Customer Churn Prediction In Telecommunication Industry Using Machine Learning Classifiers

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ABSTRACT
Customer churn is one of the main problems in telecommunication industry. This study aims to identify the factors that influence customer churn and develop an effective churn prediction model as well as provide best analysis of data visualization results. The dataset has been collected from Kaggle open data website. The proposed methodology for analysis of churn prediction covers several phases : data pre-processing, analysis, implementing machine learning algorithms, evaluation of the classifiers and choose the best one for prediction. Data pre-processing process involved three major action, which are data cleaning, data transformation and feature selection. Machine learning classifiers was chosen are Logistic Regression, Artificial Neural Network and Random Forest. Then, classifiers were evaluated by using performance measurement which are accuracy, precision, recall and error rate in order to find the best classifier. Based on this study, the output shows that logistic regression outperform compared to artificial neural network and random forest.

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Keywords
Customer Churn; Prediction; Machine Learning; Telecommunication Industry

1. INTRODUCTION
Customer are one of the asset in dynamic and competitive business [1], [2]. The slogan of "Customer is always right" which exhorts the company to give a high priority and best service to customer satisfaction and maintain the relationship. In competitive market, maintain the long-term relationship and loyal customer are broadly acknowledge and extensively applied to various fields of industry, such as telecommunication, online retail, retail market, electronics, banking and insurance, travelling, airline ticketing service and others [1], [24]. However, customers have their own option to choose the service provided, so they can easily switch a service or companies, which is termed as a churned customer [12]. In order to prevent from churning, customer retention program is one of the comprehensive strategy for developing, managing and strengthening long-lasting customer relationship [24].

Nowadays, Telecommunication industry faces a numerous competition due to many telecommunication companies service provider. According to [3], [16], telecommunication companies suffer the substantial problem of customer churn due to aggressive competition, saturated market, dynamics conditions and introduction of new offerings. Based on [21], [14], various factor that influencing the customer churn can be due to dissatisfaction, switching cost, service price, quality, security concerns, competitors with superior technology and advertising. Thus, companies need to avoid customer churn cases because customers have capabilities to influence others member to do the same thing based on their experience or review from close member.

Customer Relationship Management (CRM) is an important function for many organizations. When customers churn and end the relationship with a company, this has several implications. It is essential for company to develop strategy to prevent customer churn. A popular strategy is to use a machine learning approach that have been tested and compared such as common data mining algorithm (neural networks, decision tree, support vector machine), statistical techniques (logistic regression) and ensemble methods as well as hybrid model [18].

The aim of this research is to improve the process of analyzing customer churn in telecommunication industry in order to focus on maintaining long-term relationships with loyal customer and develop an effective prediction model as well as provide the best analysis of data visualization results.

2. RELATED WORK
Table 1 shows the comparison of churn prediction techniques. The analyzed approaches are compared and summarized based on techniques, results, limitations and recommendation of future works.

3. RESEARCH METHODOLOGY
The project framework describes the outline and method used in conducting this study. Basically, this research involves planning, literature review, model design, developing and implementation of framework project proposal as well as evaluation and reporting as a final process for results. Each process is related to research

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question in order to get the solution and research objectives is achieved. The research will be conducted phase by phase which each phase will be further discussed in Operational Framework as illustrated in Figure 1 below.

Table 1. Comparison of Customer Churn Prediction Approaches.

