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Full Length Research Paper

Machine Learning Approaches in Banking Industry for Customer Churn Analysis

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Abstract

This study explores the application of machine learning algorithms for customer churn prediction in the banking industry. By comparing supervised learning techniques such as logistic regression, random forests, and decision trees, the study aims to identify the most effective model for enhancing customer retention strategies. The research contributes to the growing field of AI in finance and supports data-driven decision-making in customer relationship management. In this study, decision tree-based classifier J48, Random Forest, and Bagging, were chosen to develop the learning model, with a dataset split into two training and testing sets, as well as with varying k-fold cross validation of parameter adjustment. The model building experiment was conducted on a dataset containing 9978 instances and 11 features collected from the Cooperative Bank of Oromia. To compensate for the influence of class imbalance on performance prediction, synthetic minority oversampling techniques were applied. The proposed method experimentation process is followed by preprocessing, feature selection, modeling, and evaluation. To identify which algorithm works best for customer churn analysis, we have conducted several learning models building experiments. Hence, when the model created using J48 with a 66% percentage split dataset, better results were obtained. The accuracy of the model was 90%, giving it the highest recall and f-measure. As a result, the J48 classifier algorithm is found to be the best to predict customer churn in the banking sector, followed by the Bagging and random forest classifier algorithms, respectively.

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1. Introduction

The term customer churn is often used to express the movement of customers leaving the service of one company in favor of another; in search of greater personal satisfaction (Zhao et al. 2021). It is the biggest challenge for competitive business organizations. Especially in banks, customers close their accounts and stop doing business with the bank due to unknown cases (Haripersad and Sookdeo 2018). The goal of Customer churn analysis is to improve long-term growth and profitability through a better understanding of customer behaviors, providing more effective feedback and improved integration to better gauge the return on investment (Verma 2020).

Bank databases; contain large amounts of customer dataset important to extract and create high-quality customer relationship strategy. Once this dataset is verified, cleaned, integrated, and stored on computers,(Abdi and Abolmakarem 2019), it can be used for market segmentation, targeting, offer development, and customer communication.

However, banking sector faces problems such as functioning in an environment with intense competition in many customer-related areas. Although the number of customers continues to grow, the number of users is decreasing for unknown reasons. Customer churning not only results in lost sales opportunities, but also in a greater need for a strategy to recruit new customers, which is five to six times more expensive than customer retention (Rosa 2019). Therefore, banks are fully returning the face of acquiring new customers to the customer loyalty strategy to avoid customer from churning because the addition of products and lower fees can never solve the customer loyalty problem. Invention machine learning techniques to the availability of sufficient customer dataset in the bank, has created a good opportunity to build better customer satisfaction in competitive business area (Leung and Chung 2020). Hence, customers churn prediction is the common machine learning application in business sectors to develop self-learning model from financial information; such as loan information, credit report, customer history, transaction and geographical data to determine the status of their customers. A retention plan tackles the correct issues and targets the right consumers may be built by acquiring an understanding of who is likely to depart.

Predictive modelling is the development of common properties among dataset in a database and classifies them into different classes, according to a classification model (Khan et al. 2019). The popular predictive algorithms include decision trees, Bayesian classification, neural

networks, k-nearest neighbor classifiers, and genetic algorithms (Khine and Myo 2019). The Machine learning model is based on the analysis of a set of training data and the model may be represented in various forms, such as classification rules, decision trees, mathematical formulae, or neural networks (L and Deepika 2017). Machine learning has been very effective in many business venues, to improve profitability (Rosa 2019). According to Jaeyalakshmi, (2020), the good customer relationship management is the single strongest weapon to ensure that customers become and remain loyal. Hence, we have proposed machine learning approaches to enhance customer relationship management for banks. The proposed method contributes comparison of different machine learning predictive models, which in turns contribute to reduce customer churn. It has been proven that increasing customer retention by 5% can enhance a bank's profit by up to 85% (Amatare and Ojo 2020). Furthermore, recruiting new customers is more expensive for any organization than retaining existing customers, who are more likely to generate more revenue. As a result, banks gain not only higher revenues, but also a competitive advantage over their competitors.

2. Methodology

The research method serves as blueprints for how to structure the process of collecting data, processing data, communicating results, implementing outcomes, and tracking changes. Therefore, we have followed the next framework design for this study.

