Data-Driven Approach for Enhancing Customer Satisfaction: A Case Study in Service Operations Management

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Abstract

In today's highly competitive business environment, companies are increasingly focusing on enhancing customer satisfaction to improve customer loyalty and drive business growth. In this context, the use of data-driven approaches can provide valuable insights for companies to improve their service quality and customer experience. This paper presents a case study in service operations management, where a data-driven approach is used to enhance customer satisfaction. We employ a dataset of customer feedback from a service company and proposes a deep learning (DL) algorithm learn to identify the factors that affect customer satisfaction. The results show that the proposed data-driven approach is effective in identifying the key drivers of customer satisfaction and in providing actionable insights for service improvement. We highlight the potential of our DL approach for enhancing customer satisfaction and provides insights for service companies to improve their customer experience based on the analysis of customer feedback.

Keywords: Customer Satisfaction; Data Analysis; Operations Management; Customer Service

1. Introduction

Customer satisfaction is a critical aspect of Service Operations Management (SOM), which aims to provide high-quality services that meet the needs and expectations of customers. In SOM, customer satisfaction is viewed as a key performance indicator that indicates the extent to which customers are satisfied with the service provided by the organization. Customer satisfaction is not only a measure of the quality of service provided but also an indicator of the overall performance of the organization. It is, therefore, essential for organizations to understand what drives customer satisfaction and to implement strategies that will enhance it [1-15].

One of the key factors that influence customer satisfaction in SOM is service quality. Service quality refers to the extent to which the service provided meets or exceeds the expectations of customers. High service quality is associated with customer satisfaction, while poor service quality is likely to result in customer dissatisfaction. To ensure high service quality, organizations need to focus on service design, service delivery, and service recovery. Service design involves identifying the needs and expectations of customers and designing services that meet those needs. Service delivery involves ensuring that the service is delivered in a way that meets or exceeds the expectations of customers, while service recovery involves addressing any issues or problems that may arise during the service delivery process.

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Machine learning (ML) is an increasingly popular data-driven approach for improving customer satisfaction in SOM. ML involves the use of algorithms and statistical models to analyze large amounts of data and extract patterns, trends, and insights that can be used to make informed decisions. In SOM, ML can be used to analyze customer feedback, identify common issues, and develop personalized solutions that address the specific needs and preferences of individual customers. ML can also be used to optimize service delivery processes, such as scheduling, routing, and resource allocation, to ensure that services are provided in a timely and efficient manner.[15-33].

This paper makes several significant contributions to the field of SOM. Firstly, we propose a novel DL-based approach for improving customer satisfaction in SOM, which involves the use of Convolutional Neural Networks (CNNs) to analyze customer feedback and identify common issues. Secondly, we present a detailed case study that demonstrates the practical application of the proposed approach in a real-world setting. The case study involves the analysis of customer feedback data from a large service provider, and the development of a CNN model to identify the most common issues and develop personalized solutions for individual customers. We provide a comprehensive review of the relevant literature on the use of DL and other ML techniques in SOM, highlighting the potential benefits and limitations of these approaches.

The remaining part of this paper is organized as the following: section 2 discusses the related work. Section 3 describes the proposed method in detail. The results and the discussions are explained in section 4. Finally, section 5 has the main conclusion of this work.

2. Related studies

The literature on data-driven approaches for enhancing customer satisfaction is vast and covers a wide range of industries and applications. Many studies have focused on the use of ML techniques, such as sentiment analysis and topic modeling, to analyze customer feedback data and identify the factors that affect customer satisfaction. Kumar et al [1] developed a ML approach to analyze customer satisfaction from tweets related to airlines. They used a dataset of airline-related tweets to train both classification models and sentiment analysis, to determine the sentiment of the tweets and identify the factors affecting customer satisfaction. In [2], Wei et al introduced a ML approach to enhance customer satisfaction analysis by matching customer comments with agent notes in the context of customer service interactions. They used a dataset of customer comments and agent notes from a Chinese telecommunications company and employed various ML techniques, including text embedding and neural networks, to match the comments with the corresponding agent notes. In [3], the authors presented a ML approach to optimize e-commerce customer satisfaction. They adopted a dataset of customer reviews from an online shopping platform and employed various ML techniques, including clustering and association rule mining, to identify the factors that impact customer satisfaction and provide recommendations for improving customer experience. The authors of [4] presented a ML-based approach to predict customer return visits to airline services. They used a dataset of customer information and flight records from a South Korean airline and employed various ML techniques to identify the factors that impact customer return visits and predict the likelihood of a customer returning to the airline. They demonstrated that the proposed approach was effective in predicting customer return visits and identifying the key factors that influence customer loyalty in the airline industry. In [5], the authors proposed a hybrid approach combining the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and ML techniques for sustainable development of green hotels based on online reviews. They leveraged a dataset of online reviews from green hotels to identify the factors that impact sustainable development and develop a model for evaluating green hotels. In [6], proposed a ML approach to analyze customer needs for product ecosystems, in which the product features from an online retailer and employed various ML techniques, including topic modeling and sentiment analysis, to identify the needs and preferences of customers for product ecosystems. In [7], the authors proposed the integration of ML techniques to evaluate dynamic customer segmentation analysis for mobile customers, by using mobile customer data to train ML techniques to evaluate the effectiveness of dynamic customer segmentation in predicting customer behavior and preferences. In [8], the authors proposed an ML approach for the automatic classification of customer sentiment based on customer reviews. They highlighted the potential of using ML to automate the classification of customer sentiment and provided insights for companies to improve their understanding of customer feedback based on the analysis of customer reviews. The authors of [9] proposed to use