Author	Dataset	Techniques	Result	Limitation & futurework
(Li et al., 2014) [19]	Orange Telecom and UCI	SVM and CSS-LRM	High value of ROC curves	Explore on positive and negative cases of imbalance, mass data and incomplete data.
(Sladojevic et al., 2011) [23]	Orange Telecom Company	Comparison of Decision Tree, ADTree, J48, Lazy IBI, Lazy Kstar, Naïve Bayes, Boosting (DecisionStump)	Boosting of decision stumps using AdaBoost achieved best results in ROC	Challenge in working with unbalanced dataset.
(Lu et al., 2011) [17]	Telecom data in 2010	Logistic Regression with AdaBoost	High accuracy in defining high risk customer group	Incapable to identify the reason for customer churn. Compare with other classification methods.
(Hossain & Miah, 2016) [15]	Telecom data	SVM kernels	Simple linear kernel achieved high accuracy	Find out an efficient algorithms for features selection
(Yihui & Chiyu, 2016) [20]	China Mxobile	OOPM feature selection and FE_RF&T feature extraction	High accuracy churn prediction and eliminate irrelevant information	No recommendation
(A. Mishra, 2017) [8]	UCI Telecom data	Ensemble based classifiers compared with SVM, DT, Naïve Bayes	High accuracy and sensitivity, less error rate	Deep Learning or Reinforcement Learning techniques used in churn prediction
(K. Mishra & Rani, 2018) [13]	IBM Watson Analytics	SMOTE, co-relation and ensemble	AdaBoost gives best result in AUC, sensitivity and specificity	No recommendation
(Mohanty & Rani, 2016) [22]	Indian Telecom	CPNN, FuzzyARTMAP, CART, J48	CART outperformed in sensitivity, fuzzyARTMAP provided best specificity and accuracy	Suggest fuzzyARTMAP and CART in churning prediction
(Rodan & Faris, 2015) [9]	Jordanian cellular telecom	Compared ESN with SVM with common machine learning	High value in accuracy and churn rate	Applicable to solve quadratic optimization problem with linear constraints
(Petkovski et al., 2017) [5]	Macedonia telecom (2012 – 2014)	Naïve Bayes, C4.5, K-NN, Logistic Regression	Logistic Regression show high value in accuracy	More time consuming for LR classifier
(Hudaib et al., 2015) [4]	Jordanian Telecom	Hybrid models which are k-means clustering, SOM and MLP-ANN	High accuracy than single model	Longer time taken for small dataset
(Dulhare & Ghori, 2018) [25]	Telecom data	Hybrid method composed of AFS and parallel DBSCAN	Efficient in time and performance	Used MapReduce to implement and explore new techniques in churn prediction

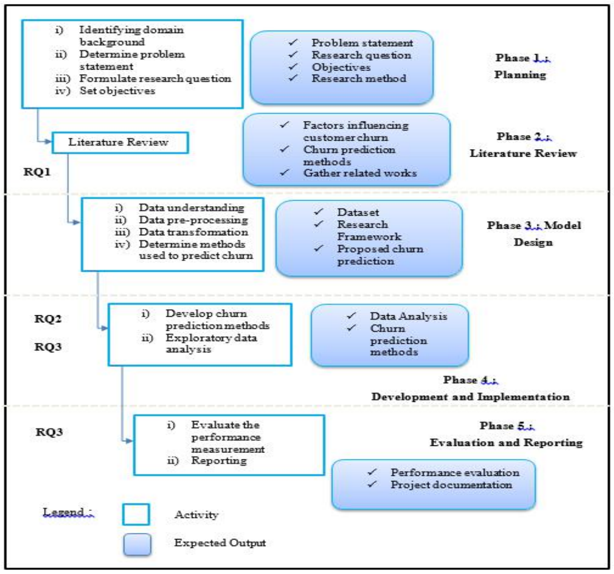

Figure 1. Operational Framework.

4. EXPERIMENTAL SETUP AND IMPLEMENTATION

The experiment run in one single machine to perform the simulation of the churn prediction algorithms and visualize the analysis of customer behavior. The machine is installed with a python software (Python 3.6.5 (Anaconda3 5.2.0)) that enable to run the code of machine learning algorithms and visualization analysis.

The design of churn prediction algorithms in telecommunication industry requires the past customer behaviour during specific period of time to predict the behaviour in the near future. Dataset which is used in this study has been collected from Kaggle open data website. The dataset consists of 7043 records and each record is described by the following 21 attributes as shown in Table 2 below. The attributes includes customer demographic information, billing information, product services and customer relationship variables. The target attribute is the churn where customer is going to churn or not and all the remaining attributes are the predictor variables, which will have some impact to identify the target attribute based on the information obtained by the attribute.

Table 2. Description of attributes.

