International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 11
DOI: https://doi.org/10.17762/ijritcc.v10i11.5803
***Article Received**: 17 September 2022 **Revised**: 27 October 2022 **Accepted**: 06 November 2022*

A Novel K-Means Clustered Support Vector Machine Technique for Prediction of Consumer Decision-Making Behaviour

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Abstract
A greater number of consumers are using social networks to express their feedback about the level of service provided by hotels. Online reviews from patrons can be used as a forum to enhance the level of service of hotels. Customer reviews are indeed a reliable and dependable source that aid diners in determining the quality of their cuisine. It is critical to develop techniques for evaluating client feedback on hotel services. In order to accurately anticipate the consumers' decision-making behaviors based on hotel internet evaluations, this study proposes a novel K-Means Clustered Support Vector Machine (KMC+SVM) technique. Principal Component Analysis (PCA) is employed to determine the characteristics from the preprocessed data while the Min-Max normalization approach is used to standardize the raw data. The performance of the suggested technique is then evaluated and contrasted with a few other methods that are currently in use in terms of accuracy, sensitivity, RMSE, and MAE. The findings demonstrated that segmenting customers based on their online evaluations can accurately predict their choices and assist hotel management in establishing priorities for service quality enhancements.

Keywords- Hotels, Online Reviews, Big Data, Decision-Making Behaviors, K-Means Clustered Support Vector Machine (KMC+SVM).

I INTRODUCTION

Recent developments in COVID-19 have contributed to the rapid expansion of online shopping and highlight the growing importance of this industry. Online shoppers are increasingly relying on reviews to guide their purchasing decisions. Consumers who have previously bought the goods and posted reviews on online shopping sites sometimes give more helpful information than the official product information supplied by the merchants. In the meanwhile, it's becoming more common for customers to talk about their purchases on social media. Many researchers have looked at how internet reviews affect consumers' decisions as a result of these shifts. There is substantial evidence from these research that the valence intensity of online reviews affects consumer intent to make a purchase. Reviews and ratings have been shown to be a valuable source of information for customers. In a similar vein, people found that customers looking for information about a well-known product are more likely to trust a review written by a member of the online community. Reviews help other customers make decisions since they are based on the experiences of real people and not on the opinions of the reviewer. According to, about 60% of consumers regularly read online product reviews, with 93% of those readers saying that the reviews aid in making more educated purchasing decisions, reducing financial risk, and increasing product options. Eighty-two percent of e-consumers read product evaluations before making purchase decisions on B2B and B2C platforms, and sixty percent of them refer to comments weekly. Ninety-three percent of customers say Internet reviews have an impact on their purchasing choices, indicating that the great majority of consumers often consult these remarks before making a purchase.

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Visual and cognitive processes come together in the psychological procedure of making a purchase choice based on internet reviews. From the existing literature, it is obvious that most investigations have focused on how online reviews affect customers' ultimate purchasing decisions but have offered very little understanding of the processes through which these ratings influence consumers' perceptions. “Few studies have looked at the thought process and data processing that go into making a purchase, despite efforts to explore the underlying processes, such as the impact of product/service information on customers as conveyed via online reviews. Eye-tracking studies have been very helpful in understanding how consumers make decisions and how the brain works. Although eye-tracking studies are becoming more common, many questions remain unanswered, such as whether or not consumers are suspicious of false comments due to gender differences in consumption, or the emotional valence & content of comments, especially negative ones, influence consumers' final decisions. There has been a rise in recent years in the amount of research showing the impact of internet reviews, particularly on consumer spending. Customers' purchase intentions for search & experience products, as well as the role of review information & reviewer agreement in establishing a review's credibility, are just a few of the issues explored in these studies. Textual qualities including subjectivity, informality, readability, and linguistic correctness have been shown to affect how often people consult product evaluations with the help of text mining. Similarly, it was discovered that shoppers' focus and actions vary from page to page, website to website, and shopping objective to shopping goal. Additionally, "it was found that positive online customer evaluations result in a greater purchase chance than negative ones." They also found that consumers' perceptions of a company's trustworthiness and diagnostic accuracy were most strongly affected when they were exposed to bad reviews posted elsewhere online. According to this research, consumers will be influenced by online product reviews; however, the precise extent of this effect will vary greatly across different contexts.

