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IMPROVED EMAIL MARKETING DECISION MAKING IN A CHURN PREDICTION CONTEXT USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

Several studies have been carried out to study the problem of churn in different fields such as telecommunications and marketing. In fact, the literature studied is based on the classic approach of machine learning as well as deep learning. Thus, we have noticed that research works related to the study of the phenomenon of churn in the field of digital marketing are limited.
Customer churn in email marketing suggests that the opportunity for both leads and potential sales are wasted, but the nightmare of any digital company is when the customers unsubscribe from the campaign list without any form of advice. Digital companies may find it hard to respond and take corrective actions to increase their profitability and revenue which is the highest priority in any business, including digital ones. To overcome these kinds of issues digital companies should take a proactive approach and identify potential customers before they leave. Thanks to the data available in several data sources, customers' transactions including purchasing habits can be extracted and then analyzed later. In this perspective of research, we present in this article a study on some of the most applied machine learning algorithms in this context, challenging customer churning difficulty by predicting their behaviors during several email marketing campaigns. In this work, we applied the model by utilizing Machine Learning algorithms. The greatest model in our study reached a predictive accuracy of 82%, measured by the F1-Score.

Keywords: *Digital Marketing; Machine Learning; Churn; Email Marketing; Prediction Models*

1. INTRODUCTION

Churn prediction [1-14] is a technique for detecting the customers are likely to quit a company or unsubscription from a service. It is an important prediction for many companies because obtaining new clients often costs more than retaining existing ones. When Marketers can identify those customers that are at risk of canceling, they should know exactly what marketing actions to make for each individual customer to maximize the chances of customer retention. Churn is a critical problem across companies in many sectors. If a company wants to grow, it has to invest in obtaining new clients. Every time a client leaves, it represents a considerable investment loss. Being able to predict when a client is likely to unsubscribe, and suggest them offers to stay, can increase return on investment (ROI). The churn rate formula is:

$$\begin{aligned} &Churn\ rate \\ &= (number\ of\ lost\ customers \\ &/\ total\ number\ of\ customers) * 100. \end{aligned}$$

E-mail marketing is one of the most important channels of communication with potential customers in digital marketing. There are many features of e-mail marketing affecting the behavior of clients. Understanding and correctly setting these features implicit the success of email marketing campaigns [25]. Customer churn is one of the most searching difficulties that influence revenue in email marketing. The relevance of campaigns is based not only on the accuracy of predicting potential churners but on equivalent greatness, it is conditional on the timing of prediction making [4]. To face the concurrence in email marketing, it is necessary to reduce the rate of email unsubscribers and complainers. For this aim, the implementation of the predictive customer churn model is an indispensable tool to be used by Marketers. Thus, understanding what motivation's customer engagement is extremely valuable knowledge, as it can help marketers to develop retention strategies and deploy operational practices aimed at keeping customers from exiting.

Today, marketers progressively rely on Machine Learning (ML) based models to prepare and send personalized campaigns and for customer relationship management. ML enables marketing managers to strategic marketing decisions-making by leveraging data that gathers insights into customer behavior[5]. These insights help marketers in increasing their decision-making capabilities, it is a critical factor for the success and relevance of marketing campaigns. In the last two decades, using ML in decision-making has been a major achievement and will further impact decision-making by marketers[23]. ML has reinterpreted digital marketing amending the way value is produced [26]. The volume of data has exploded exponentially over the past two decades due to the technological revolution and the emergence of social media. New methods and techniques including both of data mining and ML[16-22] algorithms have been integrated to treat, analyze the data, and extract valuable information which is hidden in the raw data. Among the areas that need these new technologies is the industrial domain, where clients are the most essential assets of any industry since they have been appreciated as the principal source of profit [18].

The principal causes for churn are dissatisfaction with customer service, marketers are unable to meet these needs, therefore, they do not receive the good offer at the best timing. Customer churn is a precious problem in all sectors since acquiring new customers costs more than retaining existing ones. The clients present different behaviors [4] and preferences, so they cancel their subscriptions for various reasons. So, it is important to proactively communicate with each of them in order to retain them on the clients' list. Companies need to know which digital marketing [22] personalized action will be the most successful for each and every customer, and when it will be most successful. Today, thanks to improved access to information, clients are more transient. Marketing managers are conscious of this and they are interested in identifying potential churners in order to stop unsubscribes by targeting such customers with motivation. Thus, with the purpose of retaining customers, academic researchers as well as professionals find it critical to building a churn prediction model with good accuracy in order to reduce customer churn.

