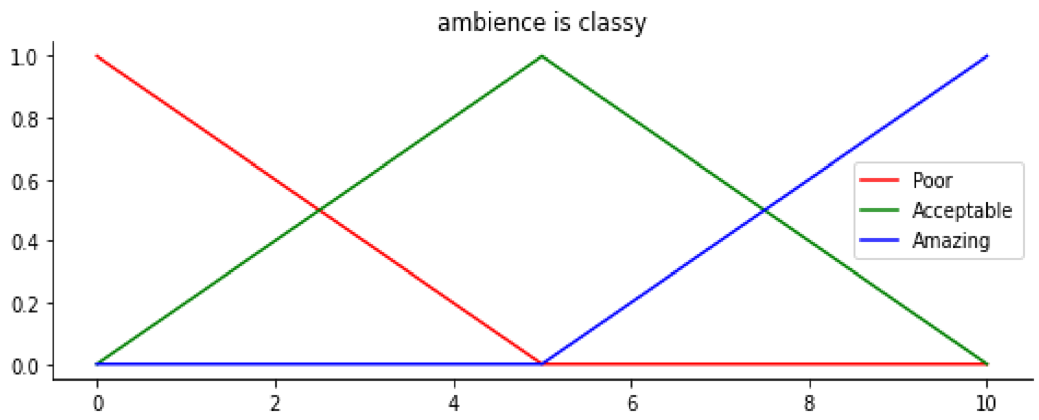

Fig 9: Fuzzy Triangle Membership sets for place

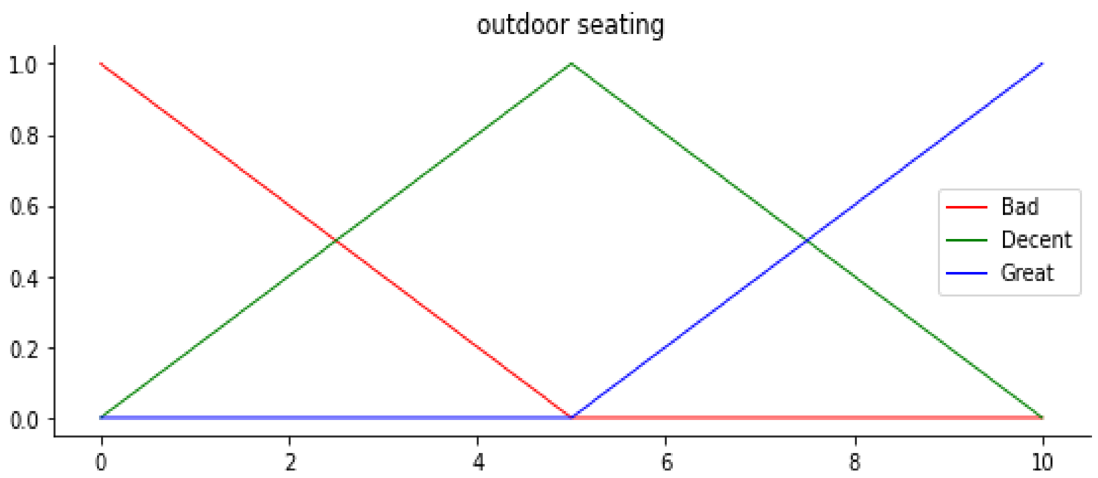

Fig 10: Fuzzy Triangle Membership sets for outdoor seating

In cases when uncertainty or fuzziness can be eliminated using membership functions, our technique can be used to do fuzzy classification. The key benefits of fuzzy rule-based systems include their high inference speed, low memory requirements, and ability for users to thoroughly review each fuzzy if-then rule. This method has the drawback that a lot of fuzzy if-then rules are typically generated for real-world pattern classification issues. As a result, inference speed is slow.

VI. Conclusion and Future Work

Fuzzy logic with high, low, and medium membership functions has been used to analyse hotel reviews and tourism destinations. The entire purpose of the analysis is to offer clients appropriate recommendations of locations, services, food quality, and rate so they can choose the best alternative available, as well as to the business owner so they can successfully make decisions utilising the triangular member function. By selecting features and improving the rule selection and different rule parameters, fuzzy rule-based systems' performance can be further enhanced.