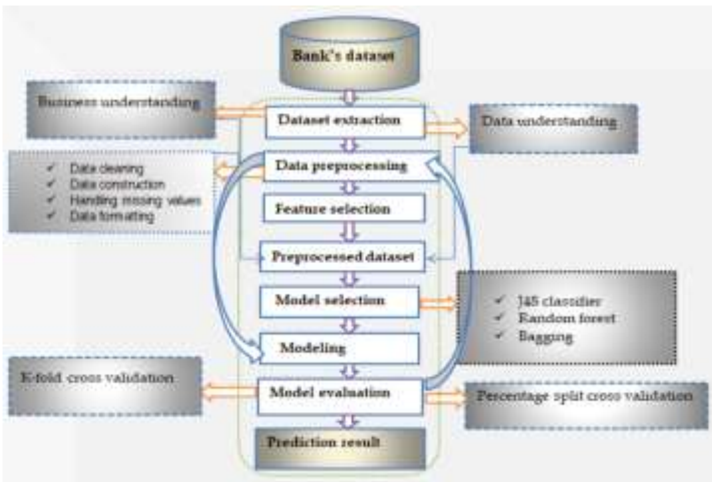

Figure 1:Framework of the study

The Cooperative Bank of Oromia was the target bank from which the dataset was gathered for customer churn analysis. The researcher used to conduct both structured and unstructured interview, the domain expert's interview with managers, data clerks who works for customer relationship management in the banking sectors.

2.1. Dataset Extraction

The data is extracted in two parts. The first section, Customer's account detail, contains information regarding the customer's account that is static. The second component contains the transactional data for the customers who were chosen in the previous part. The data expert extracts three sets of sampled datasets from three separate branches in tab delimited text format, which is then imported to excel (.xlsx) format.

Finally, Customers' names, phone numbers, and other personal information are removed from the data, and the account number is altered in a similar manner to maintain consistency is delivered researcher. Customer account table provides 4708 customers' account information, including customer demographic information and account detail features. The customers' accounts, the day-to-day transactional information is included in customer transaction table. The Customer Accounts table provides data that is largely fixed in nature, as the majority of the characteristics carry information on customers that is not expected to vary over time. Some important attributes in the Customers'Accounts table are elaborated separately as follows: - The "AcctNo (account number) feature," is used to individually identify each customer. The values in this property establish the association between each customer and its transaction in the Customers'Transaction table. As the result, this feature is critical for the further experimentation. The "AcctType (account type)" feature identifies the type of savings account to which the consumer has access. As it's mentioned, the table includes four different sorts of saving account types. In actuality, only private saving accounts (S01) are the subject of this study, and the other account types ("S02", "S03", and "S05") will not be considered for further analysis. Once the "S01" values are chosen, the other "AcctType" property is not important and is erased. The "Accountholder"attribute specifies, whether the customer is an individual "I" or a corporate(C) "C." Because the goal of the study is to predict the churning of individual private saving accounts, the attribute is no longer relevant once the individual consumers are chosen. The "CurrCode (currency code)" field specified the currency type used by the customer, and all of the values are "ETB," so the attribute is no longer required and will be removed because it no longer distinguishes between multiple currencies. The "AcctStatus (account status)" feature, which describes the current status of a particular account holder, is key for churn prediction experimentation. Despite the fact that this characteristic has roughly seven status values, only the two values "ACT" (active accounts) and "CLS" (closed accounts) are to be used in the prediction process as a class value attribute. The "DateAcctOpened" attribute specifies when the account was created or customer subscribed at the bank. This feature is critical and will be used for subsequent analysis since the duration of each customer's relationship with the bank will be derived from these dates. The "DateAcctClosedattribute," values are also listed in the "DateOfStatus" attribute of the associated customers. The parameter "DateOfStatus" specifies the date on which the customer's status and current balance are changed. As in the case of the "DateAcctOpened" attribute, its importance in determining the customer's duration is substantial and is used for further analysis. The "Current Balance" feature, which indicates each customer's balance as of the date of status, is relevant for further analysis.