Presently, companies have become conscious that they should put very much effort not only into obtaining new clients but also in keeping their existing ones. In addition to the direct loss of revenue that results from customer churn, getting new customers often costs more than retaining existing customers. Several parameters can determine customer behavior, such as information, product, ecology, price, brand, needs, communication, etc. [24]. To reduce customer churn, marketers must be able to correctly predict customer behavior and make effective strategic decisions to warrant customer retention factors. In the goal of retaining existing customers, email marketers need to understand the causes of churn, which can be found via the knowledge extracted from collected data. For this purpose, the aim of churn prediction is to detect clients with a high tendency to leave a company[18]. Churn [3] prediction is a binary classification mission, which splits churners and non-churners. The capability to predict that a client is at a high risk of churning performs a great additional potential revenue source for every company. Predictive analytics is a method to build and evaluate data-driven forecasting models. It is considered as a decision-making aid tool in the various sectors[17].

Developing a loyalty marketing strategy requires a serious investment of time, human resources and budget from marketing decision makers, but ML models can predict and reduce a company's churn rate. The methodology is clear: the continuous collection and cleaning of socio-demographic and behavioral data of individuals, in particular: surname, first name, email, pc, address, city, country, opening, sex, age, click, browser used, device (mobile , PC…), operating system (IOS, android, windows, linux…)… and the CHUR / NON CHURN target variable, with a history for a sufficient period.

Predictive churn models provide companies with a very effective and inexpensive way to predict and prevent customer abandonment. They also allow the company to become aware of the impact that predictive marketing can have in optimizing processes related to the company's sales funnel.

2. RELATED WORK

In 2021, Tjeng Wawan Cenggoro, Raditya Ayu Wirastari, Edy Rudianto, Mochamad Ilham Mohadi, Dinne Ratj, and Bens Pardamean have applied the explainable model based on vector embedding in Deep Learning. They showed that the model can communicate churning customers that can be returned to the use of the previous telecommunications service. They produced very discriminating vectors of churn and loyal customers, which qualifies the models presented to be accurately predictive in indicating whether a client will unsubscribe or not. their results showed that the best model achieved an accuracy of 81.16%, measured by F1-score [3].

In 2021, Sulim Kim and Heeseok Lee established work to achieve a customer churn prediction model related to the supposition that influencers have intense support from their followers. Korea influencer marketing agency collected the data between August 2018 and October 2020, the obtained data contains many features. In the objective of predicting customer turnover rate, researchers employ Decision Trees (DT) algorithm using Rapidminer software. The result of their analysis indicates that the best prediction accuracy is 90% measured by the F-measure. The study contributes to the prediction of customer churn from the perspective of influencers [6].

In 2012, Thomas Verbraken, Stefan Lessmann, and Bart Baesens have examined four Predictive analytics propositions, they indicated that focusing on model evaluation is insufficient. They also showed that a profit-based model-building approach yields considerably to higher profits than existing churn modeling practices. The principal suggestion of the results is that prediction models should be built taking into account the decision task they are supposed to support [17].

Our work consisting of the state of the art concerning the phenomenon of "churn" has shown that similar research is rare in the study of this phenomenon in digital marketing. In order to better understand the context and be aware of the problems of churn in one of the digital marketing channels, it is Email marketing. Subsequently, we studied the issues related to churn as well as the ideas for responding to the issues.

By understanding churn, marketers can develop better strategies to reduce customer churn and increase customer loyalty. It's also important to track churn over time to identify trends and take steps to reduce it.

In our case, Churn is a term used in the field of e-mail marketing to indicate that a customer will unsubscribe from advertising offers, or he will make complaints or he will stop positive actions such as: open, click and purchase. Churn can influence the business of email marketing in relation to all its axes, in particular, the deliverability as well as the success of marketing campaigns. The churn can be defined as clients who have a high probability of attrition from the mailing list of a marketer company.

3. PREDICTION PROCESS FOR CHURN

Email churn is a big challenge for a marketer today. Email churn is the action of customer attrition from a marketer's mailing list. This is the incapacity to keep your users engaged. Dissatisfaction is the primary reason why clients change their loyalties quickly in the digital world. One of the reasons for churn marketing.