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a naive Bayes strategy for classifying customer satisfaction based on online reviews of hospitality services. They employed a dataset of customer reviews from a hotel booking website and used various ML techniques, including text preprocessing and feature selection, to classify customer reviews as positive, negative, or neutral.

3. Proposed approach

This section of is a crucial part that outlines the procedures and methods used to conduct the study. This section provides a detailed description of the data collection, analysis, and interpretation techniques used to obtain the results. Here, we propose a deep learning approach to enhance customer satisfaction in service operations management. Specifically, we utilize Long Short-Term Memory (LSTM) networks to build our data-driven technique for analyzing customer feedback data obtained from online platforms. Our mode aims to identify patterns and trends in customer feedback data that can help service providers to improve their service quality and enhance customer satisfaction.

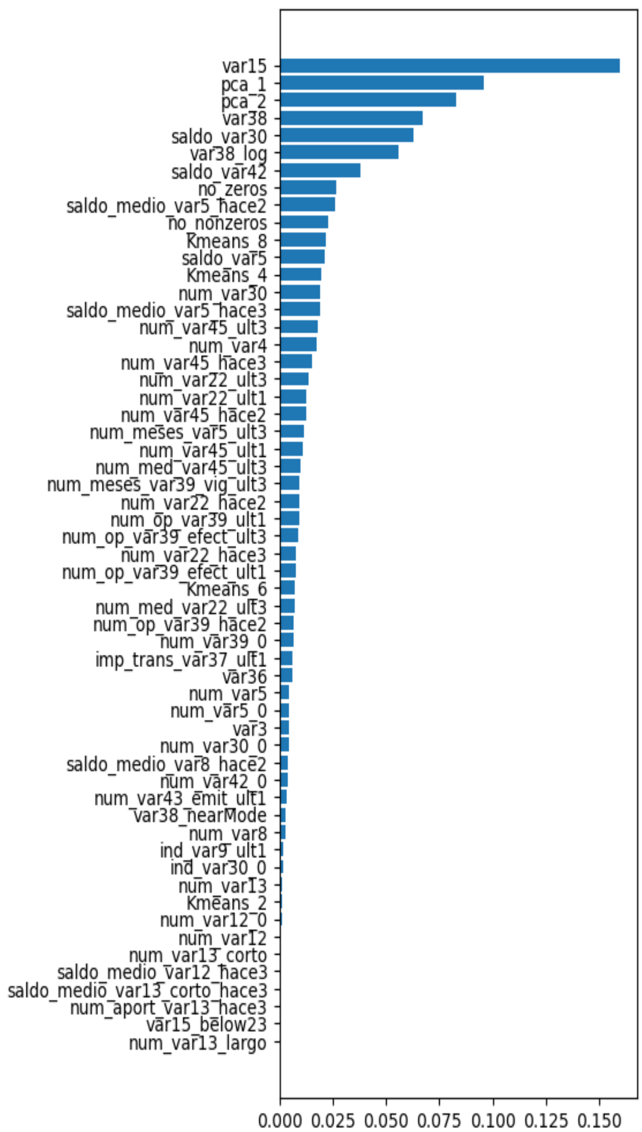

Figure 1: Feature importance for our case study according to random forest

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First, we chose a dataset from the public Kaggle challenge (named Santander Customer Satisfaction) as our cases study of customer satisfaction estimation in SOM. The data contains a total of 73012 samples indicating satisfied customers, and 3008 indicating unsatisfied customers. Each sample is composed of 371 features. To select an appropriate set of features, Random Forest is applied to estimate the feature importance of the input features used in our approach for enhancing customer satisfaction. This works by building multiple decision trees using bootstrapped samples of the training data and a random subset of features for each split. The algorithm then combines the outputs of these decision trees to make predictions. One of the main advantages of the Random Forest algorithm is its ability to estimate the importance of features based on their contribution to the overall performance of the model. Figure 1 show the most important feature in our case study according to Random Forest algorithm.