“There has also been research on OPI at a deeper level, with reports of various attempts made to comprehend the many ways in which OPI affects customers. Examples of such formats include VSPI and online reviews (vendor-supplied product information).” According to the findings, VSPI is connected to things like the popularity of internet reviews [12]. Recent studies have linked the rise in popularity of online review sites with an increase in the number of individuals making impulsive online purchases. Online product reviews have been studied for their impact on anything from consumers' willingness to buy to the effects of factors like the reviewer's gender, reputation, and emotional investment in the product. Recent research on customers' inclination to try new items and the correlation between online review variance and the two has shown that these two factors interact to impact consumers' ultimate purchase decisions [13]. Consumers' willingness to try something new depends on a variety of variables, including their capacity for restraint. Customers who can exert more self-control are more likely to buy INPs with low variance ratings, whereas those who have difficulty controlling their impulses are more likely to buy INPs with high variance evaluations. Despite this fact, studies have shown that customers' emotions have a significant effect on their ultimate purchase choices. Reviewers with "more positive emotional tendencies," "reviewers whose sentences were longer," "reviewers whose mix of the greater diversified emotional tendencies," but also "reviewers whose distinctive expressions" all had "significant favorable impact" on online comments, according to an analysis of the impact of online film reviews.

It was also shown that the box office is significantly affected by the varying degrees of positivity and negativity that are conveyed in film reviews. That implies both good and negative feelings may be found in feedback left by consumers. In most cases, favorable reviews have a powerful persuading influence on customers because they inspire the creation of emotional trust, a rise in confidence and trust in the product, and a greater likelihood of future purchases. On the other hand, unfavorable feedback might dampen buyers' enthusiasm for making a purchase. The rational conduct theory, which states that shoppers would minimize their exposure to potential harm, provides an explanation for this phenomenon. Thus, when buyers see negative feedback, they often choose not to purchase the goods. Furthermore, the vast majority of consumers believe that negative feedback is more useful than positive when making a choice.

1.1 Consumer decision making process

The goal of this study was to determine whether and how reviewers' emotional investment affected consumers' propensity to make a purchase while reading product reviews online [17]. Multiple channels facilitate consumers' rapid access to and processing of information. In many cases, online retailers pay closer attention to and make required modifications to products that get negative feedback than to those that receive positive feedback. Positive reviews for products tend to increase interest in making a purchase from customers shopping online, which

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in turn generates more revenue for sellers. People found that readers are less likely to find value in negative hedonic product evaluations than readers of utilitarian product reviews because readers of the former are more inclined to ascribe the reviewer's unfavorable judgments to internal (or non-product-related) factors. Utilitarians, on the other hand, are more inclined to conclude that a reviewer's unfavorable assessment was influenced by factors outside of the product itself.

In the field of cognitive psychology, eye-tracking has become more prevalent. Researchers from a variety of fields have been advocating for the incorporation of neurobiological, neurocognitive, and physiological methods into the field of information systems [18]. Using eye-tracking, researchers have been able to learn a lot about how people shop online. Using an eye-tracking technique, researchers discovered, for instance, that during product searches, buyers paid substantially more attention to attribute-based assessment than experience-based evaluation, whereas there was no such difference for experiential items. Additionally, their findings suggested that eye-tracking indices, such as fixation stay duration, might intuitively represent customers' search activity while reading the reviews. It was also shown that when purchasing an experiential good, women pay more attention to the visual remarks than men do, whereas when purchasing a product based on a search, they pay more attention to the textual comments. Consistency between the pricing and the comments also increases the likelihood that a customer will make a buy [19].

The eye-mind hypothesis is the foundation of the eye-tracking approach used to investigate and understand the mental processes and choices made by customers. An individual's cognitive processing may be determined via monitoring eye movement while they are gazing, which means that when they are looking, they are now seeing, thinking about, or attention to something. Several studies on consumer behavior have used eye-tracking to quantify consumers' visual attention. These studies have approached the topic from a variety of angles, such as examining the relationship between consumers' visual attention and their gender, their shopping attitudes, and the effectiveness of using human brands to influence their purchasing decisions, and so on [20]. An analysis of shopper focus and time spent on various purchase activities across categories of goods reveals that consumers pay more attention to the website for the purpose of exploring the site than for actually making a purchase. Shopping's most difficult and time-consuming process is weighing available alternatives. Using the eye-tracking approach, several studies have looked at fashion retail websites and asked questions on a wide range of topics, such as how customers engage with the different presentational elements of a product's page and how they use mobile devices to shop for clothing. However, these analyses ignored demographic characteristics of study participants, including gender. Since the purpose of this study is to investigate how gender influences consumers' ability to focus their attention, eye-tracking technology was included into the research design [21]. The results of this research suggest that customers may place higher weight on unfavorable reviews, feel cognitive dissonance when faced with seemingly conflicting fake remarks, and be unable to make a value judgment.

