IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 2, April 2025, pp. 1654~1662
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i2.pp1654-1662

Artificial intelligence algorithms to predict customer satisfaction: a comparative study

Othman Berrada Chakour[1], Abdelaziz Ettaoufik[2], Khalid Aissaoui[1], Abderrahim Maizate[1]
[1]RITM Laboratory/ESTC, CED ENSEM, Hassan II University, Casablanca, Morocco
[2]LTIM Laboratory, Faculty of Sciences Ben M'sik, Hassan II University, Casablanca, Morocco

Article Info

Article history:

Received May 14, 2024
Revised Nov 7, 2024
Accepted Nov 14, 2024

Keywords:

Artificial intelligence
Churn prediction
Customer satisfaction
Deep learning
Machine learning

ABSTRACT

Customer satisfaction is the key for every business successful. Therefore, keeping the current customer portfolio and expanding it over time is the main goal for any business. Hence, we need first to satisfy these clients. The customer satisfaction helps to retain consumers of its products, increase the life value of the customer, also make known its brand through positive word of mouth to get a better reputation and thus increase turnover. For this reason, several studies have been conducted on this subject to explore all tools and technologies that will help retain customers and reduce their churn rate. Based on various customer satisfaction studies for different types of businesses, this paper shows the review of promising research areas and artificial intelligence (AI) application models in predicting customer satisfaction. The results of this study allowed the identification of the best algorithms with the highest score of performance metrics that can be applied as part of the customer satisfaction prediction, through a detailed benchmark performed. The result shows that random forest (RF) and gradient boost (GB) algorithms in machine learning (ML) and convolutional neural network - long short-term memory (CNN-LSTM) in deep learning (DL) are giving the best performance. The most used metrics are accuracy and F1-score. In addition, DL models outperform ML models in most cases.

Corresponding Author:

Othman Berrada Chakour
RITM Laboratory/ESTC, CED ENSEM, Hassan II University
Casablanca, Morocco
Email: othman.berradachakour-etu@etu.univh2c.ma

1. INTRODUCTION

Customer satisfaction is a term widely used in marketing industry, and represents a service or product evaluation indicator, that needs to meet the client expectations. This assessment considers all the criteria that matter to the customer and that he will experience once the product/service is delivered. Customer satisfaction could have a positive influence on the retention rate and loyalty, also reduces churn rate and protects customers from other competitors especially since the competition has never been so fierce, thanks to the internet. Client satisfaction determines whether your business has a positive or negative brand image over the long term.

Furthermore, consumer expectations are constantly changing. Faced with the considerable and limitless growth for data exchanged, customer specification in terms of responsiveness and efficiency became denser. Faced with such a need for responsiveness and efficiency, it is obvious that the link with technologies was quickly established. The previous researches results show that customer satisfaction prediction can be analyzed using various types of machine learning (ML) and deep learning (DL) algorithms. Due to different data formats (such as review data or survey data), different models are recommended for different application domains. Artificial intelligence (AI), ML and DL have become vital to remain competitive for financial services companies around the globe.

The use of AI algorithms helps predict customer satisfaction and future behavior regarding the purchase of a particular product again. Having a good customer satisfaction prediction model gives insight into the future, which can help companies choose and adjust the strategies to implement and the right decisions to make to achieve a high level of customer satisfaction. AI algorithms are used today in several sectors and industries. In particular, the sub-domains of AI: ML and DL algorithms are used in banking sector to predict customer churn [1]–[3] and customer satisfaction [4], [5]. Therefore, they are used in the e-commerce industry to predict the online shopper's behavior to know if a customer will make a new purchase or not on the site [6]–[8]. Hence, ML and DL algorithms are applied in the telecommunication sector to predict customer churn [9], in airlines domain to predict the satisfaction of plane passengers [10], [11], in transportation sector for predicting car accidents [12], in agriculture field to predict demand and the products pricing [13], in healthcare and smart home to detect falls [14], in smart manufacturing applications for predicting tool wear [15], in entertainment domain for correcting postures of piano players [16], and several other fields.

Compared with other studies, our paper not only finds different relationships between factors affecting customer satisfaction prediction, but also includes comparing the performance of various ML and DL methods. This paper shows the comparative study of research domains and applications of AI models in predicting customer satisfaction. This study began by defining the methods based on the prediction process. In this section, we focused on the popular AI algorithms. In the second part of this article, we presented various researches that uses ML and DL algorithms to predict customer satisfaction. Finally, we presented an analysis of these researches through a benchmark that details for each article, the algorithms used, their types, the date of publication of the article, the metrics evaluated and the optimal algorithm in terms of performance based on the score of the different metrics.

2. METHOD

AI refers to attempts to build machines able to challenge the human on its intelligence. ML and DL represent two particularly important steps in the evolution of AI. We define ML as a subset of AI developed to imitate human intelligence. While DL is, a subset of ML based on artificial neural networks (ANNs). Figure 1 represents the relationship between AI, ML and DL.