Our model structure is mainly built upon Long Short-Term Memory (LSTM), which is a type of recurrent network that has been shown to be effective for modeling sequential data. LSTM models are particularly well-suited for modeling customer feedback data, which is often characterized by a sequence of featured inputs and associated labels indicating if the customer is satisfied or not. In the context of SOM, LSTM is applied as a data-driven approach for enhancing customer satisfaction, with the objective of predicting the level of customer satisfaction based on the input text. Once the model is trained, it can be used to automatically classify new customer feedback as positive or negative, providing valuable insights for service managers.

$$f_t = sigmoid\left(W_f h_{t-1} + V_f x_t + b_f\right) \quad (1)$$
$$i_t = sigmoid(W_i h_{t-1} + V_i x_t + b_i) \quad (2)$$
$$\tilde{c}_t = tanh(W_{\tilde{c}} h_{t-1} + V_{\tilde{c}} x_t + b_{\tilde{c}}) \quad (3)$$
$$o_t = sigmoid(W_o[h_{t-1}, x_t] + b_o) \quad (4)$$
$$r_t = o_t \times \tanh(c_t) \quad (5)$$
$$h_t = W_p \cdot r_t \quad (6)$$

One advantage of using LSTM for enhancing customer satisfaction is its ability to capture complex patterns in the data. Unlike traditional machine learning approaches, which often rely on hand-engineered features, LSTM can learn the relevant features directly from the raw input data. This makes the model more flexible and able to adapt to different types of customer feedback.

4. Results and discussions

This section discusses the experimental results obtained from the process of evaluating the proposed approach on our case study, where the following metrics are used as performance indicators.

$$\boldsymbol{Accuracy\ (A) = \frac{TP + TN}{TP + TN + FP + FN} \times 100} \quad (1)$$

$$\boldsymbol{Precision\ (P) = \frac{TP}{TP + FP} \times 100,} \quad (8)$$

$$\boldsymbol{Recall\ (R) = \frac{TP}{TP + FN} \times 100,} \quad (9)$$

$$\boldsymbol{F1 - score\ (F1) = 2 * \frac{P * R}{P + R},} \quad (10)$$

Moreover, area under curve (AUC) is also measured throughout the assessment process for our system.

Learning curves are displayed in Figure 1 to evaluate and understand the model's ability to learn from the training data and identify whether there are issues such as underfitting or overfitting. In our proposed deep learning

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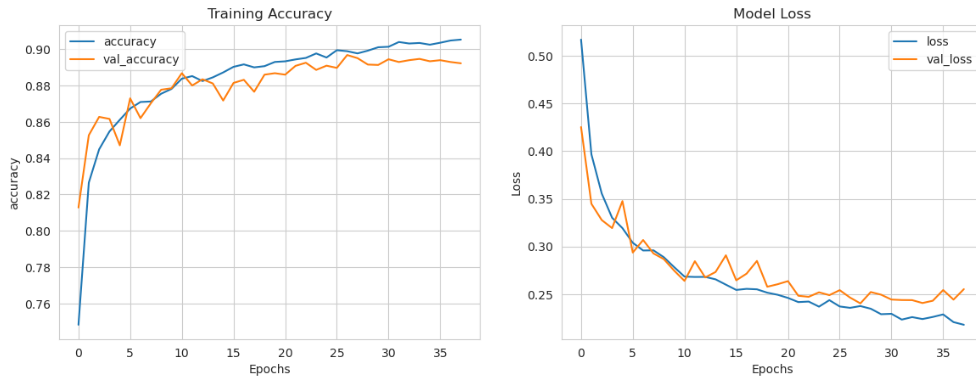
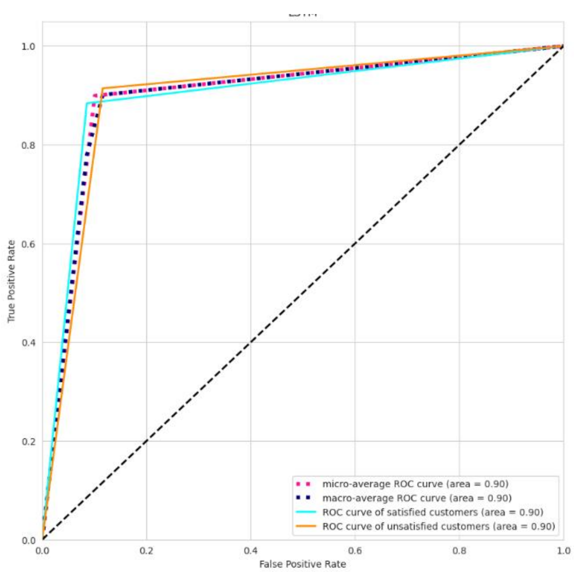