II LITERATURE REVIEW

Social media and digital technologies have greatly improved our understanding of human psychology, which is crucial for the development of the industrial sector. Travelers can write reviews of airlines on Skytrax, a social media website. Consumer reviews posted online serve as important benchmarks for service companies looking to enhance both the quality and consistency of their consumer policies. Future customers can also benefit from helping them gather knowledge about upcoming purchases before making them. As a result, recommendations made by prior customers based on online reviews are crucial when choosing an airline. The primary objective of Praphula Kumar Jain et al. (2021) is to anticipate airline recommendations using our proposed cuckoo optimized machine learning model. Data that was collected from the website https://www.airlinequality.com was used in the experimental analysis. Our findings demonstrate the superior performance of the proposed eXtreme gradient boosting classifier improved by Cuckoo Search (CS-XGB) over existing cutting-edge methods.

Using eye tracking, Tao Chen et al. (2022) looked into how online product reviews affect consumers' purchasing choices. The research methodology included (i) developing a conceptual framework of online product reviews and purchasing intentions through the moderating roles of gender and visual attention in comments, and (ii) conducting empirical research into the region of interest (ROI) analysis of consumers' fixation during the decision-making process and behavioral analysis. The findings demonstrated that consumers, particularly female consumers, paid substantially more attention to negative remarks than to good ones. In addition, the study found a strong link between customers' visual browsing habits and their propensity to buy. Additionally, it was discovered that

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consumers were unable to recognize fraudulent remarks. For the first time, the current study reveals the impact of gender on this effect and explains it from the perspective of attentional bias, which is crucial for the theory of online consumer behavior. It offers a thorough understanding of the underlying mechanism by which online reviews influence purchasing decisions. Particularly, the impacts of customers' attention to positive and negative remarks appear to be modulated by their gender, with female consumers paying substantially more attention to negative than to positive comments. These results imply that practitioners should pay close attention to unfavorable comments and respond to them quickly by tailoring product/service information while taking into account consumer characteristics, such as gender.

Consumers are exposed to a variety of indications while looking for and booking hotels online, including customer reviews, pricing, and brand names. Ji Wen et al(2020) .'s study intends to investigate the degree of diagnosticity and concurrent effects of the three significant decision-making cues: price, brand, and online reviews on consumer quality appraisal and hotel booking intention. A randomized controlled experiment comprising two factors (high versus low price) and two factors (good versus negative internet reviews) is used in Study 1. (familiar versus unknown brand). Study 2 replicates and expands on Study 1 by investigating the mediation impact of perceived quality as well as the effects of the three cues on perceived quality and booking intention. The findings show three-way interactions between various cues in consumers' decision-making processes and show that negative reviews have a dominant impact on hotel booking intention. The results also show that online reviews, brand familiarity, and price have the highest levels of cue diagnosticity.

Due to the development of Web 2.0 and the quick expansion of Tourism 2.0 applications, the internet now contains millions of user reviews and ratings for almost all lodging facilities worldwide. Millions of travelers use these evaluations and ratings every year to choose hotels. Many hotel online booking companies, such as booking.com, allow customers to publish online evaluations about the hotels they have reserved. At the moment, hotel review websites, such as tripadvisor.com, are among the most popular websites on the internet. However, given the high costs of investing in the hotel industry, consumer hotel selection behavior has long been a fascinating and pertinent research topic for tourism marketing studies. Pourfakhimi, et al(2014) 's study aims to comprehend how this massive amount of eWOM affects how modern travelers behave toward hotel selection criteria.