This customer transaction data contains about 7177 transactional values and attributes. The detail of the customer transactional data are described as follows:- The "AcctNo" attribute corresponds to the corresponding attribute in the Customers'Account table. However, unlike the

1	CustAddress	Gender	Age	cus_duration	AccNo	AveDebAm...	AveCreditA...	totalNoCre...	TotalNoDe...	Currentbal...	CustomerS...
2	Rular reside...	Female	42	1	10015634602	16190	500	1	2	101348.88	Active
3	City resident	Female	41	2	10005647311	608	83807.86	0	1	112542.58	churn
4	Rular reside...	Female	42	3	10005619304	502	159660.8	1	8	113931.57	Active
5	Rular reside...	Female	39	4	10005701354	699	6000	0	1	93826.63	churn
6	Rular reside...	Female	43	5	10005737888	850	125510.82	1	2	79084.1	churn
7	Rular reside...	Male	44	6	10005574012	645	113755.78	1	8	149756.71	Active
8	Rular reside...	Male	50	7	10005592531	822	200	1	7	10062.8	churn
9	City resident	Female	29	8	10005656148	376	115046.74	1	4	119346.88	Active
10	Rular reside...	Female	29	35	15732963	722	0	1	9	142033.07	churn
11	Rular reside...	Female	45	36	10005577657	475	134264.04	1	0	27822.99	Active
12	Rular reside...	Male	31	37	10005597945	490	145260.23	0	3	114066.77	churn
13	Rular reside...	Male	33	38	1005699309	804	78540.6	0	7	98453.45	churn
14	Rular reside...	Male	36	39	10005725737	850	0	1	7	40812.9	churn
15	City resident	Male	41	40	15585768	582	70349.48	0	6	178074.04	churn
16	Rular reside...	Male	40	41	15619360	472	0	1	4	70154.22	churn
17	Rular reside...	Female	51	42	15738148	465	122522.32	0	8	181297.65	Active
18	Rular reside...	Female	61	43	15607946	556	117419.35	1	2	94153.83	churn
19	Rular reside...	Female	49	44	10005577857	834	131394.56	0	2	194365.78	Active
20	Rular reside...	Female	61	45	10005597945	660	155931.11	1	5	158338.39	churn
21	City resident	Female	32	46	1005699309	776	108421.13	1	4	126517.46	churn
22	City resident	Female	27	47	10005725737	829	112045.67	1	9	119708.21	Active
23	City resident	Female	39	48	15771573	657	137843.8	1	9	117622.8	Active
24	City resident	Male	38	49	15766205	550	103391.38	0	2	90878.13	churn

Figure 2:Selected Features of Dataset

Customers'Account table, there are many repetitions of similar account numbers for this property. This is due to the fact that a consumer can transact with the bank multiple times in a given period of time. This attribute's primary purpose is to establish integrity with the Customers'Account table, and it will be used in the next steps in the dataset preparation process. The "AcctType" and "account holder" attributes are simply equivalents for their corresponding attributes in the Customers'Account table. The "DateOfTxn" feature, which specifies the dates the consumer transacts with the bank, is critical for dataset preparation. Its primary purpose is to determine the number of transactions that occurred during certain months. The "Transaction Type" feature is critical since it indicates the type of transaction a customer had (debit or credit) in each transaction. This attribute will be utilized for further analysis to tally the number of debited and credited transactions made by each customer during a certain period. The attributes "DrLocalAmt" and "CrLocalAmt" specify the amount debited or credited in each transaction.

2.2.Data Preprocessing

As the result of this phase, several data processing steps such as data cleaning, construction, integration, data formatting and feature selection has done for making the data appropriate for the intended model experimentation.

2.2.1. Missing Value Handling

Generally, the customer transaction table consists of 278 missing values whereas the Customer account table consists of 124 values, total 386 missed feature values in this dataset has replaced with mean for numeric dataset and mode of categorical dataset.

2.2.2. Dataset Integration

The dataset from, two tables are merged through the use Microsoft excel and Microsoft access using account number as a unique Identity in between them for ease of processing. Once, the tables are merged and become a single table, it is exported back as Microsoft excel document for further processing until the final dataset is produced. As a result of the merged table, the total combined dataset includes 11,469 instances with 11 features.

2.2.3. Redundancy Reduction

Since the redundant dataset leads to poor quality results, we have conducted a redundancy check test and found 1495 duplicated values, and have been removed with machine learning tools. The final preprocessed, formatted total dataset consists of 11 features with 9974 instances selected for further experimentation.

2.2.4. Feature Selection

Certain features in the acquired data are irrelevant for predicting churners and only the relevant features are selected with domain expert consult and weka information gain ratio for the purposes of this study. The transaction in a month in which the consumer subscribed will not be considered in order to avoid incomplete monthly transactions. As a result, an attribute, the total of the three month debited amount and the three-month credited amount must be calculated. In addition to the aforementioned attributes, a few derived attributes are included, including customer duration, which is derived from the date the account was opened and the status date, and Account Status attributes, whether ACTIVE or CHURN used as a class label. Total number of debit transaction of three months calculated from number of debit transaction of each month. The majorities of the attribute names are derived and may not exist directly in the original dataset, but are to be organized with domain expert consultation.