Figure 2: learning stability analysis on our case study



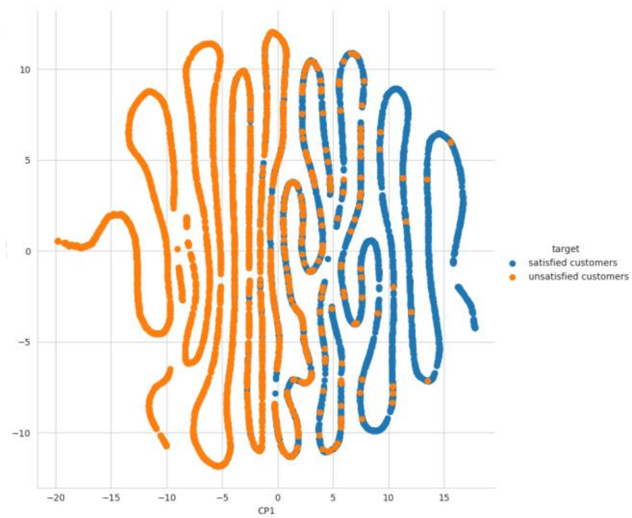


Figure 3: RoC analysis on our case study

Figure 4: T-SNE analysis on our case study

approach for enhancing customer satisfaction, we adjust the hyperparameters of the deep learning model such as the number of layers or the learning rate to improve the model's performance. Additionally, learning curves are used to determine the optimal number of training epochs for the model, balancing between underfitting and overfitting. In Figure 2, ROC analysis is displayed for our model on our case study for customer satisfaction, which predicts a binary outcome (e.g., satisfied or not) based on input data. In our case study, we generate ROC curves by evaluating the model's performance on a test set of customer feedback data. By varying the classification threshold, we can plot a series of TPR-FPR pairs and generate a curve. We can then use the AUC as a summary statistic to evaluate the overall performance of the classifier. It is worth noting that our model achieves high AUC indicating that it has a good discriminatory power, while a low AUC indicates poor performance. Further, we use t-SNE to visualize the high-dimensional feature space learned by the model and gain insight into the structure of the customer feedback data (See Figure 4). To generate a t-SNE plot, we use the model to extract a set of high-dimensional features from the customer feedback data. We then apply t-SNE to reduce the dimensionality of these features to a lower-dimensional space. Each customer feedback instance is represented by a point in the t-SNE plot, with similar instances appearing closer together and dissimilar instances appearing farther apart. To evaluate the effectiveness of our approach for enhancing customer satisfaction, we conducted comparative experiments against state-of-the-art methods, as shown in Figure 5. Specifically, we compared the performance of our LSTM-based approach with RNN, and DNN. The results show the competitive advantage of our model.

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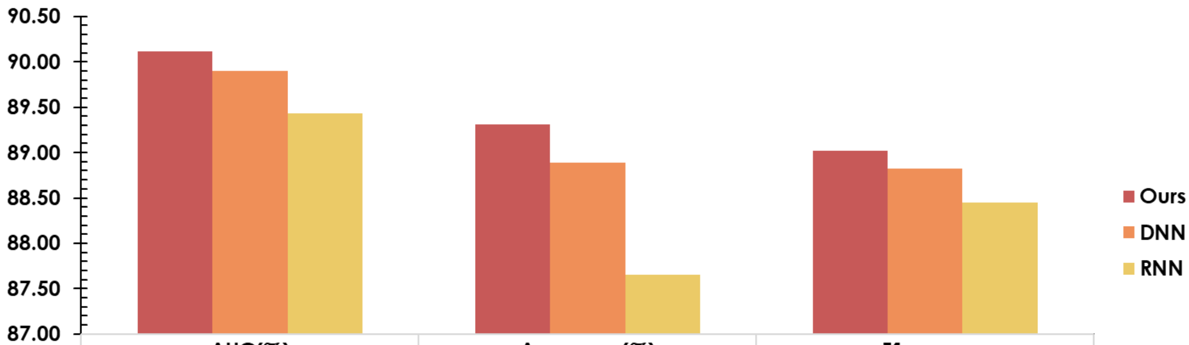