In order to identify customer behavioral trends, big social data and user-generated content have become crucial sources of timely and rich knowledge. User-generated content has been widely used in business to reveal client happiness, notably in the tourist and hospitality sectors. Numerous customer satisfaction studies that use quantitative survey methods have been conducted. However, adopting eWOM (electronic word of mouth) to expose consumer happiness using massive social data can be a useful technique to better understand client expectations. Alsayat (2022) seek to create a hybrid methodology for analyzing massive social data on travelers' choices of hotels in Mecca, Saudi Arabia, based on supervised learning, text mining, and segmentation machine learning approaches. To achieve this, we create the hybrid method using support vector regression with sequential minimum optimization (SMO), latent Dirichlet allocation (LDA), and k-means methodologies. We compile information from TripAdvisor reviews of hotels in Mecca. Based on their online hotel reviews, tourists' happiness is revealed for each component of the data after it has been segregated. The outcomes demonstrate the method's suitability for traveler segmentation and huge social data analysis in Mecca hotels. The findings are examined, and numerous suggestions and tactics are given for hotel management to increase their customer happiness and service quality.

E-commerce in the travel and hospitality industry is currently ranked No. 2 globally among all online buying categories. Visitors to a hotel booking website cannot ensure that they will make purchases, but the conversion rate is thought to be the best indicator of how well an e-commerce website is performing. Tang L. et al.'s study from 2022 sought to determine what factors affect conversion rates from both the affective content and the communication style of online reviews from customers. Eight emotional aspects from Plutchik's emotion wheel, including joy, sadness, rage, fear, trust, disgust, anticipation, and surprise, were used to evaluate the affective content, while language style matching was used to evaluate the communication style perspective (LSM). For the investigation, 111,926 customer reviews from 641 hotels across five U.S. cities were gathered in total. The findings showed that LSM and the four emotions significantly affect hotel conversion rates. This study offers useful practical applications and adds to the body of information about customer conversion habits on hotel booking websites.

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The M M Maraini et al., (2021) study is the first to offer an integrated view of the body of artificial intelligence (AI) knowledge that has been published in the literature on marketing, consumer research, and psychology. This study offers an overview of the developing conceptual framework of AI research across the three bodies of literature investigated by utilizing a systematic literature review employing a data-driven approach and quantitative methodology (including bibliographic coupling). Eight topical clusters were uncovered by the authors, including (1) memory and computational logic, (2) decision-making and cognitive processes, (3) neural networks, (4) machine learning and linguistic analysis, (5) social media and text mining, (6) social media content analytics, (7) technology acceptance and adoption, and (8) big data and robots. A total of 412 theoretical lenses were identified as being used in these studies, with the following eight being the most frequently used: (1) the unified theory of acceptance and use of technology; (2) game theory; (3) theory of mind; (4) theory of planned behavior; (5) computational theories; (6) behavioral reasoning theory; (7) decision theories; and (8) evolutionary theory. Finally, they suggest a study plan to improve the academic discussion on AI in the three literatures examined, with a focus on neglected research subjects and the cross-fertilization of theories utilized across disciplines.

The use of hotel suggestion techniques has received more attention as internet hotel booking has become more common. A new hotel recommendation method based on online reviews from customers and using interval neutrosophic linguistic numbers is offered in order to deliver customised hotel recommendations for various types of customers (INLNs). As a further development on the basis of the INLNs, this study proposes a distance formula of the interval neutrosophic linguistic numbers and the interval neutrosophic linguistic numbers power average (INLNPA) operator. The relevance of the similar groups is also taken into account in an unique integration model that we design using the INLNPA operator. The proposed approach is then applied to the hotel suggestion by J Q Wang et al. (2018). To check the validity of the suggested approach, they have extracted 1902 online reviews of 10 hotels for the case study from TripAdvisor.com. The key finding of this research is that the suggested method can increase the consistency of hotel ordering.

The goal of the article by Nag Thi Vo et al., (2021) is to emphasize the effect of online guest reviews on the hotel sector. Its goal is to improve user numbers and levels of satisfaction for successful engagement and loyalty in the setting of luxury hotels. The study has investigated the variables influencing the guest online reviews, including the guest feedback, hotel management response, and customer decision-making process, based on a keyword-driven search. In turn, they have an effect on the levels of patron engagement and satisfaction in Vietnam's hotel and tourism sectors. When there is a decrease in the number of clients, the practical issue arises. Negative online reviews are a problem for hotel management in particular. Through the use of SPSS tools, the quantitative approach evaluated the reliability of the questionnaire's measurements and the association between the constructs. Three hundred eighty-four individuals who work in the hospitality and tourism industries took part in the study. The findings demonstrate that the customer's decision-making process has the greatest influence on online guest reviews of hotels' service quality and on how well such reviews are handled by customers. The study's recommendations encourage sustainable tourism and high-end hotel management in both developed and developing nations. To gain a general grasp of past, present, and future research, its limitations and need for additional study are also covered.