2.3. Model Selection

The development of appropriate model includes selection of appropriate modeling technique, generating test design and model building experiment. To this end, we have specifically used decision tree machine learning algorithms namely J48, Random Forest and Bagging. Since decision Tree provides more accurate and interpretable models with relatively little human intervention.

Similarly, the approach is fast, both in terms of build time and in terms of application time. we have chosen the Weikaito environment for knowledge analysis (weka) which is free software application, run on any current computing platform. It includes a complete set of data preprocessing, modeling methods, the most frequently used data mining tools and is simple to use in research.

2.4.Model Evaluation

The most commonly used decision tree classifier model evaluations method namely; precision, recall, accuracy and f-measures are employed to evaluate the churn prediction model. The equation is given as follows:

Recall: is an access of correctly classified instances as correct.

Recall = TP/(FP+FN) (equation 1)

Precision: is the percentage of positive tuples that are genuinely positive.

Precision= TP/(TP+FP) (equation 2)

Accuracy: the ratio of successfully categorized tuples to the total number of occurrences.

Accuracy = (TP+TN)/(FP+FN+TP+TN) (equation 3)

F-measure: is often calculated as the average value of recall and precision.

F-measure = (2*precision*recall)/(precision + recall) (equation 4)

Where, FN stands for False Negative; FP is for False Positive, TP stands for True Positive, and TN is True Negative. As a result of predictive model selection criteria, the model with highest accuracy is selected based on f-measure which is known as harmonic mean of accuracy and precision is used to select best model. The next section deals on modeling experiments.

3. Model Building

Datasets been divided into two partitions and referred to as training sets, which aid in learning, and cross-test datasets, referred to as test sets with percentage splits and cross validation, can be used for testing purpose. Hence, the dataset is systematically divided into three training sets with its corresponding test sets. The reasoning behind choosing three trials (66%,70%,75% and k=5, k=10and k=15) training set, corresponding test set for each technique is to handle model construction for the default value, varied number of folds of cross validation, and parameter setting procedures.

3.1. Experiment Procedures

In the first experiment, learning models are constructed utilizing distinct training sets for the different percentage split for validation of each modeling technique. As a result, the three models constructed with training sets (66 percent, 70 percent, and 75 percent) are employed, each with its own test set. In the second phase, learning models were built for various cross-validation test options (K = 5, K = 10, and K = 15) using preprocessed datasets. For each learning model built in both experiments, the first and second phase, the recall, precision, and f-measures are registered separately. Then, the better models are selected for the next evaluation step after comparison. Thirdly, considering the model that was selected as the best result from two experiments, attempts to enhance the predictive performance of the model are made by changing the values of the different parameters of the algorithm. After all the possible attempts have been made, the model with the best result is considered, the best model of the specific modeling technique being used and assessed on the corresponding test set.

Experiment 1

Experiment 1:1 Modelling with bagging algorithm using percentage split dataset.

In this experiment three learning models were built using training set (66%, 70% and 75%) and 34%, 30% and 25% test set when all attributes are used. The result of accuracy, precision and f-measure are recorded in the table 1. Hence, the model built with a 75% training set outperforms the others, with 8473 (84.7%) instances correctly classified and 1528 (15.3%) instances incorrectly classified, with precision, recall, and f-measure of 83.5%, 84.7%, and 83.10%, respectively.

Experiment 1. 2: Model buildings with k-fold cross validation:

Three distinct learning models are developed by modifying different parameters of k-folds. The precision, recall, and f-measure results are stated in the table 1. From the three learning models, the model built in experiment k = 15 outperform others in better precision, recall, and f-measure. The model shows a better result with the number of correctly classified instances being 8491 (84.91%) while 1509 (15.09%) instances are incorrectly classified with 83.7%, 84.9%, and 83.6% of precision, recall, and f-measure respectively. Considering, the better result recorded in the above two experiments, the parameters of the bagging algorithm is changed. However, no positive change is obtained by changing all values. Thus, result of experiment 1.2 is better; it's taken as the best model for bagging of the both experiments.

Experiment 2

Experiment 2.1: Model building with J48 algorithm, percentage split dataset.

