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Performance of Machine Learning Models to Predict Customer Satisfaction Scores for Lao National Convention Center

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Abstract
This research paper investigates the effectiveness of various machine learning (ML) models in predicting customer satisfaction scores for the Lao National Convention Center (LNCC). By utilizing a dataset containing customer feedback, demographic data, facilities, and service-related information, the study aims to identify the best performing model for predicting customer satisfaction. In this paper, the performance of ML to predict customer satisfaction scores from the questionnaire survey dataset is evaluated. The customer satisfaction score is categorized into five classes: strongly agree, agree, neutral, disagree and strongly disagree. The analysis will compare the performance of different models, including linear regression (LR), k-nearest neighbor (KNN), support vector machines (SVM), decision trees (DT) and random forest (RF). The results show that SVM model achieved the highest accuracy rate of 95.91%, followed by KNN and LR with an accuracy rate of 95.55% and 95.49%, respectively. The findings of this study have important implications for the use of ML in improving the service-related information for LNCC and providing valuable insights for decision-makers and developers.

Keywords: Lao National Convention Center (LNCC), Customer Satisfaction, Machine Learning (ML)

1. Introduction

The Lao National Convention Center (LNCC) is a prominent venue in Laos, hosting various events and attracting numerous visitors. Understanding customer satisfaction is crucial for the LNCC's success, as positive experiences translate to repeat business, positive word-of-mouth marketing, and ultimately, increased revenue [1]. Customer satisfaction scores hold immense importance for the LNCC for several key reasons. In the competitive tourism industry, positive customer experiences are crucial for building a strong reputation and brand image. High satisfaction scores translate to positive reviews, word-of-mouth recommendations, and increased trust among potential visitors [2]. This fosters a positive perception of the LNCC, attracting more bookings and driving growth. Satisfied customers are more likely to return for future events [3], recommend the LNCC to others, and spend more during their stay. This leads to increased revenue, ensuring the sustainability of the LNCC and its contribution to the Laotian economy. Customer feedback, reflected in satisfaction scores, provides invaluable insights into areas for

improvement. This data allows the LNCC to identify areas for service enhancement, optimize operations, and enhance the overall visitor experience. Traditional methods of assessing customer satisfaction, such as surveys and feedback forms, can be time-consuming and may not capture the full picture.
Machine learning (ML) offers an efficient and data-driven approach to predicting customer satisfaction [4]. By analyzing historical data, ML models can identify patterns and relationships that contribute to customer satisfaction, allowing the LNCC to proactively address potential issues and enhance the overall customer experience. The key factors influencing customer satisfaction and building models to predict future scores [5] should be identifying, for understanding the factors driving satisfaction will enable the LNCC to prioritize resources and improve service quality in specific areas. Early identification of dissatisfied customers allows for timely intervention and resolution of potential problems, minimizing negative impact on reputation and future bookings [6]. By embracing ML, the LNCC can harness the power of data to understand customer needs, predict satisfaction levels, and proactively optimize the visitor experience. This leads to a more sustainable, successful, and customer-centric organization, contributing to the continued growth of the Lao industry.
This research contributes to the growing field of customer satisfaction prediction using ML, with specific focus on the unique context of the LNCC and its contribution to the customer services. The findings will equip the LNCC with valuable tools for data-driven decision-making, leading to a more satisfied customer base and sustainable growth for the organization. Exploring ML models for customer satisfaction prediction at the LNCC, Linear Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT) and Random Forest (RF) models are particularly useful for predicting satisfaction in dynamic environments where customer preferences and expectations might change [7]. DT and RF offers high accuracy and robustness, while LR, SVM and KNN provides a more interpretable framework for understanding the underlying patterns in customer satisfaction data. Combining these models can offer a comprehensive solution for predicting satisfaction and guiding strategic decisions at the LNCC.