To predict customer satisfaction, it was necessary to study the different algorithms to define the most efficient method. In this section, several popular ML algorithms such as logistic regression (LR), decision tree (DT), random forest (RF), gradient boost (GB), k-nearest neighbors (KNN), support vector machine (SVM), naive Bayes (NB), and DL algorithms such as ANN, convolutional neural network (CNN), long short-term memory (LSTM), CNN-LSTM are discussed. Through this section, we will define the previous mentioned algorithms and share examples of their application domain and results.

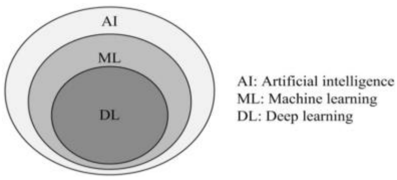


Figure 1. Relationship between AI, ML, and DL [17]

2.1. Machine learning algorithms

2.1.1. Logistic regression

LR is a ML algorithm based on mathematical model that estimates the probability of an occuring event based on a set of explanatory variables. The result of the LR is a probability that could be between zero and one. Thus, when the value is greater than 0.5, the event is likely going to occur but, if it is less than 0.5, it will not [18]. The LR algorithm is used in several application domains. The best results are represented in the following papers. LR was used to predict mobile operator's customer churn rate in the telecommunication industry [9], predict satisfaction of online banking customer in Bangladesh [4], evaluate the behavior of online shoppers in the e-commerce domain [6] and analyze consumer sentiment using online feedback in the airlines industry [19].

2.1.2. Decision tree

DT is a ML algorithm that assist on decision-making. It gathers on the same graphic various options related to a specific situation under a tree branches form, at each end of a branch, a potential decision. It allows the distribution of a given population into homogeneous groups to achieve a goal without setting aside the discriminating characteristics of this population. It facilitates the read of a complex situation and it helps to quickly execute the decision made [20]. DT is utilized in several application domains. The best performances are showed in the subsequent researches. DT was used to assess the problem of predicting credit card churn in banks [3], predict satisfaction of online banking customer in Bangladesh [4], predict e-commerce customer satisfaction [7] and analyze the propensities of South Korea airlines customers for predicting churn and customer satisfaction [16].

2.1.3. Random forest

RF is a prediction ML algorithm which was designed to obtain a reliable prediction via a system of random subspaces. It consists of several DTs, independently trained on subsets of the training dataset. Each DT produces an outcome, and it is the combination of the results that will give the final prediction. Each model is randomly distributed into subsets of DTs [21]. The RF algorithm is employed in multiple application scopes. The best results are represented in the following papers. RF was utilized to predict mobile operator's customer churn rate in the telecommunication industry [9], calculate the bank customer churn prediction [1], analyze consumer sentiment using online feedback in the airlines industry [19], and evaluate the behavior of customers for an European bank to predict churn rate [2].

2.1.4. Gradient boosting

GB is also a prediction ML algorithm. Unlike "random forest", it adjusts its training base gradually. It uses the loss function gradient (or gradient descent) to correct the errors of the previous tree and thus optimize the model results [22]. There are several types of GB algorithm. The most popular are: adaptive boosting (AdaBoost) and eXtreme gradient boosting (XGBoost). The GB algorithms are utilized in several application domains. The best results are presented in the following papers. XGBoost was employed to predict the churn rate of customers in the telecommunications industry [9] and predict consumer repurchase behavior in the e-commerce domain [23]. Moreover, AdaBoost was used to evaluate the behavior of customers of a European bank to predict the churn rate [2] and assess the problem of predicting credit card churn in banks [3].

2.1.5. Support vector machine

SVM is a classification ML algorithm whose objective is to find the optimal hyperplane to separate categories based on training data. It will focus on the closest points between the categories (vector supports). This algorithm consists of finding the maximum margin between vector supports and draw the line in the middle of it [24]. SVM is utilized in several application domains. The best performances are showed in the subsequent researches. SVM was used to predict e-commerce customer satisfaction [7], evaluate bank customer churn in the early stages by analyzing their behavior [25], predict satisfaction of online banking customer in Bangladesh [4] and evaluate consumer sentiment using online feedback in the airlines industry [19].

2.1.6. K-nearest neighbors

KNN is also a classification ML algorithm that relies on the choice of the classification metric, based only on training data. The principle of this model consists of choosing the nearest k data (Euclidean distance) of the studied point to predict its value [26]. The KNN algorithm is employed in multiple application scopes. The best results are represented in the following papers. KNN was utilized to assess the problem of predicting credit card churn in banks [3], calculate the bank customer churn prediction [1], predict the behavior of online shoppers in the e-commerce domain [6], and analyze the propensities of South Korea airlines customers for predicting churn and customer satisfaction [16].