Three learning models were generated for three training sets of 66%, 70%, and 75%, as well as a cross validation test set, using the same technique as the previous experiment 1. The following table depicts the recall, precision, and f-measure results. Three learning models were generated for three training sets of and 66%, 70%, 75%, and respective test set. However, the model built with 75% training and corresponding test set has performed better result as depicted in table 7 with 90% recall, 91.3 % precision, and 90% f-measure.

Experiment 2.2: Model buildings with k-fold cross validation

In this experiment, after varying the number of k -folds parameters (k=5, k=10, k=15), the same approach as before is followed, and three models are created. Hence, f-measure for both model of k = 15 perform the same better recall and

precision and outperform all three models. For better result obtained from above experiment accuracy measured is recorded as 8547(85.47%) instances are correctly classified whereas 1453(14.53%) instances are incorrectly classified so that precision and recall is 85.7%, 86.9% respectively with f-measure 85.6%. In general, the predicting performance of the better model in experiment 2.2 is better than the performance of the better model in experiment 2.1.

Consequently, it is accepted as the better result of experiment 2 for further evaluation. Hence, the default values of the parameters in the J48 algorithm are changed, and the improvement in the prediction accuracy of the better results of the first two experiments is checked. Only the ridge parameter shows a difference in the prediction accuracy while its value is changed. But no positive change is observed yet. Therefore, the better result of experiment 1 is selected since it has better accuracy.

the other two previous algorithms, the Random Forest model built by using the 66% achieves the better performance. In this case 8,078 instances are correctly classified and 1,896 instances are classified incorrectly.

Table 1: Model comparison

Algorithms	Evaluation criteria	Parameters	Precision	Recall	F-measure
Bagging	Percentage	66%	83.3%	84.5%	82.8%
		70%	83%	84.3%	82.9%
		75%	83.5%	84.7%	83.1%
	k-folds cross validation	K= 5	83.4%	84.7%	83.3%
		K=10	83.3%	84.6%	83.3%
		K=15	83.7%	84.9%	83.6%
J48	Percentage	66%	93%	92.5%	92.5%
		70%	88.6%	88.6%	88.5%
		75%	91.3%	90%	90%
	k-folds cross validation	K= 5	74.9%	75.8%	75.7%
		K=10	83.3%	84.6%	83.3%
		K=15	85.7 %	84.9%	85.6%
Random forest	Percentage	66%	80.7%	81.5%	81.2%
		70%	79.4%	80.4%	79.8%
		75%	79.5%	80.5%	80.5%
	k-folds cross validation	K= 5	70.7	69.3	68.8
		K=10	70.8%	69.5%	69%
		K=15	70.7%	69.3%	68.8%

Experiment 3

Experiment 3.1- Model building with Random Forest by percentage split

Following the same procedure of previous experiment, again three model built from different training set by using percentage split data partition as default 66%, 70% and 75% training set applied. The result of precision, recall and f-measure is shown in table 1. In this experiment, better results are obtained when the training set 66% are applied as the same case of

Experiment 3.2: Model building with k-fold

As an experienced, throughout the changing the number of k-folds (k=5, k=10, k=15) three different models were built following the same procedure. The model built using, k=15 provide better result compared to other k-folds. Hence, 7963 instances are correctly classified and 2037 are incorrectly classified. The performance of model built in experiment 3.1, using 66%

training set is better than the performance of model built in both experiments with adjustment of parameters of k-folds and when used with all attribute. Since the result of experiment 3:1 is better than result of the experiment 3-2, it is selected for further comparison evaluation as representative model built with Random Forest algorithm. The general experiment result is summarized in table 1.
The aforementioned criteria for comparing model is its' recall, precision and f-measure as criteria. However, based on the evaluation criteria the highest recall is selected and the model must result higher f-measure which is harmonic mean of both precision and recall. Hence, J48 has outperformed the proposed three learning models with f-measure 92.5%.

4. Findings and Discussion

To identify which of the proposed learning algorithm works best for customer churn analysis, we have conducted several learning models building experiments. Consequently, the model built in with J48 classifier algorithm at 66% percentage split outperformed the other and it is the best performance of all three algorithms. The model could be able to achieve 93%, 92.5% and 92.5% precision, recall and f-measure respectively. Whereas bagging achieved the second better performance with 83.7%,84.9% and 83.6% precision, recall and f-measure respectively. While Random Forest result in 80.7%, 81.5% and 81.2% precision, recall and f-measure severally and ranked the third. As the result, the J48 classifier algorithm is found to be the best to predict the customer churn in banking sector followed by the Bagging and random forest respectively. The following rules are extracted from the pruned tree of the best J48 model.