Attributes	Description
Customer ID	Customer unique identification number
Gender	Whether the customer is a male or female
Senior Citizen	Whether the customer is a senior citizen or not
Partner	Whether the customer has a partner or not
Dependents	Whether the customer has dependents or not
Tenure	Number of months the customer has stayed with the company
Phone Service	Whether the customer has a phone service or not
Multiple Lines	Whether the customer has multiple lines or not
Internet Service	Customer's internet service provider
Online Security	Whether the customer has online security or not
Online Backup	Whether the customer has online backup or not
Device Protection	Whether the customer has device protection or not
Tech Support	Whether the customer has tech support or not
Streaming TV	Whether the customer has streaming TV or not
Streaming Movies	Whether the customer has streaming movies or not
Contract	The contract term of the customer (Monthly, One year, Two year)
Paperless Billing	Whether the customer has paperless billing or not
Payment Method	The customer's payment method
Monthly Charges	The amount charged to the customer monthly
Total Charges	The total amount charged to the customer
Churn	Whether the customer churned or not (Yes or No)

4.1 Data Processing

Pre-processing of the data is an essential activity which will help improving the quality of the data and successively the mining results. The data pre-processing tasks include careful data selection of attributes and samples. Since, the customer churn dataset is a noisy data, some additional data cleaning and transformation are also performed. Output from data processing become a clean data that would make analysis process much easier, fast and efficient. The proposed data processing flow is illustrated in Figure 2 below.

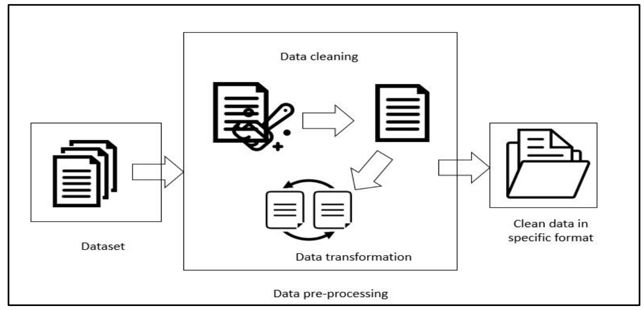

Figure 2. Data processing flow.

4.2 Data Cleaning

The information of data needed based on the objective of investigation and analysis. Some of the information are not important to solve the problem and analysis as well as improve the evaluation performance. The presence of noise, missing values, outliers and invalid values may negatively affect the performance of the machine learning algorithms by using the raw data [6]. The purpose of data cleaning is to remove the missing value and unnecessary attributes that not required in the analysis like Customer ID.Missing value can be identified by using the ".isnull()" function in pandas while function in pandas for dropping the column "drop()". After identifying the null values, it depends on each case study that makes sense to fill the missing valued with mean, median or mode, otherwise there is enough training data drop the entry completely.

4.3 Data Transformation

Data transformation techniques can significantly improve the overall performance of the churn prediction. In this stage, ignore the attributes consisting unique values which represent identity of the sample or descriptive text that serves for informational purposes and does not effect on the models training process. Then, normalize the categorical values such as 'yes' or 'no' into 0 and 1 where each value represents the corresponding category. Transform the values, 0 and 1 into the same range and assign the same labels which applied for the rest of the attributes. This part also known as a dummy variables.

As stated by [10] that dummy variable or indicator variable is an artificial variable created to represent an attribute with two or more distinct categories. Hence, the prediction produces best results when the attributes are normalized and discretized. Based on this case study, using function "data.info" to determine the attributes that are numbers but the dataset in the object format likes Monthly Charges and Total Charges variables. Besides, transform the categorical data into numerical data by using the pandas function "get_dummies()". For instance, transform the gender attributes to numerical data, the attributes will replace with "gender_female" and "gender_male". Variables transformation was conducted for some necessary numerical or categorical variables to reduce the level of skewness, because transformations are helpful to improve the fit of a model to the data.

4.4 Feature Selection

Feature selection widely used in the pre-stage of machine learning which is referred to the process of selecting a subset of relevant attributes of a set of attributes. According to [7]and [11], feature selection has been introduced since 1970's and the implement of research and development shown effectively removing irrelevant and redundant features, reducing time and resources required to train the algorithm, increasing efficient in learning tasks and improving learning performance like predictive accuracy.