2.1.7. Naive Bayes

NB is a classification ML algorithm based on the Bayes theorem that determines the probability of an event occurring from another event that has already occurred. Among the advantages of this algorithm is the ease of understanding and implementation as it uses a very simple mathematical formula. Moreover, it is fast and does not need a large dataset to output consistent results. However, this algorithm is called "naive" because it assumes that there is no correlation between the data while this assumption is wrong in most cases [26]. The NB algorithm is involved in various application domains. The best performances are showed in the subsequent researches. NB was utilized to evaluate the problem of predicting churn for credit cards in banks [3], predict customer satisfaction of internaltion airport of San Francisco in the airlines industry [15], analyze consumer sentiment using online feedback in the airlines industry [19], and predict the behavior of online shoppers in the e-commerce domain [6].

2.2. Deep learning algorithms

2.2.1. Artificial neural network

ANN is a DL algorithm inspired by the structure of a human brain. It comes in the form of at least two layers of neurons that, from a stream of learning data, will interact to learn to perform tasks [5]. The ANN algorithm is employed in different application domains. The best results are represented in the following papers. The ANN was used to predict bank customer satisfaction [5], assess the problem of predicting credit card churn in banks [3], predict customer churn based on behavioral model analysis in e-commerce domain [8], calculate the bank customer churn prediction [1], and predict churn prediction of supermarket customer in retail industry [27].

2.2.2. Convolutional neural network

CNN is a DL algorithm that learns features from large amounts of data. CNN works by ingesting and processing large amounts of data in a pattern and then extracting the most important features for classification and detection. A typical CNN consists of three types of components: pooling layer, convolutional layer, and fully connected layer. Each component has a different goal, performs a task based on input data, and learns increasing amounts of complexity [28]. The CNN algorithm is utilized in various application domains. The best performances are showed in the subsequent researches. CNN was involved to predict customer satisfaction based on previous purchases [29], predict churn prediction of supermarket customer in the retail industry [27], predict consumer repurchase behavior in the e-commerce domain [23] and analyze the propensities of South Korea airlines customers for predicting churn and customer satisfaction [16].

2.2.3. Long short-term memory

LSTM is a DL algorithm which is a variation of recurrent neural networks (RNN). LSTM introduce a new unit called a memory cell, which allows the network to store and access information over an extended period. The memory cell of an LSTM consists of several gates: an input gate, an output gate, and a forget gate. These gates regulate the flow of information within the memory cell, allowing control over what information to remember and what to forget. This gives the LSTM the ability to memorize important information over long sequences and ignore less relevant elements [30]. The LSTM algorithm is employed in different application domains. The best results are represented in the following papers. LSTM was used to predict consumer repurchase behavior in the e-commerce domain [23], analyze consumer sentiment using online feedback in the airlines industry [19], predict user satisfaction based on sentiment analysis for social media data in Saudi Arabia's [31] and predict customer abandonment in the telecommunication industry [32].

2.2.4. Convolutional neural network - long short-term memory

CNN-LSTM is a DL algorithm that represents a sequence of two networks: CNN and LSTM. This type of data has a memory mechanism that allows it to retain information from one prediction to another. Therefore, CNN-LSTM is a CNN whose final output is sent directly into an LSTM, which will then realize its prediction [33]. The CNN-LSTM algorithm is employed in various application domains. The best performances are showed in the subsequent researches. CNN-LSTM was used to analyze the propensities of South Korea airlines customers for predicting churn and customer satisfaction [16], analyze consumer sentiment using online feedback in the airlines industry [19], predict user Satisfaction based on sentiment analysis for social media data in Saudi Arabia's [31], and predict consumer repurchase behavior in the e-commerce domain [23].

2.3. Performance evaluation of the model

Evaluating the performance of a ML model is one of the important steps in building an effective ML model. Various metrics are used to assess the quality of the model. These performance metrics help us understand how well our model performs for the given data. There are a variety of evaluation metrics available in ML. These metrics are based on 4 concepts: true positive (TP) denotes that the customer is satisfied, and the model predicts that the customer is satisfied; true negative (TN) indicates that the customer is not satisfied, and the model predicts that the customer is not satisfied; false positive (FP) shows that the customer is not satisfied, but the model predicts that the customer is satisfied; and false negative (FN) denotes that the customer is satisfied, but the model predicts that the client is not satisfied. TP, TN, FP, and FN are shown in Figure 2 that represents the confusion matrix.