A survey of the literature on hotel internet pricing policy is provided in this work by Manuela Pulina et al. (2018). Demand, supply, and regional factors are covered from three separate angles when discussing pricing methods. The examined literature demonstrates that e-WOM has an impact on hotel room revenue and overall performance from the demand side. Additionally, e-WOM provides essential data that hotel management can use to comprehend guests' wants as well as their level of happiness and loyalty. In particular, reputation, based on online customer reviews, plays a bigger part in online pricing strategy. Research is still limited and largely attached to the traditional framework of competition on the supply side. The analysis shows that in an online market that is quite turbulent and dynamic, hotel pricing strategy needs to be more innovative. In addition, this paper further generalizes the result that the degree of accessibility to and mobility within an area has a significant impact on hotel online pricing strategy.

III PROPOSED METHODOLOGY

Online review sites will have an effect on the customers' decisions regarding whether or not they will review a hotel, with positive ratings leading to an increase in trust in the hotel and, as a result, an increase in hotel bookings and negative reviews leading to a decrease in both trust and hotel reservations. Figure 1 depicts the flow work of the methodology.

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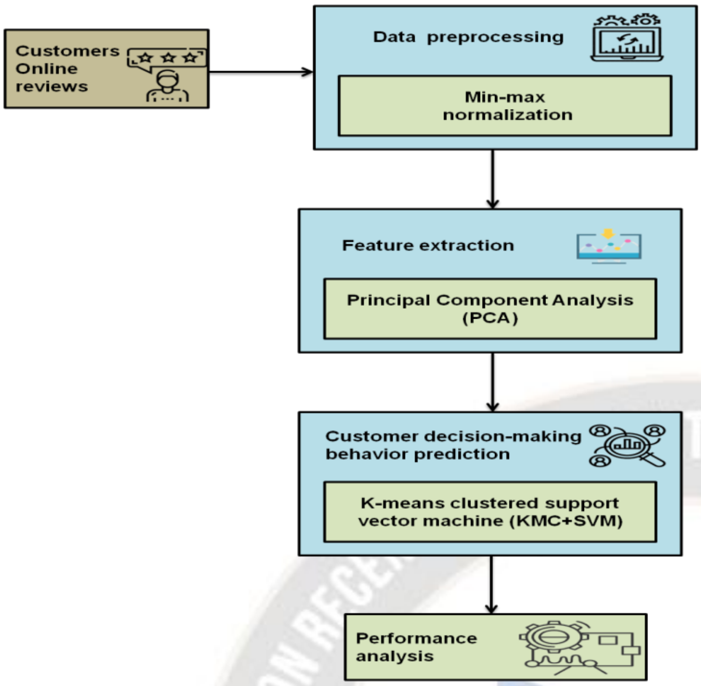

Figure 1: Flow work of the methodology

A. Data processing using normalization

We provide data-preprocessing, which includes normalization, and deal with all inaccurate data, errors, including similar data when the device data set contains some missing or erroneous data in addition to redundancy in format throughout generate a sense. A formula was used to standardize the consumer decision making process AH^{pv} inside the domain [0, 1], which significantly decreased the perception of consumer decision making.

$$Data\_Y_{norm} = \frac{AH^{pv} - Data\_Y_{min}}{Data\_Y_{max} - Data\_Y_{min}} \times [max_{value} - min_{value}] + min_{value} \quad (1)$$

$Data\ (Y_{norm})$ Max-value and Min-value represent the range of a normalized input data, with max-value = 1 and min-value = 0, respectively. Y_{norm} represents the normalised value of a raw data, Y_{min} denotes the minimum of a raw data, Y_{max} denotes the maximum value of a dataset, and AH represents the original value of a online review data source.

B. Feature extraction using Principal Component Analysis (PCA)

After standardizing the data, PCA was used to explore the curve's underlying attributes. Principal component analysis was used to transform a large number of variables into fewer variables that accounted for the most variability. The math answer was similar to finding the eigen value, and the other variables were functional major components.