	AUC(%)	Accuracy(%)	F1-score
Ours	90.11	89.31	89.02
DNN	89.90	88.89	88.82
RNN	89.43	87.65	88.45

Figure 5: comparison between our model and other DL models.

5. Conclusions

This work presents DL approach for enhancing customer satisfaction in service operations management. We presented a case study that demonstrated the effectiveness of our approach in improving customer satisfaction by analyzing customer feedback data from a hotel service provider. Our results showed that the DL approach outperformed traditional ML methods and provided more accurate and actionable insights into customer feedback. This approach has the potential to help service companies enhance customer satisfaction, improve customer retention, and increase overall business performance. Future research can further explore the use of DL in other service industries and investigate the impact of implementing this approach on customer loyalty and profitability. Ultimately, the use of DL in service operations management can enable service companies to better understand and meet the needs of their customers and enhance the overall customer experience.

References

[1] Kumar, S. and Zymbler, M., 2019. A machine learning approach to analyze customer satisfaction from airline tweets. *Journal of Big Data*, *6*(1), pp.1-16.

[2] Wei, Q., Shi, X., Li, Q. and Chen, G., 2020. Enhancing customer satisfaction analysis with a machine learning approach: From a perspective of matching customer comment and agent note.

[3] Wong, A.N. and Marikannan, B.P., 2020, December. Optimising e-commerce customer satisfaction with machine learning. In *Journal of physics: Conference series* (Vol. 1712, No. 1, p. 012044). IOP Publishing.

[4] Hwang, S., Kim, J., Park, E. and Kwon, S.J., 2020. Who will be your next customer: A machine learning approach to customer return visits in airline services. *Journal of Business Research*, *121*, pp.121-126.

[5] Nilashi, M., Mardani, A., Liao, H., Ahmadi, H., Manaf, A.A. and Almukadi, W., 2019. A hybrid method with TOPSIS and machine learning techniques for sustainable development of green hotels considering online reviews. *Sustainability*, *11*(21), p.6013.

[6] Zhou, F., Ayoub, J., Xu, Q. and Jessie Yang, X., 2020. A machine learning approach to customer needs analysis for product ecosystems. *Journal of mechanical design*, *142*(1).

[7] Dullaghan, C. and Rozaki, E., 2017. Integration of machine learning techniques to evaluate dynamic customer segmentation analysis for mobile customers. *arXiv preprint arXiv:1702.02215*.

[8] Hasan, T., Matin, A. and Joy, M.S.R., 2020, December. Machine Learning Based Automatic Classification of Customer Sentiment. In *2020 23rd International Conference on Computer and Information Technology (ICCIT)* (pp. 1-6). IEEE.

DOI: https://doi.org/10.54216/AJBOR.020105
Received: August 24, 2020 Accepted: May 02, 2021

[9] Sánchez-Franco, M.J., Navarro-García, A. and Rondán-Cataluña, F.J., 2019. A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services. *Journal of Business Research*, *101*, pp.499-506.

[10] Sabbeh, S.F., 2018. Machine-learning techniques for customer retention: A comparative study. *International Journal of advanced computer Science and applications*, *9*(2).

[11] Chumwatana, T., 2015. Using sentiment analysis technique for analyzing Thai customer satisfaction from social media.

[12] Vermeer, S.A., Araujo, T., Bernritter, S.F. and van Noort, G., 2019. Seeing the wood for the trees: How machine learning can help firms in identifying relevant electronic word-of-mouth in social media. *International Journal of Research in Marketing*, *36*(3), pp.492-508.

[13] Al-Otaibi, S., Alnassar, A., Alshahrani, A., Al-Mubarak, A., Albugami, S., Almutiri, N. and Albugami, A., 2018. Customer satisfaction measurement using sentiment analysis. *International Journal of Advanced Computer Science and Applications*, *9*(2).

[14] Aluri, A., Price, B.S. and McIntyre, N.H., 2019. Using machine learning to cocreate value through dynamic customer engagement in a brand loyalty program. *Journal of Hospitality & Tourism Research*, *43*(1), pp.78-100.