4.5 Machine Learning Approaches for Churn Prediction

Machine learning classifiers are used to classify the churn prediction. There are many techniques that have been proposed for customer churn prediction in telecommunication industry. In this study, we will analyze and evaluate three machine learning algorithms : logistic regression, artificial neural network and random forest. Figure 3 below illustrated the flow of machine learning approaches for customer churn prediction.

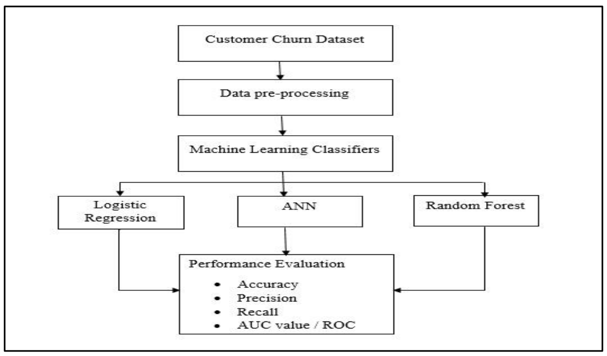

Figure 3 : Machine Learning approaches flow.

4.5.1 Training and Testing Sets

After pre-processing part, the customer churn dataset need to be trained and tested. Function "train_test_split" provided by scikit-learn model selection library to split the dataset into training and testing. X represent the data with independent attributes, while y represent the data with dependent attributes. Commonly researcher divided the dataset by 80 : 20 percent ratio where 80% data was used for training purposed and the remaining 20% data for testing purposed. Otherwise, 75 : 25 and 70 : 30 percent ratio also can be used as a split factor parameter. As stated by [2], the best performance is obtained if the split factor parameter is setting 70 : 30 percent ratio for train and test respectively. Thus, this will avoid reusing the training set for the test and no over-fitting is involved when apply the machine learning classifiers.

4.6 Performance Metrics

The performance of any classification model can be evaluated with the help of accuracy, precision, recall and error rate. To evaluate the performance characteristic confusion matrix model was chosen. A confusion matrix used to identify the efficiency of classification model on a group test data for which the true values are known. From the confusion matrices, the value of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are presented as Table 3 and Table 4 below. Then, applying the value in the equation below for the performance measurement of the model.

Table 3. Confusion Matrix.

Predicted samples			
Actual Samples		True	False
	True	TP	FP
	False	FN	TN

Table 4. Description of Confusion Matrix.

Terminologies	Descriptions
True Positive	Measure the number of instances when the predicted churner is truly a churner.
True Negaive	Measure the number of instances when the predicted non-churner is truly a non-churner.
False Positive	Measure the number of instances when the predicted churner is truly a non-churner.
False Negaive	Measure the number of instances when the predicted non-churner is truly a churner.

The following performance metrics which can be computed from confusion matrix are describes :

Accuracy – the proportion of prediction which are right. Number of all correct predictions divided by the total number of dataset.

$$\text{Accuracy} = TP + TN / N$$

Error rate – the proportion of incorrectly classified examples. Number of all incorrect predictions divided by total number of dataset or can be easily calculated one minus accuracy.

$$\text{Error Rate} = 1 - \text{Accuracy}$$

Precision – the proportion of predictions of the class interest which were right. In case of churn prediction, proportions of customers were model predicted that they should churn and they really churn. Number of correct positive predictions divided by the total number of positive predictions.

$$\text{Precision} = TP / (TP + FP)$$

Recall – the proportion of correctly classified churners. Number of predicted churned customer divided by number of all churned customers.

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

5. Experimental Result And Analysis

In this experiment, the dataset was visualized to identify the features that influencing customer churn in telecommunication industry. Mostly, bar plots and pie charts are used for categorical variables to identify the counts of categories, while histograms used to plot for numeric variables to determine the distribution. Overlapping density plots typically used for comparison between numeric and categorical variables. The dataset contained 73.4% of customers who stayed loyal with the service provider and 26.6% of customers who churned as provided in Figure 4 below.

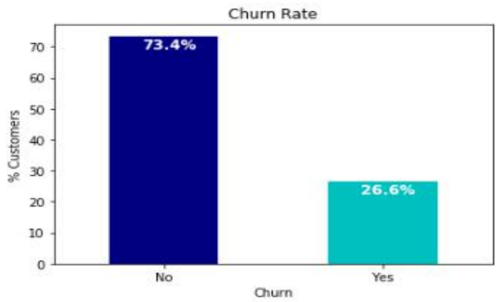

Figure 4. Percentage of Customer in Dataset.