The tested function had data on multiple variables at many time points. If time was the independent variable in the functional context, the work faced dimensionality challenges. Functional PCA can reduce a problem's dimensions. PCA was used to predict traffic flow patterns, which prevented similar functional aspects as charging. In (2) similar to the multivariate technique $\beta(r)y_k(s)$ was compared to βy_k for different variables.

$$g_k = \int \beta(r) y_k\,(s) = \int \beta y_k \quad (2)$$

Where, $\beta(r)$ = Weight value.

C. K-Means Clustered Support Vector Machine

K-means clustering is an input algorithm used for predictive analytics analysis. K-means divides n observations into K clusters; all observations belong to the prototype cluster. The K-Means Approach is an iterative technique that begins with initial partitioning and converges on best results with diminishing sum squared error. Several successful heuristic algorithms can swiftly locate the algorithm because of how they progress towards a global optimum through iterative refining. Hence, the consumer decision making process can be made through online reviews.

The classical K-means clustering approach reduces prediction error by finding the equation (3) set Y of K clusters di with cluster mean di.

$$F = \sum_j^l = 1 \sum yj \in di||di - yj||^2 \quad (3)$$

$$||y - x|| = \sqrt{\sum_{j=1}^{s} |Yj - Xj|^2} \quad (4)$$

F is the sum of all objects with cluster means for the K cluster (4), where ||... || denotes the Mertie distance between a cluster mean and a data point $yjdi$.

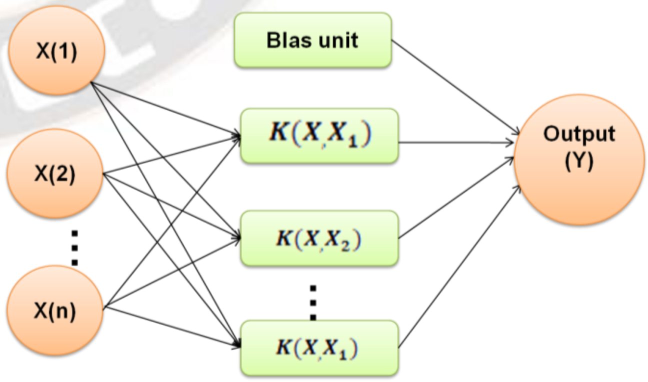

Figure 2: Architecture of the SVM

Fig. 2 shows the SVM architecture. The figure shows the eigenvector, activation functions, output vector, and bias term. Final model decision function:

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$$\mathrm{e(y)} = \mathrm{sgn}\left(\sum_{j=1}^{n} \mathrm{U_j}\ \mathrm{L}(\mathrm{y}, \mathrm{Y_j}) + \mathrm{a}\right) \qquad (5)$$

The basis function radial exhibits the best predictive performance, as can be seen. Either in the goodness of fit, the fitting error, or the time cost, it takes absolute benefits of consumer decision-making process. As a result, this technique uses a radial basis function as the kernel function, with the Gaussian function being one of the most popular choices.

$$T(t_q - d_j) = exp\left(-\frac{1}{2\sigma^2} y_q - d_j^2\right) \qquad (6)$$

Where, T is the Gaussian function's variance, d_j is the centre of the Function and $t_q - d_j$ is the Euclidean norm. The radial basis function neural network structure produces the following as its output:

$$x_j = \sum_{j=1}^{g} u_{ji} exp\left(-\frac{1}{2\sigma^2} y_q - d_j^2\right), i = 1,2, \dots, m \qquad (7)$$

where wij is the connection weight, $j = 1,2, \dots, g$ g is the number of nodes, and $y^q = (y_1^q, y_2^q, \dots, y_m^q)$ is the q^{th} input sample, $q= 1,2,3,\dots,q$, q is the total number of samples.

The least squares approach can be used to express the variance of the basis function as:

$$\sigma = \frac{1}{Q} \sum_i^n c_i - x_i d_I^2, \qquad (8)$$

The ratio of the number of characteristics is frequently used as the default value for the gamma function's parameter of consumer decision making process. Equation (5) can be changed into a new choice function based on (6) and (7), and this new decision function is:

$$e(y) = sgn \sum_{j=1}^{n} U_I\, exp\left(-gammax_j - y^2\right) + a \qquad (9)$$

Moreover, the SVM's penalty term (c) and gamma term (g) should be specified to ensure the model's best predicted performance. The preferred weight of the two indices can be adjusted and optimised by the penalty term in the direction of the allowable error. The probability of under fitting increases with decreasing penalty term value, whereas the probability of over fitting increases with increasing penalty term value.