2.3.1. Accuracy

Accuracy is an important and intuitive metric as it calculates the proportion of correct predictions out of the total number of predictions [34]. It measures how often a ML model correctly predicts the outcome. This metric is simple to calculate and understand. Accuracy can be calculated by (1).

$$Accuracy = \frac{\sum True\ positive + \sum True\ negative}{\sum Total\ population} \times 100 \quad (1)$$

2.3.2. Precision

Precision appears to be an important metric in monitoring model performance, as it generally calculates the ratio between the best predicted results and the effective results [34]. It measures the frequency of ML predicting the positive cases. Precision can be calculated by (2).

$$Precision = \frac{\sum True\ positive}{\sum False\ positives + \sum True\ positive} \times 100 \quad (2)$$

2.3.3. Recall

Recall is the ratio of the number of correctly predicted positive instances (TP) to the total number of actual positive instances [34]. In other words, it measures the completeness of the ML model when it identifies positive cases. Recall can be calculated by (3).

$$Recall = \frac{\sum True\ positive}{\sum True\ positives + \sum False\ negative} \times 100 \quad (3)$$

2.3.4. F1 score

F1 score provides a single metric that encapsulates both dimensions of a model's accuracy. It is a weighted comparison of average precision and recall [34]. This metric ensures that precision and recall contribute equally to the score. The F1 score is particularly insightful when you need a single measure to balance precision and recall. F1 score can be calculated by (4).

$$F1\ Score = 2 * \frac{\sum Recall * \sum Precision}{\sum Recall + \sum Precision} \times 100 \quad (4)$$

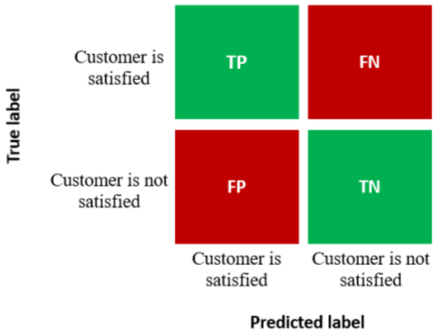


Figure 2. Confusion matrix

3. RESULTS AND DISCUSSION

Because it is more expensive to acquire a new customer; It is five times more expensive than retaining an existing customer [9], henceforth, there is a need to ensure the customer satisfaction which is an important metric in every business, and a key of increasing customer lifetime value, retaining customers and thus reducing churn. In addition, a good predictive model for customer satisfaction can help any organization making the right decisions, improving their performance, and enhancing their market position. The subject has been active for a long time and is still active today with multiple publications.

After reviewing all the previous algorithms, a key information comparative study was performed to answer the following questions:

- Which AI algorithms were tested?
- What were the best algorithms and what were their score and performance?
- What metrics were employed to evaluate the suggested algorithms?
- In which sector and application domain these algorithms have been tested?

The responses to all these questions are available in the comparative study. It provides a benchmark for the factors involved in the process of building a smart AI algorithm that works well to predict customer satisfaction.

Overall, 18 papers related to customer satisfaction and AI techniques are viewed. The benchmark results are summarized in Table 1. While earlier studies have explored relationships between factors influencing customer satisfaction prediction within specific domains and evaluated different AI algorithm to determine the most effective one. This study presents a diagnosis of these researches through a benchmark to identify AI algorithms that perform best for predicting customer satisfaction across a wide range of domains.

Table 1 summarizes the significant articles related to customer satisfaction prediction using AI approaches. It also provides informations about the years of publication, the sector and application domain, the algorithms utilized, the performance metrics used, the best algorithms and the best scores. Most papers were published between 2018 and 2023. 50% of papers deal with customer satisfaction using ML algorithms, while the other half use DL algorithms. Figure 3 represents 39% of the papers related to the banking sector, 22% papers are related to the e-commerce sector, 17% papers are linked to the Airlines industry, 17% papers are in the telecommunications sector and 5% in the retail domain. Figure 4 shows that the most used metrics include accuracy first, then F1-score, recall, and precision.

Figure 5 indicates that among the most used ML algorithms, RF obtains the first position, then SVM, GB, and DT. RF and GB give the best performance. Figure 6 shows that the most used DL algorithms are CNN, LSTM, and the combination of this 2 algorithms CNN-LSTM. The optimal algorithm in terms of performance is CNN-LSTM. We can also notice that DL models exceed ML models in most cases if these 2 types of AI algorithms are used in the same paper.