Increased customer churn means a significant reduction in business opportunities. Thus, it is the reason why most email marketers are trying every possible strategy to retain their loyal customers. The main quality of machine learning is the establishment of models qualified for detecting patterns in data and learning from it without the need for specific programming. In the case of customer churn prediction, these are real-time behavior[20] properties that point to customers' dissatisfaction with offers arriving in their inbox. As with any machine learning task, data scientists first need o collect and prepare the data to analyze and fix the issue of customer churn in email marketing. In our research objective, we specified the data to be collected. Then, the data is prepared, processed, and transformed into an appropriate form for establishing ML models. Developing accurate methods, selecting and evaluating the models, and selecting the best performance is another important part of the study. The model that performs predictions with the greatest accuracy is selected, so data scientists can put it into production to improve decision-making by marketers. Figure 1 shows the main steps for a successful customer churn prediction process.

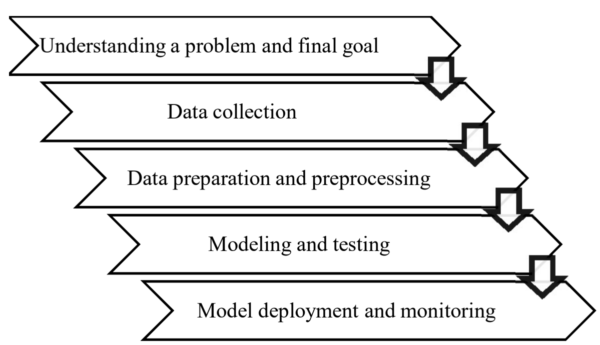

Figure 1: The major stages to successfully

predict customer churn

Predictive analytics involves the use of predictive analytics to solve customer churn management problems, and support marketers in the creation of personalized loyalty offers. Geographic, demographic, social, and transactional customer data is collected and enables predicting future customer behavior through data-driven[27]. The prediction of customers according to their probability of unsubscription estimated by the model, which is often carried out by classification methods, is the first step in the marketing campaign planning process. Considering the large variety of available methods, performance assessment and model selection are significant issues. Several performance indicators have been proposed.

The process of feature selection[15] is practical in producing a list of metrics that are correlated with customer churn. The next goal is to apply these features to predict correctly the customer churn in email marketing. To this end, we set up a supervised learning experiment using k-fold cross-validation, then we developed different supervised learning algorithms on data collected over a period from January 01 to December 31, 2021.

Prediction Accuracy is one of the most frequent classification evaluation metrics to adopt Machine Learning models, it's the number of true predicted observations made as a fraction of total predictions. Nevertheless, it's not the perfect metric when we have a class imbalance problem. Thus, let us sort the results based on the AUC value which is nothing but the model's capability to differentiate between positive and negative classes.

The evaluation of the model is most often carried out by the technique of "K-fold Cross-Validation" which mainly enable us to fix the variance. The variance issue comes in the case of obtaining good accuracy when applying the model on a training set and a test set, however, the accuracy seems different when the model is applied on another test set.

Thus, in order to solve the variance issue, usually, k-fold cross-validation divides the training set into 10 folds and trains the model on 9 folds before testing it on the test fold. This enables us the pliability to train the model on all 10 combinations of 9 folds. It is profitable to reevaluate the model using ROC Graph, it indicates a model's ability to differentiate classes in terms of the average AUC score.

4. METHOD

4.1 Features collection

In this study, we have collected many features from each campaigns, such as: the subject-line, the from-line, preheder, Email sender, Email content(typically contains Offerlink, unsubscribe link, and pictures), offers, vertical , geolocation[12-19], the DateTime that email is sent and the DateTime that email is opened, number of delivered emails, open rate, click rate, Number of unsubscribers. Additionally, the client profile features used in this work include the geolocation of the client, the device, the operating system, the response time and the ISP(Internet Service Provider). However, it should be mentioned that some of the features can only be collected after a customer action on the email. Table 1 presents the features for campaigns.

Table 1: Features for campaigns

Features	Description
Delivered email	Number of delivered emails
Bounced emails	Number of bounced emails
Deferred emails	Number of deferred emails
Sent days	The day that the campaign was sent
Action days	The day when the email is opened by the client
Open timing	The time when the email is opened by the client
Vertical	Beauty, cash, health, …
Open Rate	Open Rate
Click rate	Click rate
Emails Churn	Emails Churn
Classification	Categories: • churn • no churn

The features of the email recipients are also crucial in email churn prediction. Among the important features is the geographic location, so, the researchers indicate that it is essential for large applications to know the customer's distribution and allow the marketers to provide location-based advertising services. Therefore, in this study, we also considered this feature important to predict the churn in the field of email marketing. This research has been accomplished by identifying the geolocation based on client IP addresses using the "ip2location" API, so we identified the customer's country, state, and city according to its IP address, and we included it as one of the customer's features. We collected many features such as the OS, the Device, the Browser, and the ISP(Internet Service Provider) of email that are significant for the treatment of this subject research. Table 2 shows these detailed features.