IV EXPERIMENTAL RESULT

In this paper, we proposed the K-Means Clustering with Support Vector Machine [KMC+SVM] on the prediction of Consumer decision-making behaviour based on hotel online reviews under computer dynamic recommendation. Experiment used accuracy, sensitivity, RMSE, and MAE. The suggested approach (KMC+SVM) is contrasted with existing techniques like "Convolutional Neural Network" (CNN) [22], "deep belief network" (DBN) [23], and "long short term memory" (LSTM) [24].

By dividing the total number of statements by the number of accurate classifications, we may determine the truthfulness of a statement. The accuracy of this approach is dependent on the classifier's ability to correctly identify normal and abnormal brain scans. Accuracy in mathematics can be defined as,

$$Accuracy = \frac{(\mathrm{TP + TN})}{(\mathrm{TP + TN + FP + FN})}$$
(10)

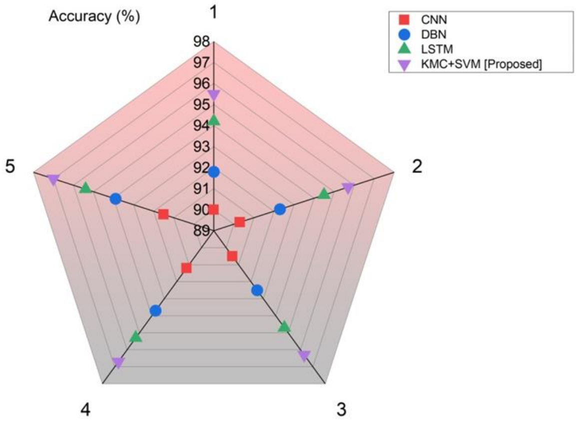

Figure 3: Comparison of the accuracy

The accuracy comparison is shown in Figure 3. The proposed method KMC+SVM shows more significance precision than the other existing methods like CNN, DBN and LATM.

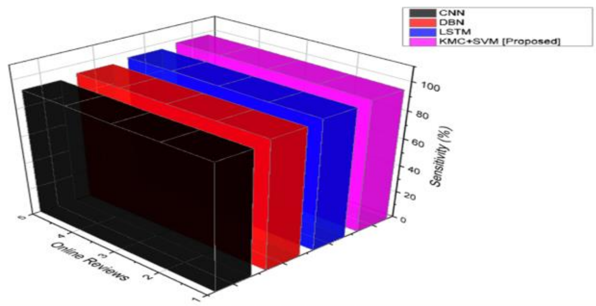

Figure 4: Sensitivity of the proposed and existing methods

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Figure 4 depicts the comparison of the sensitivity. False-positive test sensitivity can be described in a variety of ways, such as the capacity to recognise a true positive, the true positive rate, a measure of the program's capacity to correctly associate each respondent with the situation of interest, or, if 100%, the association of those who test positive with the condition of interest. The suggested KMC+SVM have more sensitivity than existing approaches like CNN, DBN and LATM.

When comparing state vectors in a dataset to coordinate values from a highly independent source, the RMSE is found by taking the square root of the biggest network measurement point difference between the two sets of data. The gap between the expected and observed hotel review for each connection has a significant relationship with the objective measure of accessibility, even though the numbers are summed in different ways.

$$\text{RMSE} = \sqrt{\sum_{l}^{H} \frac{[\,count_l - model_l]^2}{N}} \quad (11)$$