Table 1. Summary of papers related to customer satisfaction using AI

Ref.	Year	Algorithm type	Sector	Application domain	Algorithms	Metrics	Best Algorithm	Best score (%)
[9]	2023	ML	Telecom	Churn prediction	LR, RF, DT, XGBOOST	Accuracy F1-score Recall Precision	XGBOOST	Accuracy: 96,2 F1-score: 83,6 Recall: 83 Precision: 54
[1]	2022		Banking	Churn prediction	RF, NB, GB, ET, AB, KNN, SVC, DT, LR, ANN, and NB)	Accuracy F1-score	RF GB	Accuracy: 86 F1-score: 86
[2]	2022			Churn prediction	LR, SVC, GBDT, RF, AdaBoost	Accuracy Recall F1-score Precision	AdaBoost	Accuracy: 81,1 Recall: 71,76 F1-score: 59,9 Precision: 51,4
[4]	2021			Customer satisfaction	LR, RF, NB, SVM, DT, KNN	Accuracy F1-score Precision Recall	RF DT LR	Accuracy: 96 F1-score: 97 Precision: 98 Recall: 96
[25]	2020			Churn prediction	KNN, DT, SVM, RF	Accuracy	RF	Accuracy: 92
[3]	2020			Churn prediction	RF, AdaBoost, SVM, KNN, XGBOOST, NB, DT, ANN	Accuracy F1-score Recall	RF	Accuracy: 88,7 F1-score: 91 Recall: 89
[6]	2022		E-commerce	Online shopper's behavior	NB, KNN, SVM, LR, RF, GB, AdaBoost	Accuracy Precision F1-score Recall	GB	Accuracy: 90,5 Precision: 76,1 F1-score: 68,9 Recall: 63
[7]	2020			Online shopper's behavior	DT, RF, ANN, SVM	Accuracy F1-score	RF	Accuracy: 87,6 F1-score: 93
[15]	2018		Airlines	Customer satisfaction	NB, K-Star, IBK	AUC	IBK	AUC: 97,59
[29]	2023	DL	Banking	CRM	CNN	Accuracy F1-score AUC	CNN	Accuracy: 77 F1-score: 83 AUC: 84
[5]	2015			Customer satisfaction	MultiLayer Perceptron ANN	Accuracy	MLP ANN	Accuracy: 73
[16]	2022		Airlines	Customer satisfaction	ML: KNN, DT, RF, XGBoost DL: CNN, CNN-LSTM	Accuracy F1-score Precision Recall	CNN-LSTM	Accuracy: 94 F1-score: 93 Precision: 94 Recall: 94
[19]	2021			Consumer Sentiment Analysis	ML: LR, NB, DT, SVM, DL: CNN, LSTM, CNN-LSTM	Accuracy F1-score Precision Recall	CNN-LSTM	Accuracy: 91,3 F1-score: 87,5 Precision: 87,8 Recall: 87
[8]	2018		E-commerce	Online shopper's behavior	Multi-layered ANN	Precision	ANN	Precision: 80
[23]	2021			Consumer Repurchase behavior	ML: SVM, RF, XGBoost DL: CNN, LSTM, CNN-LSTM	Accuracy Recall F1-score	CNN-LSTM	Accuracy: 87,5 Recall: 83,9 F1-score: 85,6
[32]	2024		Telecom	Customer abandonment	LSTM	Accuracy	LSTM	Accuracy: 95
[31]	2023			User Satisfaction Based on Sentiment Analysis	LSTM, GRU, BiLSTM, CNN-LSTM	Accuracy Sensitivity Specifity F1-score	LSTM	Accuracy: 97 Sensitivity: 93 Specifity: 98 F1-score: 95
[27]	2022		Retail	Churn prediction of Supermarket customer	ANN, CNN	Accuracy Precision Recall	CNN	Accuracy: 97 Precision: 97 Recall: 97