Rule 1: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 39043.29 and AveDebAmount <= 776: churn

Rule 2: Cus_duration < = 307 and Age < = 35 AveCreditAmount < = 39043.29 and AveDebAmount > 776: Active

Rule 3: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn < = 0 and Gender = Female: Active

Rule 4: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn <= 0 and Gender = Male: churn

Rule 5: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn > 0 and CuStAddress = Rular resident and Gender = Female and AveCreditAmount < = 51962.91: Active

Rule 6: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn > 0 and CuStAddress = Rural resident and Gender = Female and AveCreditAmount and A > 51962.91: churn

Rule 7: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn > 0 and CuStAddress = Rural resident and Gender= Male: Active

Rule 8: Cus_duration < = 307 and Age < = 35 and AveCreditAmount < = 139875.2and totalNoCreditTXn > 0 and CuStAddress= City resident: Active

Rule 9: Cus_duration < = 307 and Age <= 35 and AveCreditAmount > 139875.2 and TotalNoDebTXN < = 8: churn

Rule-10: Cus_duration < = 307 and Age < = 35 and AveCreditAmount > 139875.2 and TotalNoDebTXN > 8: Active Rule-11: Cus_duration < = 307 and Age > 35 and Currentbalance < = 14917.09: Active

Rule-12: Cus_duration < = 307 and Age > 35 and Currentbalance > 14917.09: churn Rule-13: Cus_duration < = 307 Age > 38:

Active Rule1-14: - Cus_duration > 307: churn

The model has generated total 14 valid rules which indicate either the customer is churning customer or loyal based on customer history and transaction record. The six rule identifies the churning customer while the rest indicates active classes based on training dataset. According to the result from the customer history, customers are more active at the beginning of first three month (> =307 days) but, as duration increase (>=307 they needs to change banks for unknown reasons. But, customer with the same duration (<=307days) with bank, the age blow 35 and similar average credit amount is only churning if they are reducing their average debit amount in three months to 776 or less. Unless the male customer churning indicator from this data is when number of total credit transaction reduced to zero.

Moreover, this could be true for female customer living rural areas of the country. Even with average credit amount greater than to fifty thousand. But the entire customer aged less than 38 years, with current balance greater than approximately fifteen and customer duration greater than 307 days are churning customers. This is because the account left without operation in three to six month goes to inactive state. Generally, customer address, duration with banks, age, balance, credit transaction, debit transactions are the major indicator for churning customer in banking sector.

5. CONCLUSION

In this study, an attempt has made to address the issue of customer churn prediction using the customer data stored in the bank database. To conduct the study, a sampled dataset containing Account Number, Average Debit Amount, Average Credit Amount, Total Number of Credit Transaction, Total Number of Debit Transaction, Current Balance, and Customer Status, as well as demographic information such as Customer Address, Gender, Age, and Customer Duration, was collected from the Cooperative Bank of Oromia. Decision tree classifiers, J48, Random Forest, and Bagging, are chosen to develop a model for predicting customer churn.

To identify which algorithm works best for customer churn analysis, we have conducted different models building experiments. Hence, the J48 classifier algorithm is found to be the best to predict the customer churn in banking sector. In addition to its highest result in predicting the customer churners, the J48 modeling technique is the easiest to understand for individuals who are not domain experts. This is because the outcomes of the models in J48 are given in a form of a tree that anyone can simply extract rules out of it. Hereafter, 90% of the total churning customer has predicted correctly as overall performance of the model. The business objective of cooperative bank of Oromia is to reduce churning customers by 85% improve customer relationship management. Hence, about 5% of additional churners are predicted as a contingency for the next churn management steps. Therefore, the J48 algorithm has a reasonable potential for deployment in banks for customer churn analysis and management.

6. Recommendation

We strongly encourage banks to consider machine learning algorithms in customer relationship management since they will gain from doing so, particularly as J48 has the ability to support customer prediction based on customer history and traction. As a result, we discovered a very promising result using the J48 classifier algorithm; nevertheless, future researchers must conduct their research using important features in addition to our features, such as credit card, Mobile banking, and ATM transactions.

Author contributions

Drafting, Conceptualization and methodology were carried out by Enshishu Tsegaye and Shume Berhanu. The Original draft writing and subsequent editing were also performed by

Enshishu Tsegaye and Shume Berhanu. All authors have reviewed and approved the final version of the manuscript for publication.

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