Table 2: Features for email customer profiling

Type	Data source	Examples
Country	IP address (https://www.ip2location.com/)	US, UK, NL, . . .
State	IP address (ip2location : https://www.ip2location.com/)	California, . . .
OS	User-Agent string	iOS, Android, ...
Device	User-Agent string	iPad, PC, . . .
Browser	User-Agent string	Chrome, ...
Domain	The domain part of recipient's email address	yahoo.com, gmail.com, hotmail.com,…

4.2 Predicting models establishment

The creation of the model for predicting Email Churn has been carried out by using four ML algorithms: Bagging classifier, Decision tree [1-6-10], Random Forest, and Adaptive Boosting. Every algorithm has its advantages and disadvantages, but an important parameter to mention is that this mission requires a well-featured dataset for the establishment of the model that will be able to predict accurately customer churn.

Table 3: Machine Learning Algorithms for models establishment

Algorithm	Accuracy	F1	AUC	Amount of data
Decision tree	0.75	0,74	0,62	1000000
Bagging classifier	0.75	0,75	0,67	1000000
Adaptive Boosting	0.82	0,75	0,72	1000000
Random Forest	0.74	0,74	0,68	1000000

5. RESULTS AND DISCUSSION

In this study, we developed four algorithms to predict churners. generally, it is challenging to select the best algorithm, because the decision depends on several parameters, namely: accuracy, data processed, learning time, etc. Based on experience, we agree that stability is very important. We have combined accuracy and stability to approve the suitable model. Thus, the results showed that the "Adaptive Boosting" algorithm is more stable when tested on different samples of the data.

The use of precision and recall separably are useless to evaluate a machine learning model, because if the prediction of the model was always "positive", the recall will be high, By cons, if it was always negative, the precision will be high. For this reason we used F1-score In this study, which is the combination of both recall and precision, it enables a good evaluation of the performance of the proposed model. In addition, and in order To evaluate each algorithm, we also used the AUC-ROC curve, The ROC curve describes the performance of a model via two metrics: sensitivity and specificity. The area under AUC-ROC curve globally calculates the performance of a classification model. The AUC (Area Under the Curve) is the degree or extent of separability. This metric shows how many models are able to differentiate classes. The high value of the AUC, means that the model is able to separate classes efficiently. The ROC curve is plotted with True positive rate (TPR) versus False positive rate (FPR). Finally, the four coefficients of the confusion matrix : True Positive, False Positive, True Negative, False Negative, can be used to calculate precision, recall, F1-score, accuracy, etc.

Accuracy (1)- it is the most intuitive performance measure. It is calculated as the ratio between the number of correct predicted observations to the total number of observations. higher the value of the accuracy, the more the model is better.

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \ (1)$$

Precision (2)- Precision is the ratio between the number of Positive samples correctly classified to the total number of samples classified as Positive. Precision answers the following question: for all positive classes, how many correct predictions do we have. It should be as high as possible. When the model establishes many incorrect Positive classifications, or few correct Positive classifications, this makes the precision small.

$$Precision = TP / (TP + FP) \ (2)$$

Recall (3)- is the ratio between the number of Positive samples correctly classified as Positive to the total number of Positive samples.

$$Recall = TP / TP + FN \ (3)$$

F1 score (4) - The F1 score combines precision and recall measures into a single measure. Therefore, it takes both false positives and false negatives into consideration. The F1 score was designed to perform well on unbalanced

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data.

$$F1 - score = 2 * (Recall * Precision) / (Recall + Precision) \quad (4)$$

In this work, the results showed that AUC is equal to:

- 0.62 for the Decision Tree algorithm;
- 0.67 for the Bagging classifier algorithm;
- 0.68 for the Random Forest algorithm;
- 0.72 for the Adaptive Boosting algorithm, which signifies that there is a 72% chance that the model can discriminate between positive and negative classes.