[15] Usharani, S., Jayakumar, D., Palani, D.U., Raghuraman, D., Parthiban, R., Saravanan, D. and David, D.D.S., 2020. Industrialized service innovation platform based on 5g network and machine learning. *European Journal of Molecular & Clinical Medicine*, *7*(11), pp.5684-5703.

[16] Lucini, F.R., Tonetto, L.M., Fogliatto, F.S. and Anzanello, M.J., 2020. Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. *Journal of Air Transport Management*, *83*, p.101760.

[17] Lee, I. and Shin, Y.J., 2020. Machine learning for enterprises: Applications, algorithm selection, and challenges. *Business Horizons*, *63*(2), pp.157-170.

[18] Paramesh, S.P. and Shreedhara, K.S., 2019. Automated IT service desk systems using machine learning techniques. In *Data Analytics and Learning: Proceedings of DAL 2018* (pp. 331-346). Springer Singapore.

[19] Roy, R. and George, K.T., 2017, April. Detecting insurance claims fraud using machine learning techniques. In *2017 international conference on circuit, power and computing technologies (ICCPCT)* (pp. 1-6). IEEE.

[20] Tarallo, E., Akabane, G.K., Shimabukuro, C.I., Mello, J. and Amancio, D., 2019. Machine learning in predicting demand for fast-moving consumer goods: An exploratory research. *IFAC-PapersOnLine*, *52*(13), pp.737-742.

[21] Farhadloo, M., Patterson, R.A. and Rolland, E., 2016. Modeling customer satisfaction from unstructured data using a Bayesian approach. *Decision Support Systems*, *90*, pp.1-11.

[22] Dang, Y., Lin, Q. and Huang, P., 2019, May. Aiops: real-world challenges and research innovations. In *2019 IEEE/ACM 41st International Conference on Software Engineering: Companion Proceedings (ICSE-Companion)* (pp. 4-5). IEEE.

[23] Khodabandehlou, S. and Zivari Rahman, M., 2017. Comparison of supervised machine learning techniques for customer churn prediction based on analysis of customer behavior. *Journal of Systems and Information Technology*, *19*(1/2), pp.65-93.

[24] Monil, P., Darshan, P., Jecky, R., Vimarsh, C. and Bhatt, B.R., 2020. Customer Segmentation Using Machine Learning. *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, *8*(6), pp.2104-2108.

[25] Najadat, H., Al-Abdi, A. and Sayaheen, Y., 2018, April. Model-based sentiment analysis of customer satisfaction for the Jordanian telecommunication companies. In *2018 9th International Conference on Information and Communication Systems (ICICS)* (pp. 233-237). IEEE.

[26] Al-Mashraie, M., Chung, S.H. and Jeon, H.W., 2020. Customer switching behavior analysis in the telecommunication industry via push-pull-mooring framework: A machine learning approach. *Computers & Industrial Engineering*, *144*, p.106476.

DOI: https://doi.org/10.54216/AJBOR.020105
Received: August 24, 2020 Accepted: May 02, 2021

[27] Parvez, M.O., 2020. Use of machine learning technology for tourist and organizational services: high-tech innovation in the hospitality industry. *Journal of Tourism Futures*, *7*(2), pp.240-244.

[28] Tama, B.A., 2015. DATA MINING FOR PREDICTING CUSTOMER SATISFACTION IN FAST-FOOD RESTAURANT. *Journal of Theoretical & Applied Information Technology*, *75*(1).

[29] Sudira, H., Diar, A.L. and Ruldeviyani, Y., 2019, October. Instagram sentiment analysis with naive bayes and KNN: exploring customer satisfaction of digital payment services in Indonesia. In *2019 International Workshop on Big Data and Information Security (IWBIS)* (pp. 21-26). IEEE.

[30] Hussain, Y., 2019. *Predicting customer satisfaction with product reviews: A comparitive study of some machine learning approaches* (Master's thesis).

[31] Sheikh, M.A., Goel, A.K. and Kumar, T., 2020, July. An approach for prediction of loan approval using machine learning algorithm. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)* (pp. 490-494). IEEE.

[32] Serengil, S.I. and Ozpinar, A., 2017. Workforce optimization for bank operation centers: A machine learning approach.

[33] Micu, A., Geru, M., Capatina, A., Avram, C., Rusu, R. and Panait, A.A., 2019. Leveraging e-Commerce performance through machine learning algorithms. *Ann. Dunarea Jos Univ. Galati*, *2*, pp.162-171.

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