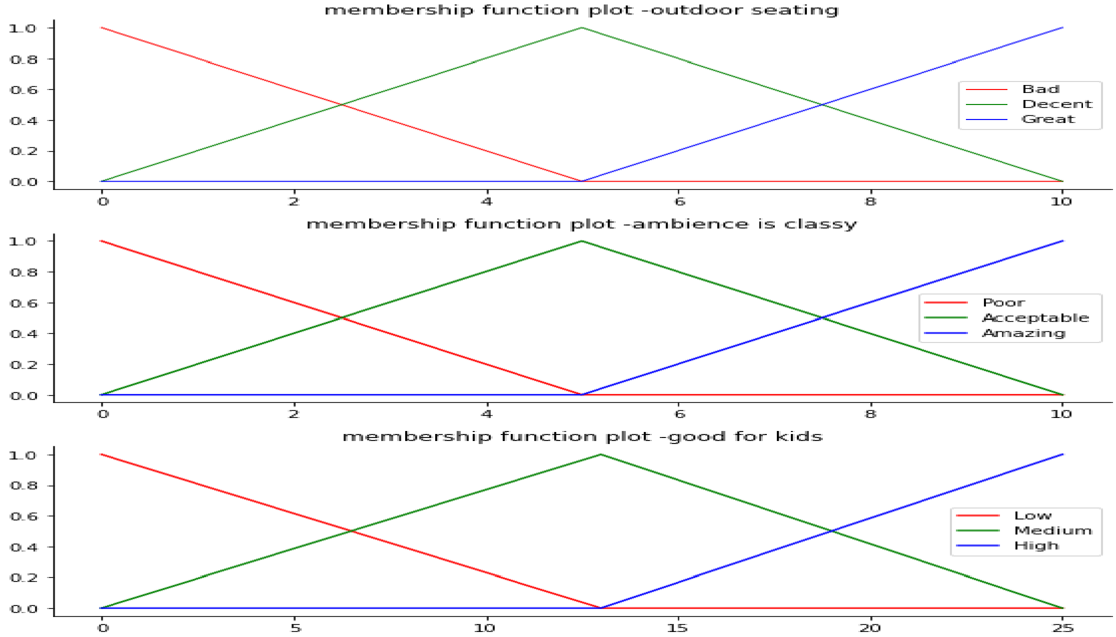

Fig 11: Fuzzy logic designer showing change in tip rate membership functions

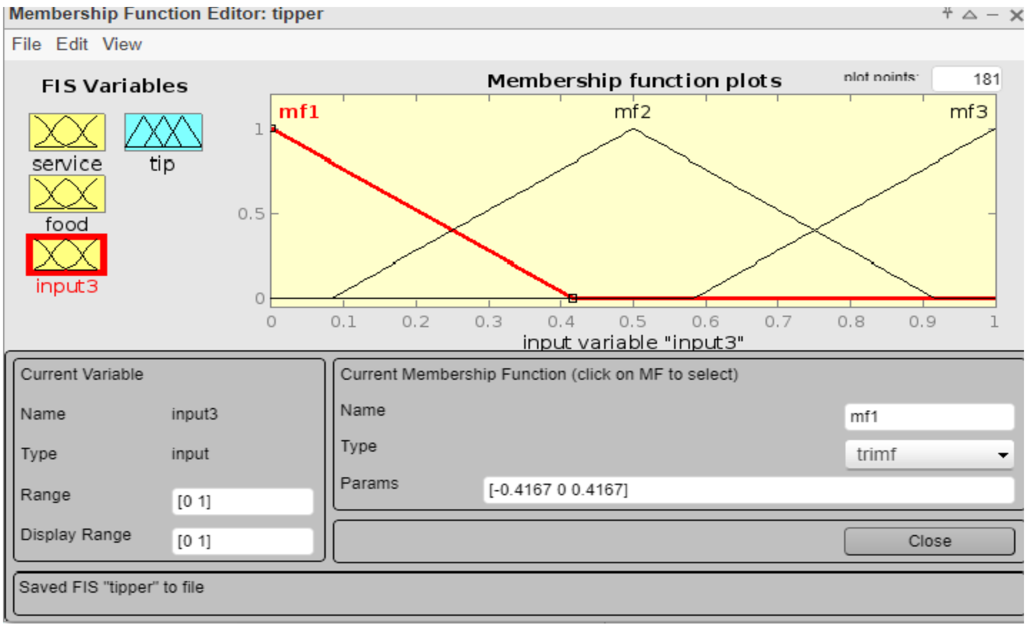

Fig 12: Fuzzy logic designer showing change in location membership functions

References

[1] A. A. Wadhe and S. S. Suratkar, "Tourist Place Reviews Sentiment Classification Using Machine Learning Techniques," 2020 International Conference on Industry 4.0 Technology (I4Tech), Pune, India, 2020, pp. 1-6.