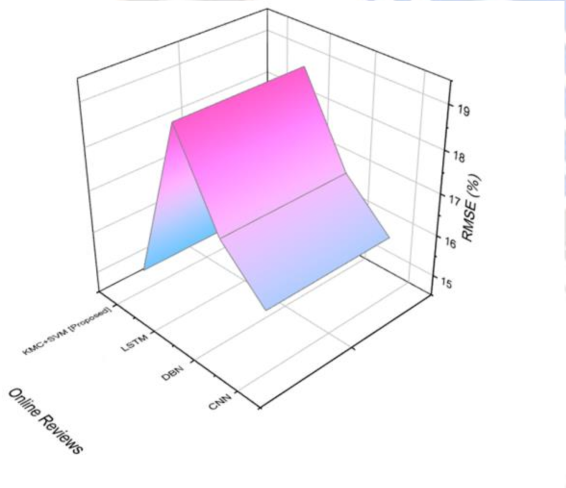

Figure 5: RMSE of the proposed and existing method

Figure 5 depicts the comparison of the RMSE. A average error between measured and predicted prediction of Consumer decision-making behaviour based on hotel online reviews is measured by the RMSE which are metrics of customer online hotel review prediction efficiency. The suggested approach KMC+SVM has a less root mean square error compared to current methods like as CNN, DBN, and LATM.

The mean absolute error of a method on a test data set is the simple average of the individual prediction mistakes made for each instance in the validation set. It is common for lower values of the metrics to reflect better quality of prediction. It could be necessary to perform a visual assessment of the prediction error to complete the efficiency evaluation metrics.

$$\text{MAE} = \frac{\sum_{k=1}^{l} |h_i|}{N} \quad (12)$$

Where,

$|h_i|$ = total of all errors.

N = the level of the prediction errors.

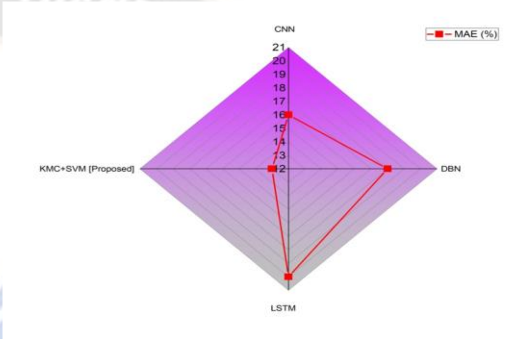

Figure 6: MAE of the proposed and existing methodology

The mean absolute errors are shown in Figure 6. When compared to well-established algorithms like CNN, DBN, and LATM, the suggested KMC+SVM have minimal MAE.From the study, we can observe that different types of customers rely more on word of mouth than they do on digital word of mouth. Electronic word of mouth is still frequently used by both groups and is often regarded as an important resource. In particular, while doing so online for hotel stays. Further evidence that the theoretical model accurately describes the interaction between various consumer behaviour characteristics and online reviews was found when we found that both groups were affected by online reviews of hotels. This study's comparative elements show that high-end customers place a higher value on customer evaluations due to a correlation between their familiarity with online reviews and their willingness to spend more on a hotel based on what they read. Both categories appear to be less influenced by customer reviews when booking luxury hotels and more influenced by reviews when booking budget hotels, based on a comparison between the two types of stays. Results indicate that customer reviews have an impact on the public's impression of a hotel's brand, as was previously noted. This suggests that customer reviews have a greater impact on the brand image of low-end hotels than high-end hotels.

As a result, the reputation of budget hotels is more vulnerable to the accumulation of negative customer evaluations than that of luxury hotels, as guests tend to be more wary when booking the former. However, if there are many favourable customer evaluations, the brand image of a budget hotel may improve more than that of a high-end hotel. The brand image of luxury hotels is already perceived as more reliable than the brand image of budget hotels; therefore, positive customer reviews may be more beneficial to budget hotels, despite the fact that they provide a lower price.

V CONCLUSION

A larger number of consumers are using social networks to share their comments regarding the level of service given by hotels. Hotels can learn from their customers' feedback on review websites to improve their service. Customer reviews are undoubtedly a reputable and trusted tool that aid diners in deciding the quality of their cuisine. It is crucial to create methods for analysing guest comments on hotel performance. This study recommends an unique K-Means Clustered Support Vector Machine (KMC+SVM) method for predicting consumer behaviour in response to online hotel reviews. The raw data is normalised using the Min-Max method, then Principal Component Analysis (PCA) is performed to extract the characteristics from the cleaned data. The accuracy, sensitivity, RMSE, and MAE of the proposed method are then measured and compared to those of several other popular approaches. The results proved that customer evaluations online may be used to divide consumers into groups whose preferences can be correctly predicted and whose opinions can aid hotel management in setting priorities for improving service quality.

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