2. Related Works

Existing research has demonstrated the successful application of ML in predicting customer satisfaction across various industries [8] [9] [10]. Studies have employed various techniques, including: LR, KNN or SVM can be valuable tools for predicting customer satisfaction at the LNCC, providing insights into the relative importance of different factors. However, it's essential to consider its limitations and explore other models, like DT or RF, to capture nonlinear relationships in the data. non-linear analysis of airline customer experience using LR and Artificial Neural Networks (ANN) for predicting customer satisfaction in the airline industry [11]. It finds that both models achieve good performance, but LR is simpler to implement and understand. Cross-sector application of ML in telecommunications through comparative analysis of ensemble methods [12]. This study examines LR and SVM in predicting customer satisfaction in the telecom industry. It concludes that LR performs well, especially when dealing with a large number of features. To explore LR and ANN for predicting customer satisfaction in e-commerce [13], they observe that LR provides satisfactory results and is a suitable option for simple prediction models. A powerful tool for customer satisfaction prediction [14] outlines how companies can utilize LR to understand customer satisfaction drivers and improve their offerings. These studies have highlighted the potential of ML to effectively predict customer satisfaction and provide valuable insights for business. To predicting customer satisfaction in the hotel industry, KNN is applied and performed well, especially when dealing with complex data with non-linear relationships [15]. Customer satisfaction prediction in e-commerce using KNN and SVM concludes that KNN can achieve high accuracy, especially when the data is relatively small [16]. The banking industry examines the effectiveness of SVM in predicting customer satisfaction in the banking sector [17]. It finds that SVM outperforms traditional statistical methods and offers a robust approach to understanding customer sentiment. The hospitality industry using DT algorithm for predicting customer satisfaction [48]. It finds that DT is a suitable choice for identifying key factors influencing satisfaction and building a simple yet interpretable model. To compare DT and RF for predicting customer satisfaction in e-commerce [4]. the decision-making process behind customer satisfaction concludes that DT is effective for understanding, while RF offers higher accuracy. RF is a valuable tool for predicting customer satisfaction, offering high accuracy, robustness, and insights into feature importance. Its ability to handle complex relationships and large datasets makes it a suitable choice for various applications. However, it's important to consider the computational cost and carefully tune its parameters to optimize performance.

3. Methodology

This study employs a quantitative research methodology to investigate customer satisfaction with service-related information in LNCC. Figure 1 illustrates the structured approach taken in this study. It has three main phases: (1) dataset collection, (2) prediction, and (3) performance evaluation.

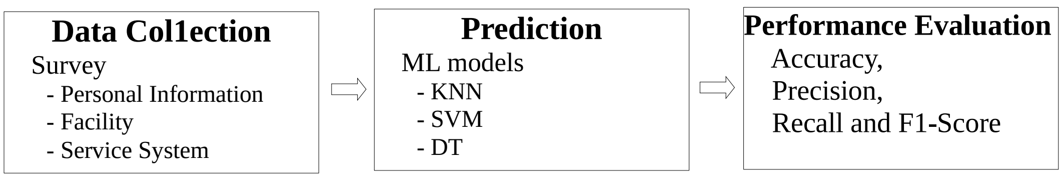

Figure 1. An overview of the research methodology.

3.1. Dataset Collection

To obtain a more targeted evaluation of users' satisfaction, this study adopted a question-aire survey targeting service-related information in LNCC. The survey link and QR code were distributed through WhatsApp, where many users are active. The survey questions were provided in Lao to facilitate easier and more convenient participation which encompassed various factors related to service-related information in LNCC. The questionnaire was structured into three sections, as shown in Table 1. The questions aimed to capture factors affecting service users' satisfaction, including personal information about the
participants, facilities and service-related information.

Table 1. The questionnaire direction.

Area of Investigation	Content of Investigation
Demographics	Gender, Age, Job Position
Facilities	Type of room, Internet Connection, Air Condition, Voice System, Food, Restroom
Service-Related Information	Registration Management, Event Management,

Specific areas covered by the questions included the adequacy and efficiency of facility support and the satisfaction of service-related information. All measurements in the survey were based on Likert scales, with responses initially captured on a 5-point scale. To address potential class imbalances that could affect the ML models, the responses were recoded into a 2-point scale: ‘Strongly Agree’, ‘Agree’ and ‘Neutral’ were combined into ‘Satisfied’; ‘Disagree’ ‘Strongly Disagree’ and were combined into ‘Unsatisfied’. This study observes a different distribution among participants based on their gender, age and job position. Table 2 displays the distribution of participants.

Table 2. Demographic Profile Distribution Among Survey Respondents.