[2] Gharzouli, Mohamed, Aimen Khalil Hamama, and Zakaria Khattabi. "Topic-based sentiment analysis of hotel reviews." Current Issues in Tourism 25.9 (2022): 1368-1375.

[3] E. Cambria, "Affective Computing and Sentiment Analysis," in IEEE Intelligent Systems, vol. 31, no. 2, pp. 102-107, Mar.-Apr. 2016, doi: 10.1109/MIS.2016.31
[4] Varshneya, Daksh, Pawan Dhananjay, and Dinesh Babu Jayagopi. "Restaurant attribute classification using deep learning." 2016 IEEE Annual India Conference (INDICON). IEEE, 2016.
[5] Lai, Siew Theng, and Mafas Raheem. "Sentiment analysis of online customer reviews for hotel industry: an appraisal of hybrid approach." International Research Journal of Engineering and Technology (IRJET) 7.12 (2020): 1355-1359.
[6] Wawre, Suchita V., and Sachin N. Deshmukh. "Sentiment classification using machine learning techniques." International Journal of Science and Research (IJSR) 5.4 (2016): 819-821.
[7] Afzaal, Muhammad, and Muhammad Usman. "A novel framework for aspect-based opinion classification for tourist places." 2015 Tenth International Conference on Digital Information Management (ICDIM). IEEE, 2015.
[8] Li, Wei, et al. "User reviews: Sentiment analysis using lexicon integrated two-channel CNN–LSTM family models." Applied Soft Computing 94 (2020): 106435.
[9] Ma, Yufeng, et al. "Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep leaning." International Journal of Hospitality Management 71 (2018): 120-131.
[10] Chang, Yung-Chun, Chih-Hao Ku, and Chien-Hung Chen. "Using deep learning and visual analytics to explore hotel reviews and responses." Tourism Management 80 (2020): 104129.
[11] K. Gaihre and P. Shrestha (2022) Comparative Study of Deep Learning Techniques for Hotel Rating Prediction".
[12] Anoop Kumar and Ravi Kumar Jatoth(2022)Hotel Classification Using Online Reviews: A Comparative Study of Machine Learning Techniques.
[13] Arora, Harsh, and Mamta Bansal. "Comparative analysis of hotel reviews using proposed LSTM based deep learning model with classical machine learning techniques." AIP Conference Proceedings. Vol. 2481. No. 1. AIP Publishing, 2022.
[14] Saravanan, B., V. Mohanraj, and J. Senthilkumar. "A fuzzy entropy technique for dimensionality reduction in recommender systems using deep learning." Soft Computing 23 (2019): 2575-2583.
[15] Sultanuddin, S. J., Devulapalli Sudhee, Priyanka Prakash Satve, M. Sumithra, K. B. Sathyanarayana, R. Krishna Kumari, Jonnadula Narasimharao, R. Reddy, and R. Rajkumar. "Cognitive computing and 3D facial tracking method to explore the ethical implication associated with the detection of fraudulent system in online examination." *Journal of Intelligent & Fuzzy Systems* Preprint (2023): 1-15.
[16] Sunitha, G., Reddy Madhavi, K., Avanija, J., Srujan Raju, K., Kirankumar, A., Raji Reddy, A. (2023). Ensemble Model for Lidar Data Analysis and Nocturnal Boundary Layer Height Estimation. In: Bhateja, V., Carroll, F., Tavares, J.M.R.S., Sengar, S.S., Peer, P. (eds) Intelligent Data Engineering and Analytics. FICTA 2023. Smart Innovation, Systems and Technologies, vol 371. Springer, Singapore. https://doi.org/10.1007/978-981-99-6706-3_28