After modeling and testing the four algorithms object of the study, we obtained the results indicated in figures: "2,3,4,5" and tables "3,4,5,6,7", and according to These results, we can notice that the "Adaptive Boosting" classifier works better compared to the other algorithms, on the report of to all parameters. However, the sensitivity of these algorithms is scheduled for future work.

We examined all features, and we selected the features that high importance including: geolocation, State, subject-lines, Browser, device, vertical, OS, from-lines, offer, timing, etc. After the fit and training of the four algorithms mentioned above, we obtained the results presented in Table 3. Thus, according to these results we can observe that "Adaptive Boosting" algorithm performs better compared to Decision tree, Bagging classifier and Random Forest, and this, depending on the three evaluation measurements shown in table 3, namely: Accuracy, AUC and F1-Score.

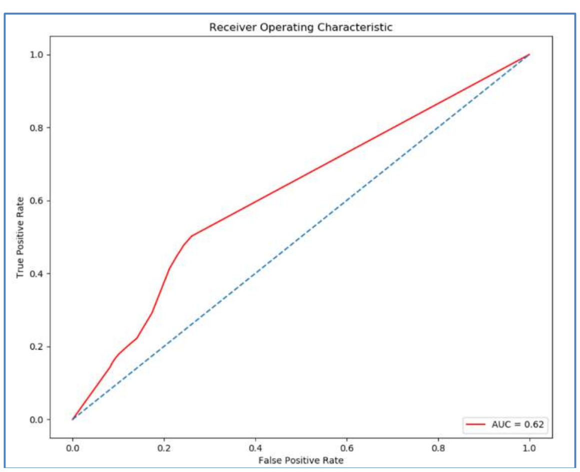

Figure 2: AUC-ROC Curve to evaluating

Decision Tree classifier

Table 4: Prediction results for the Decision Tree

	Decision tree		
	Recall	***Precision***	***F1***
No churn	0.86	0.84	0.85
Churn	0.22	025	0.24
Weighted Average	0.75	0.73	0.74

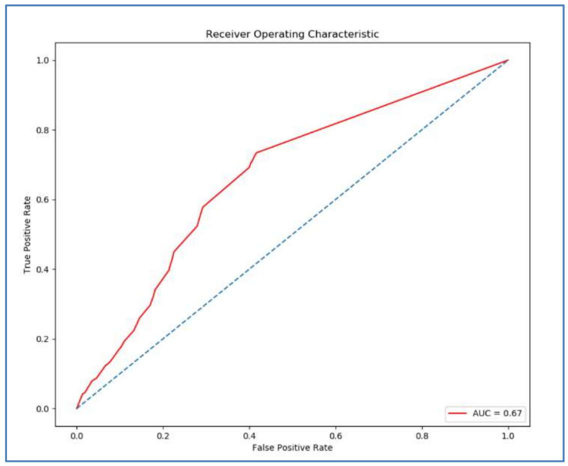

Figure 3: AUC-ROC Curve to evaluating Bagging classifier

Table 6: Prediction results for the Bagging classifier

	Bagging classifier		
	Recall	***Precision***	***F1***
No churn	0.86	0.84	0.85
Churn	0.24	027	0.25
Weighted Average	0.75	0.74	0.75

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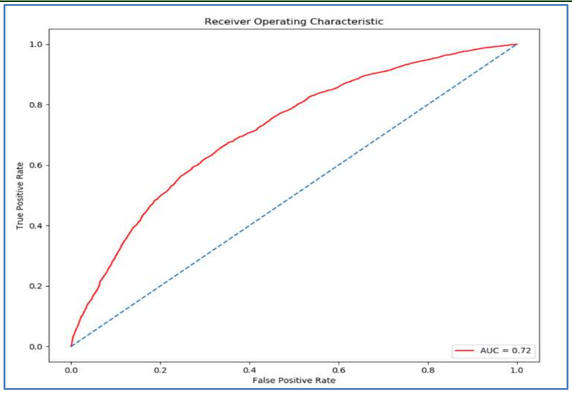

Figure 2: AUC-ROC Curve to evaluating Adaptive Boosting classifier

Table 5: Prediction results for the Adaptative Boosting

	Adaptive Boosting		
	Recall	***Precision***	***F1***
No churn	1	82	0.90
Churn	0	63	0.01
Weighted Average	0.82	0.79	0.75