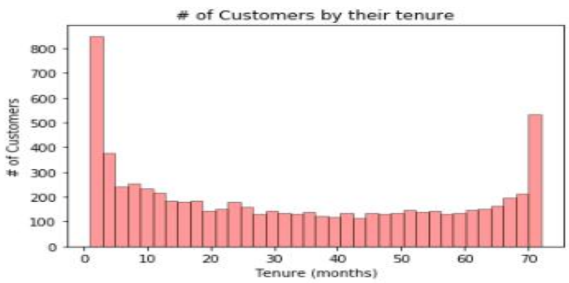

Figure 5. Customer Churn by Tenure.

Based on Figure 5 above, majority customers have been using the service provider for just two months and almost 72 months. This could be potentially because different customer applied different types of contracts which are monthly contract, one year or two year contract. Therefore, based on the contract, customer could be more or less easy to stay or leave the service provider. The tenure based on contracts is illustrated in Figure 6 below.

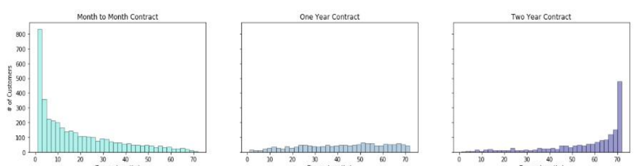

Figure 6. Tenure by Contracts.

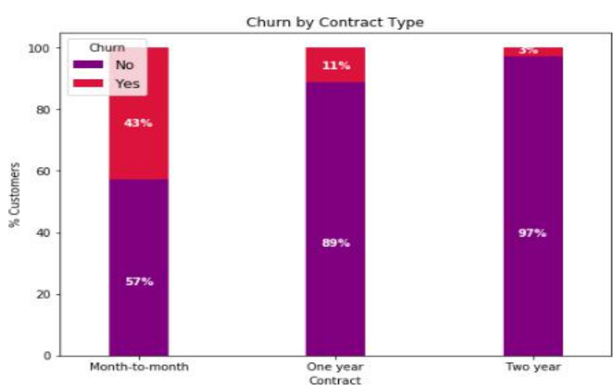

Figure 7. Customer Churn by Contracts.

Figure 7 represents that most of the monthly contract last for two to four months, while two year contract tend to last for about 72 months. This show that the customers applying a longer contract are more patriotic and loyal to the service provider and tend to stick around for a longer period of time. Therefore, Figure (Customer Churn by Contracts) proves that only three percent customers tend to churn when apply two year contract and the rest stay loyal with the service provider compared with the monthly contract that 43% of customer churn. Figure 8 below illustrates the most important features to predict if the customer will leave or stay. The highest features influencing customer churn are total charges, monthly contract and fiber optic Internet service which is up to 50%. Throughout the analysis, fiber optic provides fast internet would makes customer stay, but its list on top of a positive impact on churn. Hence, we need to explore more for better understanding and get some context of data.

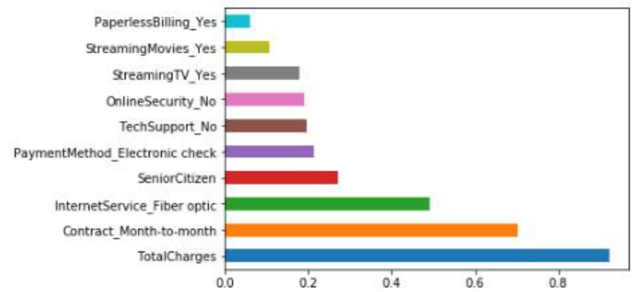

Figure 8. Top 10 important features in churn prediction.

Machine learning algorithms that have been chosen are Logistic Regression, Artificial Neural Network and Random Forest. The dataset was split into 70% training data and 30% testing data. This means that 4922 of the customer churn dataset will be the training data and the remaining 2110 of dataset will be the testing data.