Gender	Male		Female			
	62%			38%		
Age	<= 30	<=50		>50		
	26%	61%		13%		
Job	Government employees	Private employees	Business people		Students	Other
	41%	28%		20%	9%	2%

The sample consists of 328 individuals, with 62% male, 38% female. The majority of participants are government employees (41%), followed by private employees (16%) and business people (12%). The data indicate that students constitute the smallest participation rate (9%), followed by the ’other’ category (2%). These findings highlight the significance of government employees as the largest group of participants. The distribution of participants by gender, age, and job provides important insights for researchers and practitioners in the service-related information. In order to evaluate the distribution of participant responses regarding the factors influencing their satisfaction with the service-related information of LNCC, it is important to measure the validity and reliability of the study instrument. In this study, Cronbach’s alpha was computed as part of the initial analysis to ascertain the dataset’s consistency and validity. The value obtained for the survey instrument was 0.825, significantly surpassing the commonly accepted threshold of 0.7, indicating a high level of internal consistency [19].

3.2. Prediction

This phase of the study entails predicting customer satisfaction of service-related information, utilizing the dataset collected from the previous phase. This is performed through the implementation of various ML models. The customer satisfaction prediction is the target feature in this study, it is denoted by (Y) which is the dependent variable and the estimated value of Y is denoted by (y). Different models are fed with the encoded values of the captured measurements to calculate the prediction. These variables are shown in Table 3.

Table 3. The encoded prediction measurements.

Variable	Measurement	Variable	Measurement
X_1	Gender	X_7	Voice System
X_2	Age	X_8	Internet Connection
X_3	Job Position	X_9	Food

X_4	Type of room	X_{10}	Restroom
X_5	light	X_{11}	Reception Staffs
X_6	Air Condition	X_{12}	Management

The dataset is split into training and validation sets with a training size of 80% and a validation size of 20%. Before building the ML models, the data are normalized to scale the features to a range of 0 to 1. This is performed separately for both the training and validation sets. The ML models included are LR, KNN, SVM, DT and RF.

4. Performance Evaluation

This section is devoted to discussing the results of the performance evaluation. Specifically, the use of ML models proved effective in predicting satisfaction levels, and the study's findings highlight the importance of factors, including facilities and service-related information. The performance of various models is evaluated using accuracy, precision, recall, and F1-score [20]. Table 3 shows the performance of various ML models.

Table 3. Performance of ML models in predicting satisfaction in percentage.

Model	Accuracy	Precision	Recall	F1-Score
LR	95.49	96.24	95.08	95.11
KNN	95.55	96.82	99.16	98.35
SVM	95.91	96.52	95.68	95.68
DT	94.29	94.64	94.72	93.89
RF	94.54	94.63	94.48	93.79

The results in the above table 3 are ranked based on the accuracy rate. However, it is important to note that accuracy alone does not always provide a complete picture of the model's performance. The highest accuracy score is achieved by the SVM model, followed by KNN and LR. The SVM model performs better than any other models. SVM is a useful model in prediction studies [12]. In this study, the SVM algorithm archives a 95.91% accuracy rate in satisfaction prediction. However, KNN archives a high rate in other measurements like precision and recall, which indicates its ability to balance precision and recall. The F1-score is a measure of the model's ability to balance precision and recall. Precision measures the number of correct positive predictions out of all positive predictions, while recall measures the number of correct positive predictions out of all actual positive instances. The KNN model's superior F1-score suggests that it accurately identifies both true positives and true negatives [20]. Table 3 shows that KNN has the highest F1-score (98.35%), while RF has the lowest F1-score (93.79%). For the precision metric, which measures the proportion of true positives among all positive predictions, we also can see that RF has the lowest precision score (94.63%), while KNN has the highest precision score (96.82%). Overall, the nature of ML models makes it difficult to understand how they make predictions and enhance the performance.

5. Conclusions

This study aimed to predict satisfaction in service-related information of LNCC using ML techniques. The results show that SVM model achieved the highest accuracy rate of 95.91%, followed by KNN and LR with an accuracy rate of 95.55% and 95.49%, respectively. The other models also demonstrated varying degrees of performance, with the lowest accuracy rate of 94.29% achieved by the DT. Additionally, some models showed higher precision than recall, while others showed the opposite pattern. Overall, SVM, KNN and RL proved to be effective ML models for predicting satisfaction. However, its limitations in terms of linearity and independence between predictor variables need to be considered for future analysis. Also, the limited number of participants makes it hard to obtain a full understanding. Overall, this study highlights the potential of ML techniques in predicting satisfaction, informing decision making in service-related information to enhance the quality of services. In the future, this framework could be used to develop a new tool for predicting satisfaction with service-related information. Moreover, further studies could expand upon the range of service-related information examined satisfaction in varying operational environments.

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