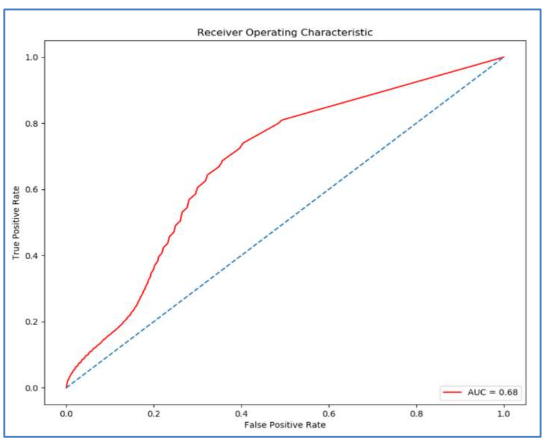

Figure 4: AUC-ROC Curve to evaluating Random Forest classifier

Table 7: Prediction results for the Random Forest

	Random Forest		
	Recall	***Precision***	***F1***
No churn	0.84	0.84	0.84
Churn	0.24	0.25	0.24
Weighted Average	0.74	0.73	0.74

This study enabled us to predict the “churn” and the “no churn” of marketing via the e-mail channel using a learning model. The model is based on the features collected by company teams from January 2021 to December 2021 and four classifiers are used for the prediction. Our results indicate that the prediction analysis models achieved a prediction accuracy rate of approximately:

- ✓ 82% on the "churn" for the "Adaptive Boosting" classifier;
- ✓ 75 % on the “churn” for the "Decision tree classifier" ;
- ✓ 74 % on the “churn” for the "Random Forest classifier" ;
- ✓ 75 % on the “churn” when the "Bagging classifier" is used;

During this study, we confronted the issues related to the constraints of the deliverability of the email marketing campaigns, therefore, some advertising messages do not arrive in the customer's inbox, they are classified by the Spam filter, in the spam folder, or there is the case of a soft bounced, this problem has negatively impacted the results obtained, for this purpose, marketing managers must meet the requirements of the spam filter because fixing deliverability problems can help us achieve better data correlation and more accurate results.

The predictive churn models that we have implemented provide marketers with a very effective and inexpensive way to predict and prevent customer abandonment. They also allow the company to become aware of the impact that predictive marketing can have in optimizing processes related to an effective digital marketing strategy. On the other hand, several similar studies carried out in this context are based on deep learning. To this end, in future research, we will integrate deep learning algorithms and their comparison with the classical approach that we have adopted, also, we will improve the deliverability, and those, in order to optimize the results.

6. CONCLUSION

Churn prediction provide companies with a very effective and cost-effective way to predict and prevent customer abandonment. In this sense, various studies have been conducted to examine the problem of customer churn in various fields such as telecommunications and marketing. In fact, the studied literature is based on classical methods of machine learning and deep learning. Therefore, we find that the research on the phenomenon of churn in the field of digital marketing is limited.

The main objective of this paper is the establishment of a detailed study on ML algorithms in the process of predicting customer churn in the email marketing sector. In this work, we achieved customer churn rate prediction based on the data collected by marketers during the period from January 2021 to December 2021 including the opens, clicks, unsubscription, geolocation, State, subject-lines, Browser, device, vertical, OS, from-lines, offer, timing, the purchase information such as purchase item, and payment amount, etc. to achieve the goal of predicting customer churn, we applied four algorithms: Bagging classifier, Decision tree, Random Forest and Adaptive Boosting. The result of our analysis shows that the adopted model is the "Adaptive Boosting classifier" with 82% of prediction accuracy.

Among the obstacles encountered in this work is the deliverability constraint of email marketing campaigns, so, some advertising messages do not arrive in the customer's inbox, they are classified by the Spam filter, in the spam folder, or there is the case of a soft bounced, this critical problem negatively impacts the prediction analysis, for this purpose, we will collaborate with marketing managers to meet the requirements of the spam filter because fixing deliverability problems can help us achieve better data correlation and more accurate results.

In future work, we will create a combination of the methods, and we will apply Deep learning by Convolutional Neural Network (CNN) for churn prediction to achieve good performance compared to the obtained results. In addition, we defy to implement a study related to marketing automation, this can optimize the investment in human resources, material resources, etc. Therefore, a delivered email campaign can be established much faster with a smaller margin of error with minimal human resources, also marketing campaigns will be relevant and personalized. This work will help marketers to increase customer actions on offers received, such as opens, clicks and purchases, thus improving the return on investment (ROI).

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