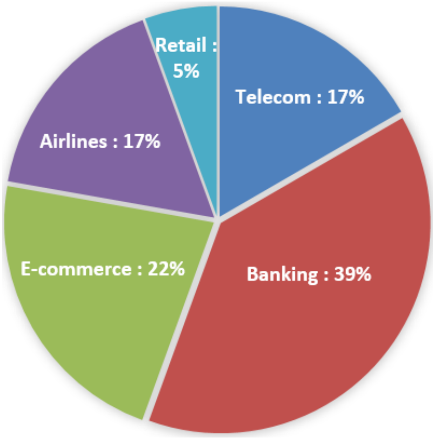


Figure 3. Paper distribution by sector

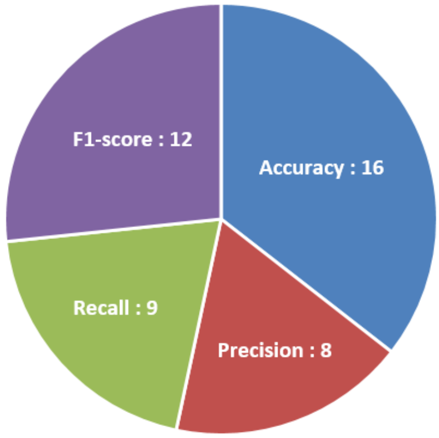


Figure 4. Paper distribution by used metrics

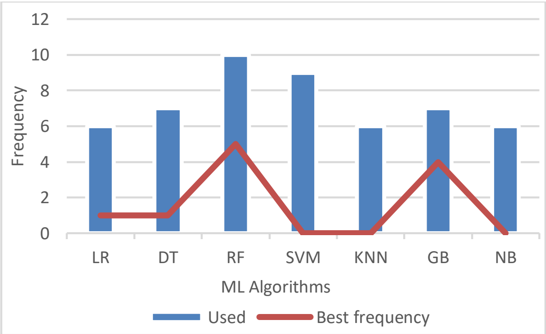


Figure 5. Paper distribution by used ML algorithms

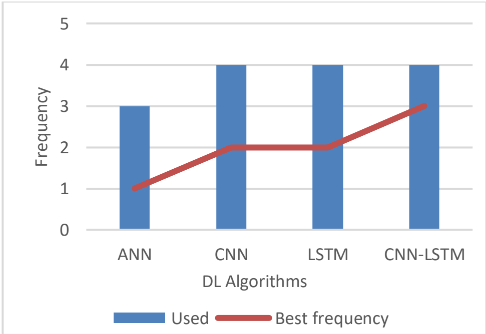


Figure 6. Paper distribution by used DL algorithms

In our study, we discovered that many studies on predicting customer satisfaction highlight issues with data availability and question the reliability of findings. Therefore, customer satisfaction is considered subjective, relative, dynamic, and influenced by individual perceptions and subject to change over time, making its definition and measurement challenging. However, further, and in-depth studies are warranted to explore alternative data sources that could mitigates the limitations explained before, such as collecting qualitative data from client feedback sessions or integrating data from emerging technologies like sentiment analysis of social media posts. Future studies may explore to gather real-world data on customer satisfaction and implement regular satisfaction surveys focusing on emotional factors. Based on our study we concluded that the customer satisfaction's prediction is applicable on a multitude domain. Certainly, there are some limitations that we already listed previously in this paper, but following implications mentioned also for future research should focus on developing robust methodologies for data cleaning and preprocessing to enhance the reliability of predictions.

4. CONCLUSION

In summary, this paper explains the importance of customer satisfaction for any business, which pushes decision makers to be proactive by implementing strategies based on correct predictions and close to reality. To predict customer satisfaction, it was necessary to study the different prediction algorithms to define the most efficient one in terms of accuracy and precision. This paper aims to find the most accurate prediction model for customer satisfaction. The study's results showed that RF and GB algorithms in ML and CNN-LSTM in DL provide the best performance. In addition, DL algorithms outperform ML in most cases. Over this study, it turns out that most articles related to the prediction of customer satisfaction report the unavailability of data and question their reliability. Therefore, customer satisfaction is subjective, relative, and evolving, because it depends on the individual perception of the client and can vary over time. Satisfaction is never purely rational; it is also a matter of emotions. This is what makes it so difficult to define and measure. As next step, we intend to collect real data related to customer satisfaction, also set up frequent satisfaction surveys considering the factors related to the customer emotions.

REFERENCES

[1] S. C. K. Tékouabou, Ș. C. Gherghina, H. Toulni, P. N. Mata, and J. M. Martins, "Towards explainable machine learning for bank churn prediction using data balancing and ensemble-based methods," *Mathematics*, vol. 10, no. 14, Jul. 2022, doi: 10.3390/math10142379.

[2] P. Chen, N. Liu, and B. Wang, "Evaluation of customer behaviour with machine learning for churn prediction: The case of bank customer churn in Europe," in *Proceedings of the International Conference on Financial Innovation, FinTech and Information Technology, FFIT 2022,* Shenzhen, China, EAI, 2023, doi: 10.4108/eai.28-10-2022.2328450.

[3] A. Muneer, R. F. Ali, A. Alghamdi, S. M. Taib, A. Almaghthawi, and E. A. A. Ghaleb, "Predicting customers churning in banking industry: A machine learning approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 26, no. 1, pp. 539-549, Apr. 2022, doi: 10.11591/ijeecs.v26.i1.pp539-549.

[4] S. F. Shetu, I. Jahan, M. M. Islam, R. A. Hossain, N. N. Moon, and F. N. Nur, "Predicting satisfaction of online banking system in Bangladesh by machine learning," in *2021 International Conference on Artificial Intelligence and Computer Science Technology (ICAICST)*, IEEE, Jun. 2021, pp. 223–228, doi: 10.1109/ICAICST53116.2021.9497796.

[5] N. Zeinalizadeh, A. A. Shojaie, and M. Shariatmadari, "Modeling and analysis of bank customer satisfaction using neural networks approach," *International Journal of Bank Marketing*, vol. 33, no. 6, pp. 717–732, Sep. 2015, doi: 10.1108/IJBM-06-2014-0070.

[6] V. Parihar and S. Yadav, "Comparative analysis of different machine learning algorithms to predict online shoppers' behaviour," *International Journal of Advanced Networking and Applications*, vol. 13, no. 06, pp. 5169–5182, 2022, doi: 10.35444/IJANA.2022.13603.

[7] A.-N. Wong and B. P. Marikannan, "Optimising e-commerce customer satisfaction with machine learning," *Journal of Physics: Conference Series*, vol. 1712, no. 1, Dec. 2020, doi: 10.1088/1742-6596/1712/1/012044.