Table 5 shows the parameter of confusion matrices for churn prediction using machine learning algorithms in terms of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The values of TP and TN will affecting the accuracy value, which means the higher values of TP and TN, the highest accuracy of the performance measurement. For instance, value of TP and TN for logistic regression higher will lead to higher value of accuracy. This has been proof as shown in Table 6.

Table 5. Confusion Matrix for Churn Prediction Model.

Classifiers	TP	TN	FP	FN
Logistic Regression	1639	471	0	0
ANN	1512	293	127	178
Random Forest	1648	429	0	33

Table 6 represents the accuracy and AUC value for proposed classifiers before and after applying feature selection recursive feature elimination (RFE). One of the benefits performing feature selection is improved accuracy which fits the model by removing weakest feature and also reduces over fitting data.

Table 6. Comparison with and without RFE.

Classifiers	Without RFE		With RFE	
	Accuracy	AUC	Accuracy	AUC
Logistic Regression	0.8005	0.73	1.000	1.00
ANN	0.8028	0.72	0.8555	0.77
Random Forest	0.7773	0.69	0.9844	0.96

Table 7. Performance Measure for Churn Prediction Model.

Classifiers	Accuracy	Error rate	Class	Prec ision	Recall
Logistic Regression	**1.000**	0.00	Non-churn	1.00	1.00
			churn	1.00	1.00
ANN	0.8555	0.145	Non-churn	0.80	0.92
			churn	0.70	0.62
Random Forest	0.9844	0.0156	Non-churn	1.00	0.99
			churn	1.00	0.93

Table 7 show the churn prediction using logistic regression displays highest accuracy of 100%, followed by random forest classifier with 98.44% accuracy, while ANN classifier has the lowest accuracy of 85.55%. In terms of the computational time needed for training and testing, the performances of the machine learning algorithms are similar, except the logistic regression, which is several times slower than the rest because of its iterative nature. For churn class of logistic regression and random forest model achieve 1.00 precision value, while ANN model achieves 0.70 precision. Precision value shows that how many churned users did logistic regression and random forest classifiers predicted correctly, which is 100% correctly. Moreover, recall value for churn class represent that logistic regression is the highest with 1.00 followed by random forest 0.93 and ANN 0.62. The meaning of recall value shows how many churned user the classifiers missed to predict correctly. As can be seen from the comparison of the algorithms, every classifiers produce good results with high accuracy over 85%. The classifier obtained by logistic regression shows the best results, but the disadvantages is generated the computational time.

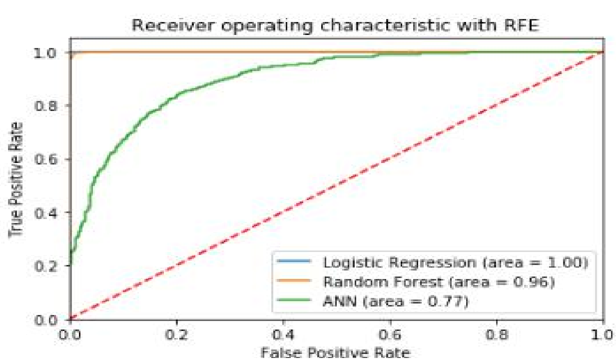

Figure 9. ROC curves for different classifiers.

AUC (area under a ROC curve) has a value in the range between 0 and 1. AUC is an important measure of a model as it presents the probability that the model will rank randomly chosen positive sample higher than a randomly chosen negative sample. In this study , the AUC will randomly choose churn predicted sample rather than non-churn sample. Figure 9 depicts the logistic regression outperforms with AUC of 1.00. ROC curve for logistic regression and random forest display best threshold for separating positive samples into appropriate classes.

6. CONCLUSION

The exploratory data analysis helps the service provider monitor which products service influence customer to churn and they will recommend or promote the best service or plan to retain the customer. The top three of features that influencing customer churn is total charges with 0.9, followed by monthly contract 0.7 and fiber optic internet service is 0.5. Throughout the analysis, fiber optic provides fast internet would makes customer stay, but its list on top of a positive impact on churn. Hence, we need to explore more for better understanding and get some context of data. Based on the experimental result, every classifier produce good results with high accuracy over 85%. The classifier obtained by logistic regression shows the best results, but the disadvantages is generated the computational time.

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