[8] S. Agrawal, A. Das, A. Gaikwad, and S. Dhage, "Customer churn prediction modelling based on behavioural patterns analysis using deep learning," in *2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE)*, IEEE, Jul. 2018, pp. 1–6, doi: 10.1109/ICSCEE.2018.8538420.

[9] J. Maan and H. Maan, "Customer churn prediction model using explainable machine learning," *International Journal of Computer Science Trends and Technology (IJCST),* vol. 11, no. 1, pp. 33-38, Mar. 2023.

[10] S. S. Roy, D. Kaul, R. Roy, C. Barna, S. Mehta, and A. Misra, "Prediction of customer satisfaction using naive bayes, multiclass classifier, K-star and IBK," in *Advances in Intelligent Systems and Computing*, vol. 634, 2018, pp. 153–161, doi: 10.1007/978-3-319-62524-9_12.

[11] S.-H. Park, M.-Y. Kim, Y.-J. Kim, and Y.-H. Park, "A deep learning approach to analyze airline customer propensities: the case of South Korea," *Applied Sciences*, vol. 12, no. 4, Feb. 2022, doi: 10.3390/app12041916.

[12] B. K. Mohanta, D. Jena, N. Mohapatra, S. Ramasubbareddy, and B. S. Rawal, "Machine learning based accident prediction in secure IoT enable transportation system," *Journal of Intelligent & Fuzzy Systems*, vol. 42, no. 2, pp. 713–725, Jan. 2022, doi: 10.3233/JIFS-189743.

[13] T. Chuluunsaikhan, G. A. Ryu, K. H. Yoo, H. Rah, and A. Nasridinov, "Incorporating deep learning and news topic modeling for forecasting pork prices: The case of South Korea," *Agriculture*, vol. 10, no. 11, pp. 1–22, Oct. 2020, doi: 10.3390/agriculture10110513.

[14] N. Thakur and C. Y. Han, "A study of fall detection in assisted living: Identifying and improving the optimal machine learning method," *Journal of Sensor and Actuator Networks*, vol. 10, no. 3, Jun. 2021, doi: 10.3390/jsan10030039.

[15] R. Xie and D. Wu, "Optimal transport-based transfer learning for smart manufacturing: Tool wear prediction using out-of-domain data," *Manufacturing Letters*, vol. 29, pp. 104–107, Aug. 2021, doi: 10.1016/j.mfglet.2021.08.004.

[16] S. H. Park and Y. H. Park, "Audio-visual tensor fusion network for piano player posture classification," *Applied Sciences*, vol. 10, no. 19, pp. 1–15, Sep. 2020, doi: 10.3390/app10196857.

[17] C. Bhatt, I. Kumar, V. Vijayakumar, K. U. Singh, and A. Kumar, "The state of the art of deep learning models in medical science and their challenges," *Multimedia Systems*, vol. 27, no. 4, pp. 599–613, 2021, doi: 10.1007/s00530-020-00694-1.

[18] C. Lawson and D. C. Montgomery, "Logistic regression analysis of customer satisfaction data," *Quality and Reliability Engineering International*, vol. 22, no. 8, pp. 971–984, Dec. 2006, doi: 10.1002/qre.775.

[19] P. K. Jain, V. Saravanan, and R. Pamula, "A hybrid CNN-LSTM: A deep learning approach for consumer sentiment analysis using qualitative user-generated contents," *ACM Transactions on Asian and Low-Resource Language Information Processing*, vol. 20, no. 5, pp. 1–15, Sep. 2021, doi: 10.1145/3457206.

[20] H. Gou, L. Su, G. Zhang, H. Li, and Z. Li, "Research on telecom customer satisfaction prediction strategy," in *2023 8th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2023*, IEEE, Apr. 2023, pp. 593–598, doi: 10.1109/ICCCBDA56900.2023.10154738.

[21] S. Ray, "A quick review of machine learning algorithms," in *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, IEEE, Feb. 2019, pp. 35–39, doi: 10.1109/COMITCon.2019.8862451.

[22] A. -All-Tanvir, I. A. Khandokar, A. K. M. M. Islam, S. Islam, and S. Shatabda, "A gradient boosting classifier for purchase intention prediction of online shoppers," *Heliyon*, vol. 9, no. 4, Apr. 2023, doi: 10.1016/j.heliyon.2023.e15163.

[23] C. Zhu, M. Wang, and C. Su, "Prediction of consumer repurchase behavior based on LSTM neural network model," *International Journal of System Assurance Engineering and Management*, vol. 13, no. S3, pp. 1042–1053, 2022, doi: 10.1007/s13198-021-01270-0.

[24] A. Mawaddah, M. H. Dar, and G. J. Yanris, "Analysis of the SVM method to determine the level of online shopping satisfaction in the community," *SinkrOn*, vol. 8, no. 2, pp. 838–855, Apr. 2023, doi: 10.33395/sinkron.v8i2.12261.

[25] M. Rahman and V. Kumar, "Machine learning based customer churn prediction in banking," in *Proceedings of the 4th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2020*, IEEE, Nov. 2020, pp. 1196–1201, doi: 10.1109/ICECA49313.2020.9297529.

[26] A. Nurdina and A. B. I. Puspita, "Naive Bayes and KNN for airline passenger satisfaction classification: comparative analysis," *Journal of Information System Exploration and Research*, vol. 1, no. 2, Jul. 2023, doi: 10.52465/joiser.v1i2.167.

[27] O. F. Seymen, E. Ölmez, O. Doğan, O. Er, and K. Hiziroğlu, "Customer churn prediction using ordinary artificial neural network and convolutional neural network algorithms: a comparative performance assessment," *Gazi University Journal of Science*, vol. 36, no. 2, pp. 720–733, Jun. 2023, doi: 10.35378/gujs.992738.

[28] S. Pouyanfar *et al.*, "A survey on deep learning: algorithms, techniques, and applications," *ACM Computing Surveys*, vol. 51, no. 5, pp. 1–36, Sep. 2018, doi: 10.1145/3234150.

[29] E. M. Elgohary, M. Galal, A. Mosa, and G. A. Elshabrawy, "Smart evaluation for deep learning model: churn prediction as a product case study," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 2, pp. 1219–1225, Apr. 2023, doi: 10.11591/eei.v12i2.4180.

[30] A. Boukhalfa, A. Abdellaoui, N. Hmina, and H. Chaoui, "LSTM deep learning method for network intrusion detection system," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 3, pp. 3315-3322, Jun. 2020, doi: 10.11591/ijece.v10i3.pp3315-3322.

[31] M. A. Alshamari, "Evaluating user satisfaction using deep-learning-based sentiment analysis for social media data in Saudi Arabia's telecommunication sector," *Computers*, vol. 12, no. 9, Aug. 2023, doi: 10.3390/computers12090170.

[32] S. Beltozar-Clemente, O. Iparraguirre-Villanueva, F. Pucuhuayla-Revatta, J. Zapata-Paulini, and M. Cabanillas-Carbonell, "Predicting customer abandonment in recurrent neural networks using short-term memory," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 10, no. 1, Mar. 2024, doi: 10.1016/j.joitmc.2024.100237.

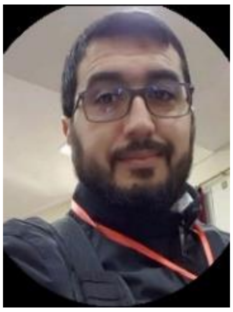
[33] R. Mutegeki and D. S. Han, "A CNN-LSTM approach to human activity recognition," in *2020 International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2020*, Feb. 2020, pp. 362–366, doi: 10.1109/ICAIIC48513.2020.9065078.

[34] E. Ismanto, H. Ab. Ghani, and N. I. B. Md Saleh, "A comparative study of machine learning algorithms for virtual learning environment performance prediction," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 4, pp. 1677-1686, Dec. 2023, doi: 10.11591/ijai.v12.i4.pp1677-1686.

BIOGRAPHIES OF AUTHORS

Othman Berrada Chakour holds an engineering degree in software engineering from ENSIAS, Mohamed V University, Rabat in 2014 and a bachelor's degree in mathematics and computer science from Hassan II University, Casablanca in 2011. His research includes customer satisfaction prediction via machine learning and deep learning. He can be contacted at email: othman.berradachakour-etu@etu.univh2c.ma or ber.othman@gmail.com.

Dr. Abdelaziz Ettaoufik is Professor in the Department of Mathematics and Informatics at Faculty of Sciences Ben M'Sik, Hassan II University, Morocco. His research interest includes computer sciences, big data & cloud computing, intelligence artificial, data warehouse optimization, data lake, and blockchain. He can be contacted at email: aettaoufik@gmail.com.



Dr. Khalid Aissaoui completed his Ph.D. at University Hassan II/ENSEM Casablanca Morocco in 2020. Received an engineering degree in 2008 at ENSSAT- Lannion France. Working as Professor Researcher at higher institute of applied engineering IGA, Casablanca Morocco. His research focuses on security & IAM in cloud computing, big data, and artificial intelligence. He can be contacted at email: aissaoui.khalid@gmail.com.

Dr. Abderrahim Maizate obtained his engineering diploma in computer science from the Hassania School of Public Works in 2004, followed by a DESA degree from ENSIAS in 2007. He completed his Ph.D. at Chouaib Doukkali University. Currently, he serves as a Professor Researcher at Hassan II University in Casablanca, Morocco. His research focuses on wireless communication, mobile communication, wireless sensor networks, quality of service (QoS) guarantees, and big data. He can be contacted at email: abderrahim.maizate@etu.univh2c.ma or abderrahim.maizate@gmail.com.